Tampere University

JUHA PANULA-ONTTO

Probabilistic Logics in Foresight

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ACADEMIC DISSERTATION
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ABSTRACT

A prudent decision-maker facing a complicated strategic decision considers the factors relevant to the decision, gathers information about the identified factors, and attempts to formulate the best course of action based on the available information. Careful consideration of any alternative course of action might reveal that in addition to the desirable intended consequences, a number of less desirable outcomes are likely to follow as well. Facing a complicatedly entangled net of considerations, entwined positive and negative outcomes, and uncertainty, the decision-maker will attempt to organize the available information and make the decision by using some strategy of reasoning on the information.

A logic is a way of reasoning adherent to rules, based on structured knowledge. A *modeling language* and *inference rules* comprise a logic. The language of a logic is formal, consisting of a defined set of building blocks having well defined meanings. The decision-maker can use a modeling language to describe the information pertinent to the decision-making problem, and organize the information by giving it a structure, which specifies the relationships between the individual considerations. While reasoning about the extensive amount of information in its disorganized form may be overwhelming, in a structured form the information becomes much more useful for the decision-maker, as now it can be analyzed in a systematic fashion. Inference is systematic reasoning about structured information. As the information is described in a formal and structured way and the process of reasoning about it is systematic, the inference may be *automated*. Computational inference permits reasoning that would not be possible by intuition in cases where the amount of considerations and their interdependencies exceeds human cognitive capacity. The decision-maker may direct the efforts to describing the decision factors and knowledge with the formal language, with a narrower and more manageable frame of attention, and perform the inference with a computer.

Probabilistic language gives room for *haziness* in knowledge description, and is

thus suitable for describing knowledge originating from humans, conveyed to the decision-maker in a non-formal format, such as viewpoints and opinions. Many domains of decision-making and planning use human sourced knowledge, especially if the informants are knowledgeable people or *experts* with relevant, developed understanding on the domain issues. The expert views can augment the knowledge bases in cases where other forms of information, such as empirical or statistical data, are lacking or completely absent, or do not capture or represent considerations important for the decision-making. This is a *typical* setting for strategic decision-making, long range planning, and foresight, which have to account for developments and phenomena that do not yet exist in the form they might in the future, or at all.

This work discusses approaches for decision support and foresight oriented modeling of expert knowledge bases and inference based on such knowledge bases. Two novel approaches developed by the author are presented and positioned against previous work on cross-impact analysis, structural and morphological analysis, and Bayesian networks. The proposed approaches are called EXIT and AXIOM. EXIT is a conceptually simple approach for structural analysis, based on a previously unutilized computational process for discovery of higher-order influences in a structural model. The analytical output is, in relation to comparable approaches, easier to interpret considering the causal information content of the structural model. AXIOM is a versatile probabilistic logic, combining ideas of structural analysis, morphological analysis, cross-impact analysis and Bayesian belief networks. It provides outputs comparable to Bayesian networks, but has higher fitness for full model parameterization through expert elicitation. A guiding idea of the methodological development work has been that the slightly aged toolset of cross-impact analysis can be updated, improved and extended, and brought to be more interoperable with the Bayesian approach.

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ABBREVIATIONS

ADVIAN	Advanced Impact Analysis
AXIOM	Advanced Cross-Impact Option Method
BASICS	Battelle Columbus Division cross-impact approach
BBN	Bayesian belief network
CIB	Cross-Impact Balances technique
DEMATEL	Decision Making Trial and Evaluation Laboratory
e.g.	for example, from Latin *exempli gratia*
et al.	and others, from Latin *et alii*
EXIT	Express Cross-Impact Technique
FAR	Field Anomaly Relaxation
FCM	Fuzzy Cognitive Map
GHCIA	Gordon-Hayward cross-impact technique
GMA	General Morphological Analysis
ID	Influence Diagram
MICMAC	Matrice d' Impacts Croisés Multiplication Appliquée au Classement, matrix multiplication method for classification and analysis
SMIC	Système et Matrice d' Impacts Croisés, Cross Impact Systems and Matrices

ORIGINAL PUBLICATIONS

Publication I	J. Panula-Ontto, S. Kuikka and A. Lehikoinen. Probabilistic Reasoning in Foresight: Aims and Approaches. *Technological Forecasting and Social Change* (2018). Submitted to journal 12.11.2018.
Publication II	J. Panula-Ontto. AXIOM Approach for Modeling and Analysis of Complex Systems. *Proceedings of the conference "Futures of A Complex World"*. Ed. by R.Saarimaa and M.Wilenius. 2018, 72–90. ISBN: 978-952-249-499-3.
Publication III	J. Panula-Ontto. The AXIOM Approach for Probabilistic and Causal Modeling with Expert Elicited Inputs. *Technological Forecasting and Social Change* 138 (2018). DOI: `10.1016/J.TECHFORE.2018.10.006`.
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1 INTRODUCTION

When faced with a decision-making problem, a prudent person considers the factors relevant to the decision, gathers information about the identified factors, and attempts to formulate the best course of action based on the available information. If the decision contemplated is important, and time is available for intelligence gathering on the relevant considerations, a significant amount of background information may be collected to serve the decision-making. Single pieces of information may lend support to one alternative decision, others might sanction an opposite course of action. Careful consideration of any alternative might reveal that in addition to the desirable intended consequences, a number of less desirable outcomes are likely to follow as well. Facing a complicatedly entangled net of considerations, positive and negative outcomes, and uncertainty, the decision-maker will attempt to *organize* the available information and make the decision by using some *strategy of reasoning* on the information. A *logic* is a way of reasoning adherent to rules, based on structured knowledge.

A *modeling language* and *inference rules* comprise a logic. The language of a logic is *formal*, meaning that it consists of a defined set of building blocks having well defined meanings with little ambiguity. The decision-maker can use such a language to describe the information pertinent to the decision-making problem, and organize the information by giving it a structure, which specifies what kind of relationships exist between the individual considerations. While reasoning about the extensive amount of information in its disorganized form may be overwhelming, in its structured form the information becomes much more useful for the decision-maker, as it can now be analyzed in a more systematic fashion.

Systematic reasoning about structured information is called *inference*. Inference is said to "produce statements about the unknown on the basis of the known" [54]. As the information is described in a formal way and the process of reasoning about it is systematic, the inference may be *automated*. Computational inference permits reasoning that would not be possible by intuition, as the amount of considerations and their interdependencies exceeds human cognitive capacity. The decision-maker may direct the efforts into describing the considerations and knowledge with the formal language, with a narrower and more manageable focus: the computationally complex inference is delegated to a computer.

The information relevant to decision-making and described in the modeling language involves uncertainty. The uncertainty concerns both the description of the information and the information itself. Facts relevant to decision-making are often uncertain, and the way the information about the relationships of these facts is described may be incomplete, not fully describing every possible detail, case and exception, as such description might be both unfeasible to create and impractical to use. Describing knowledge in a *language of probability* can give consideration to both types of uncertainty [104]. A probabilistic language gives room for ambiguity and haziness in knowledge description, and is thus suitable for describing knowledge originating from humans, conveyed to the decision-maker in a non-formal format, such as viewpoints and opinions.

Many domains of decision-making and planning can benefit from being able to use human informant sourced knowledge, especially if the informants are knowledgeable people or *experts* with relevant, developed understanding on the domain issues. The expert views can augment the knowledge bases in cases where other forms of information, such as empirical or statistical data, are lacking or completely absent, or do not capture or represent considerations important for the decision-making. This is a *typical* setting for strategic decision-making, long range planning, and foresight, which have to account for developments and phenomena that do not yet exist in the form they might in the future, or at all.

Bayesian belief networks are an established approach for description of knowledge bases in a probabilistic and causal way and providing a systematic way for reasoning with the knowledge. While Bayesian belief networks are successfully used in a host of decision support and planning applications [39, 55, 78, 132], the approach has features that may limit its usability in cases where expert informants are the primary or sole information source and the decision-making context is foresight-oriented. The field of foresight has produced methodological proposals which pre-date the Bayesian network approach, and are more heuristic in nature, having advantages, as well as significant disadvantages, over Bayesian networks in the foresight niche.

This work presents two novel modeling approaches contributing to the field of expert informant oriented systems modeling and foresight-oriented decision support. The approaches are developed by the author, building on the previous work on cross-impact analysis, structural and morphological analysis, and Bayesian networks. A guiding idea has been that the slightly aged toolset of cross-impact analysis can be updated, improved and extended, and brought to be interoperable with the Bayesian approach. The proposed approaches are called AXIOM [93, 98, 99] and EXIT [100, 101]. The thesis discusses a number of conceptually and functionally related approaches, positioning AXIOM and EXIT to the state of the art. The included publications detail the approaches and illustrate their use in modeling, systems analysis and decision support use.

2 CONCEPTUAL FRAMEWORK

2.1 Systems thinking, modeling and simulation

This work is about tooling for systems modeling. Therefore it is appropriate to start by asking what is a system. The Merriam-Webster dictionary [87] tells us that in its most generalized sense, a system is understood to be “a regularly interacting or interdependent group of items forming a unified whole” such as “a group of interacting bodies under the influence of related forces”. This definition underlines the standing relationship of the items that form the system. Another widely restated definition for a system is given by the [58], in the form “A system is a collection of elements that together produce results not obtainable by the elements alone”. This alludes to the *synergy* or *emergent properties* such a collection, when *set up as a system and working together*, is thought to have, resulting from the interaction of the elements.

Various real world phenomena can be abstracted and conceptualized by applying systems thinking for the purpose of viewing them as a system. A business process of a company can be viewed as a system, comprised of the products, personnel and other assets, clients or customers, as well as the market competitors. The technical infrastructure, made up by computers and other technical assets the company uses, forms a technical system, which can be thought to be a *subsystem* in the larger business process system. The company operates in a larger context of society, legal framework of the country it operates in, and the natural environment, which too are systems by their own right and in which the company, as a system, exists as a subsystem. From the perspective of the company in question, better understanding of these systems, which exist within the company or the company exists within or interfaces with, is useful in making better decisions, improving its business processes, and strategy formulation for the eventuality that the larger *supersystem* of the company’s operating environment changes or realigns.

Figure 2.1 presents a *conceptual model* of China’s electricity sector, outlining the

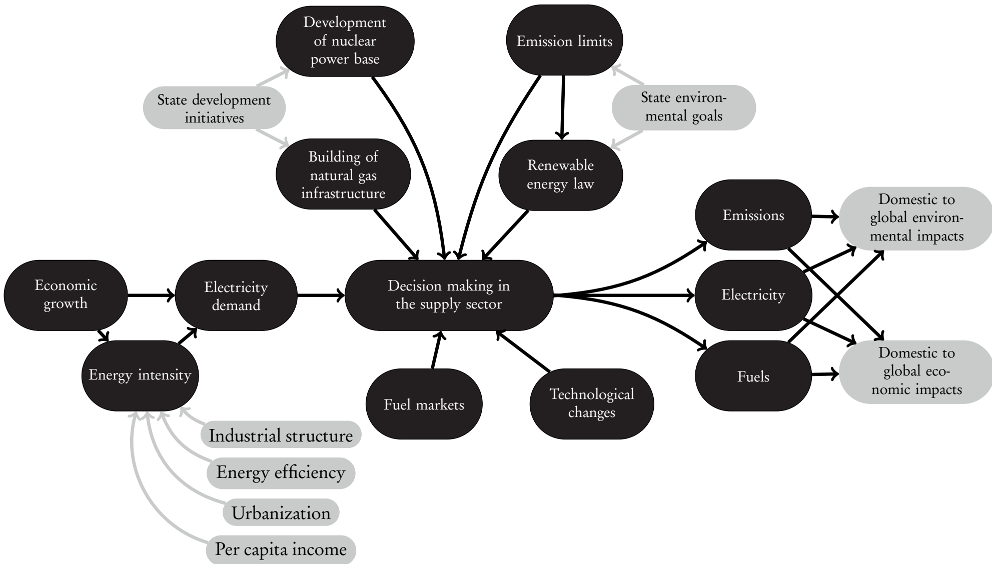


Figure 2.1 A *conceptual model* of the development of China's electricity sector. Adapted from Steenhof and Fulton [120].

important drivers and considerations influencing the development of the electricity sector and mapping the general dependencies these forces have on each other, in an *informal* way. This type of informal model of an electricity system is undoubtedly useful for understanding the important, pivotal elements of the system. Its use is nevertheless limited to assisting in forming a conceptual-level overview of the system components and their relationships. A conceptual model can be a starting point of a more *formal* description of the system, where the elements and their relationships are described in more detail and higher formality, enabling a higher level of analytic scrutiny of the description of the system.

Figure 2.2 presents a *cognitive map* [122] depicting the causal influences related to cocaine availability in the United States. This model has more information and a higher level of formality than the conceptual model of the Chinese electricity system presented in Figure 2.1. It describes the forces influencing or driving illegal cocaine availability in the United States market, using a graphical representation of the cocaine market, outlined as a system. The graph nodes represent the perceived elements of this system and the arcs or *graph edges* represents causal influences the system elements have on the *analytical focal point*, drug availability, and on each other. The arcs are directed, indicating which elements are thought to be *causes* and

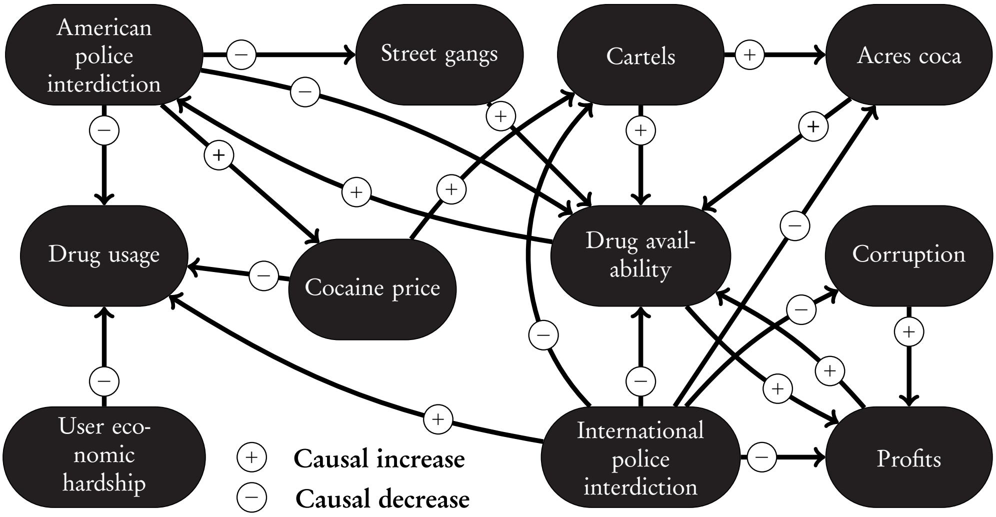


Figure 2.2 A *cognitive map* depicting the promoting and obstructing causal influences driving cocaine availability in the US market. Adapted from Taber [122].

which are *effects* in the causal relationships. The arcs additionally specify whether the causal influence is promoting or obstructing the effect.

System description of this degree of formality can already be used [8] for *formal inference* based on the available information. The number of causal links from a node to other nodes (or in graphical terms, the *outdegree*) reflects, to some extent, the *system-level influence* an element has. The number of incoming causal links (or *indegree*) in turn reflects the systemic *dependence*, the degree to which the system element is dependent on other factors.

The systemic relationship between two elements, that is, the causal influence an element has on another not only directly, but also indirectly, through causal influences routed through or *mediated* by intermediary elements, could be assessed by analyzing the causal paths connecting the elements extant in the system. Whether an indirect causal path influences the 'effect' element in a promoting or an obstructing way can be determined by counting the number of negative links in this path: an odd number of negative links means that the causal influence through this path is obstructing; an even number means that the influence is promoting. The reasoning behind this is that a negative causal link will reverse the direction of the influence, but another negative causal link in the causal chain will reverse the direction again. This is further illustrated in Figure 4.1 on page 68.

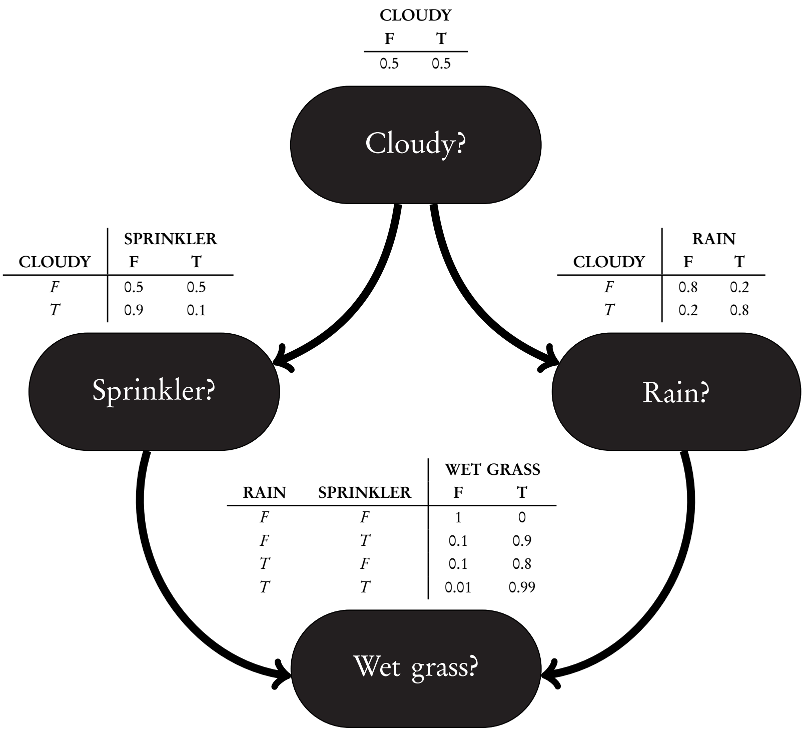


Figure 2.3 A *Bayesian network* model composed of four descriptor variables, and their *probabilistic causal* relationships described with node-specific conditional probability tables.

Finally, all the possible causal paths in the system could be discovered, the nature of their impact reasoned and the balance of the total impact assessed by counting the obstructing and promoting influences. The picture formed of the total impacts between any cause element and effect element would be somewhat hazy, as the system description contains no information about the magnitudes of the impacts, meaning that there is no way to relate them to each other in terms of significance. Developing this causal model further, some additional information about the impact magnitudes would enable a more detailed analysis and a more justified process of inference about the causal structure of the system.

Figure 2.3 displays a simple system of forces and elements influencing a *lawn*, the analytical focal point being whether or not the grass of the lawn is wet. The system is represented by a Bayesian network. The network is a graph, where the nodes are *system descriptors*, carrying information about the possible *states* the system elements influencing wetness of grass directly (sprinkler or rain) or indirectly (cloudy sky) can be in. The statement that sky is cloudy can be true or false; Sprinkler can be on (true) or off (false); and rain can occur (true) or not occur (false).

The graph edges represent causal relationships the system elements have: wetness of the grass *depends* on the state of the sprinkler and rain, both of which in turn depend on the cloudiness of weather. The state of the sprinkler and whether it is raining or not are related to the cloudiness of the sky in a *probabilistic* way: in conditions of cloudy weather, the probability of rain is 0.8, whereas in non-cloudy conditions the probability for rain is only 0.2. This can be read from the conditional probability table positioned above the 'Rain?' node in Figure 2.3. Weather turning cloudy from non-cloudy also decreases the probability of sprinkler being on from 0.5 to 0.1.

These forces in the system influence the state of grass (wet or non-wet) directly, as is the case with rain and sprinkler, or indirectly, as the weather does. Given a piece of information about the state of one of the system elements, or possibly several elements, updated probabilities of the states of uncertain elements, capturing the improved situational awareness or knowledge about the system, can be inferred using *Bayesian inference* [63, 64]. A Bayesian network specifies the causal relationships of the system in terms of conditional probabilities in a very specific and detailed way, and analytically can deliver more versatile and justified outputs than the cognitive map shown in Figure 2.2. Creating a Bayesian network representation of a system requires that the conditional probabilities of the system states can be observed from the real system or estimated in some other way. Compared to a conceptual model or a cognitive map discussed earlier, the additional information required for the definition of a Bayesian network means that it is a more costly way to represent a system, measured as the work required to arrive at such a representation.

As these three examples of system representations illustrate, the study of any system must involve identifying the parts of the system, and understanding what results from the interaction of the system parts. Identification of the relevant parts must be based on an idea of the system, which exists before its parts are identified. This idea of a system is related to what the synergy or emergent properties produced by the system parts working in co-operation are: what the system does. System is the explanation of its outcome: System is expressed by its functioning. The idea of what the system does and what is its function or purpose is the starting point in outlining a representation of a real world object or phenomenon as a system. The perceived function of the system governs how the system as a *complex whole* is outlined, divided into elements, and how it is delineated from its environment and other systems.

Systems thinking, when it is successful in organizing real world complexity into conceptual abstractions, can lead to system *models*. A system model is a representation of a system, depicting the system at some level of abstraction or possibly multiple levels of abstraction [118, p. 5]. The system representations of Figures 2.1, 2.2 and 2.3 are all models of varying levels of formality. A model is an attempt to capture the essential parts of the 'real' system and the way they are connected from the perspective of the perceived function of the entire system. What is seen as essential depends on the perspective and the information needs of the modeling endeavor. Models come in varying degrees of formality: some models might simply be a list of system components or aspects that are thought to be involved in and relevant to the functioning of the system, but models can also strive to represent the system "in a mathematically reliable fashion" [118]. Differences in level of formality of models and their information content determine how the model can be analytically used to understand the systems they depict. If a model is a purely conceptual model, itemizing the relevant components of a system and outlining the structure of their relationships in an informal way, the model can deliver a quick conceptual reference, an overview of the parts of the system assumed important, and perhaps a common vocabulary for the people using it to understand the system. A more formal model with more logical and perhaps quantified information about the system components and their relationships might be used to compute some derived information about the model. This information, depending on the information contents and the details of the computational inference, reflects in some way the emergent characteristics of the modeled system.

Kelly et al. [69] identify 5 uses for models:

Developing system understanding resulting from summarizing and integrating available knowledge into the model, as well as deriving observations from the model and its outputs without a specific prediction, forecasting or decision support objective. Models mainly aiming at better understanding of the system they represent can often also include components whose functioning, operating logic and relationships to other components are less certain or not fully understood, with the aim of enabling testing various assumptions about the system and its rules.

Prediction or projecting a value for a single system characteristic based on a known configuration of the system with regard to other characteristics. Predictive models may often be structurally simple, as predictive performance often does not improve with increased model complexity, and they often have a strong reliance on historical data. It must be noted that this need not be the case even for predictive models, even when these characteristics are typical.

Forecasting or projecting values for system characteristics without a known configuration for the system with regard to other characteristics than the forecasted ones. This type of modeling is strongly driven by theories and assumptions of the relationships between the system components. Forecasting use of models is characterized by using less information and data than prediction-oriented modeling, especially relative to the number of predicted values or the amount of information inferred and output from the input data. For this reason, it deals with more uncertainty and is more reliant on theories and assumptions.

Decision support use of models means answering simulation-type or optimization-type questions with the help of the model. Simulation-type questions are 'what if'-questions projecting a system development as a context for decision-making, whereas optimization refers to finding a 'best' option under a set of objectives and constraints. Modeling approaches and tools with fitness for multi-objective optimization and multi-criteria analysis can provide insight into the trade-offs between competing objectives, associated risks, and unintended consequences.

Social learning is a processual outcome of modeling. The experts and stakeholders included in the modeling effort will have to explicate their mental models, as well as their interests and values, while simultaneously being exposed to the mental models and preferences of other parties. The conceptual framework behind the model is usually refined and developed as a result of the social learning processes.

As Kelly et al. [69] note, there is a great deal of overlap between these different aims of modeling in actual modeling exercises, and the mentioned purposes are clearly not mutually exclusive. The emphasis of a modeling approach on these aims may vary, but building models of any level of formality could always be said to support social learning and system understanding [118], and depending on the type of information in the model also the other mentioned aims with differing utility profiles.

To be able to use models for prediction, forecasting or decision support, a logical or computational *transformation* on the model information contents is normally necessary. As system components and their relationships are inputs for the modeling, the output of modeling must, to have some value, tell something about what happens as a result of the interaction between the system components: transformation aims to infer in some way what are the emergent or systemic properties of the system. The transformation summarizes the complex information included in the model to deliver a simplified account of these systemic properties, such as the level of influence or dependence a single component might have in the system at large or a specific other component. Several such transformations are discussed in Publication I, and in Chapter 3 of this thesis. The transformation can be an *analytic transformation* where a computation reveals some characteristic of the model without the process emulating the actual operation of the system, or the transformation can be a *simulation*.

In the same way a model represents a system, simulation represents the *operation* of the system [9, 136]. Simulation has a temporal aspect. The representation of the operation can mean a continuous-time representation, if sufficient details are available in the model. On the other hand, the operation can also be represented as a starting point and an end point. In this two-step description of the operation of the system, a starting state is fed to a transformation and a transitioned state is output as the end result. This type of approach to simulation is sometimes called *analytical* simulation [82].

2.2 Data-driven approach to modeling and simulation

Systems modeling is often said to be strongly data-driven [118, p. 5] [84], meaning that the formal descriptions or definitions of the relationships between the model components are estimated on the basis of statistical data. These formal descriptions are normally presented as mathematical equations relating the model variables. Often techniques such as regression analysis are used for parameterization of the relationships [118]. Even when the estimation of details of the relationships is based on data, such model is still considered "a formal representation of a theory" [2]; Data-driven modeling is fundamentally based on theoretical-level understanding of the system rather than 'hard' empirical evidence.

A common problem in systems modeling is data inavailability [118], due to difficulties in quantifying the essential parts of the modeled system at the precision required by data-driven modeling approaches or the costs of data acquisition. Data inavailability limits modeling, both in application area of systems thinking and modeling (as only systems with good data availability will be modeled) and utility and reliability (as only system aspects for which data is available will be included in the models). These limitations might result in incomplete or biased models, which leave possibly crucial aspects of the system unmodeled and unaccounted for. The methodological limitations of modeling are reflected in the decision-making process using the modeling results, as their strategic and policy scope omits important considerations.

In some modeling domains, empirical data is an impossibility. For instance, foresight-oriented modeling of complex socio-techno-economic systems has to account for changing or emerging system characteristics that are not manifested in existing statistical data, as well as possible occurrence of singular and unique historical events for which no data reporting occurrence frequencies can exist. Historical data does not necessarily capture or reflect the way the modeled system is changing, even when the change and the dynamics involved might be well understood by experts of the modeled system [14, 106, 133, 134].

Data-driven modeling is often called mathematical modeling, and thus contrasted with modeling approaches emphasizing an intuitive-logical way of describing the properties of the modeled systems. Highlighting the mathematical nature of modeling, in the experience of the author, easily leads to a false impression of the model resting on a solid mathematical foundation. The irrefutability of mathematics lends itself to the outputs of the model, and the model may even become akin to a magical object delivering incontestable, but poorly understood results. However, in data-driven modeling, the fundamental choices about the model structure, logic and causal relationships and interdependencies are made based on theory, expertise, intuition, or even guesswork, instead of some axiomatic mathematical principles and empirical evidence. The theoretical foundation of models and simulations can sometimes be obscured by their claimed mathematicity. Often this theoretical foundation of the model is laid out in a rather informal and unstructured way, by a small modeling team or just one single person doing the modeling, and the foundation and theoretical choices made are not explicated or documented. Given the high technical expertise requirement of data-driven modeling approaches the model-building team might consist of experts of the utilized *modeling approach*, instead of substance experts of the modeled domain.

The theory-based structure of causalities and dependencies of models built using the data-driven approach is often nontransparent. Understanding the logical structure of the models might require good understanding of the underlying mathematics. Even with such expertise, understanding the structure might often be laborious. This cognitive cost of examining and understanding the model will often make the models 'black boxes' [14, 106] whose output is used without good grasp of the logical structure underlying the model: from a user perspective, the general causal logic of the model might remain unclear.

From a model user perspective, understanding the model structure, the causalities and the interdependencies of the model components is often very important for acceptance of the model results [106, 118]. The only way modeling and simulation, or any type of strategic foresight activity for that matter, can ultimately bring benefits, is by informing and influencing decision-making. If the model is intended to support decision-making, the opaque, black box nature of data-driven models can be a serious hindrance for the use of model in actual decision-making and strategy formulation. Models are also used to facilitate strategic discussion of alternative courses of action and exploration of possible options. A model with a muddy causal structure requires almost blind trust from the users to be used in an important role in decision support. Such models, whose logic is poorly understood by the end users, cannot be easily used for facilitation of discussion and exploration of strategic prospects [14, 27, 106].

2.3 The niche of expert informant oriented modeling

The expert informant-based approach to modeling, or expert elicitation of model inputs, is an alternative to data-driven modeling [14, 62, 106, 107]. *Expert informants* are knowledgeable people in possession of relevant understanding of the characteristics and operating logic of the modeled system. An expert informant does not need to possess expert-level competence in *all* knowledge domains relevant for the system being modeled. In many cases the expertise of the informant only partially covers the system knowledge, with the focus often being on a specific area. An ensemble of such expert informants may *jointly* cover the expertise required for the modeling. The formulation of an expert knowledge base into a formal system model is a collaborative process, where the expert informants discuss the model structure, logic, and parameterization, and seek consensus on the various model design and valuation choices emerging in the process.

Foresight-oriented modeling, especially in the context of complex, weakly quantified systems with system descriptors and interactions of high abstraction level, such as socio-techno-economic systems, often has to rely, at least partly, on expert elicitation for model structure and parameters [62]. Modeling changing systems and operating logics cannot rely on existing statistical data for parameterization of the model. These derived characterizations reflect the current logic of the system and not necessarily how this logic might change in the future, due to changes in the environment at large and interventions, such as new policies. These changes create new dependencies between system elements, as well as altogether new elements. Modeling utilizing expert informants to a high degree can cover the expertise area relevant and required for the modeling by mustering the aid of a group or groups of experts, providing a large knowledge base. An ensemble of expert informants also enable triangulation of the theories, mental models, and assumptions that form the modeled knowledge base. Expert insight of the modeled system may cover domains or system aspects for which data in the format required for modeling does not exist, but which are still known at some level of detail, enough to base the modeling on [25, 40, 75].

Expert informants suitable for building an expert sourced model based on the conceptual model presented in Figure 2.1 might include people knowledgeable on different energy technologies such as nuclear energy and natural gas, economists, urbanization experts and energy policy experts, as well as political scientists. Ideally the expertise of this informant group would be triangulated by involving not only Chinese, but also non-Chinese experts of these fields. In the case of the system Figure 2.2, law enforcement officials, criminologists, and sociologists with specialization in drug use would be of high relevance for covering the pertinent aspects of the system. In practice, the aims, ambitions and available resources of the modeling effort place constraints on what kind of expert group can be mobilized, and how

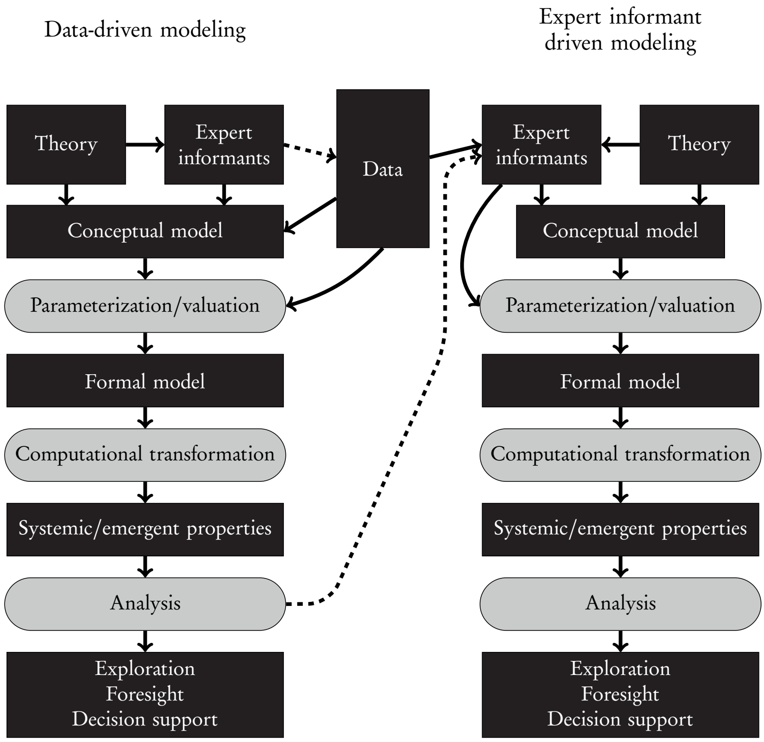


Figure 2.4 Data-driven and expert informant driven modeling processes.

much time they can allocate for the exercise.

Figure 2.4 illustrates the flow of the process in data-driven modeling, contrasted against a process of expert informant oriented modeling. The parameterization of the formal system model is the most important difference between the orientations. Empirical and statistical data and other 'hard' evidence is used in the expert informant oriented modeling as well, but it is filtered through the *expert informant layer*, and the experts perform the model parameterization instead of it being done *directly* on the basis of data. In the data-driven orientation, data also influences the conceptual model, as it is easily compelled to conform to the data that is available: The conceptual model easily ends up not including the things data is not available for.

In a modeling process based on expert elicited inputs, it should be obvious that the processual intricacies of the elicitation process are of decisive importance to the entire modeling effort and the quality of its outputs. Important questions include *a)* identification of relevant expertise *b)* identification of experts with this expertise *c)* securing their commitment *d)* organizing the elicitation *e)* facilitating the expert work *f)* synthesizing the elicited views into format suitable for the model, and *g)* facilitating analysis work of the model outputs with the experts. As foresight and futures thinking methodologically often revolve around facilitating the work of expert informants to elicit views and estimates about future developments and attempting to build a coherent synthesis of these views, such expert processes have been studied in the field of foresight [5, 7, 10, 28, 36]. Practices for and auxiliary techniques of expert elicitation have also been investigated and applied outside the futures field, especially in the context of formulating models as Bayesian belief networks and influence diagrams, and augmenting them with expert knowledge [62, 91, 106].

A structured and relatively well-known process employed in foresight is the Delphi technique, which is described as a "communication and collaboration technique used with expert panels" [81]. There are many variations of the Delphi method, but the basic process is as follows: People with expertise considered relevant for a studied topic answer questions and provide verbalized reasoning about their answers anonymously. The Delphi facilitator summarizes the answers and the reasoning and presents the summary to the panel, maintaining the anonymity of answers and reasoning. Discussion about the results may or may not take place. On the basis of the summary, expert participants reconsider and revise their answers. This usually leads to answers converging and the range of answers narrowing. These phases may be reiterated until some halting condition is met; the halting condition may be that a consensus is reached or that answers do not converge further or change anymore. If there is no consensus, a mean, median or mode of the answers can be used. This consensus or iterated average expert opinion is then considered to be the result of the Delphi process and to be close to the 'real' value or at least be information of higher value than the initial expert opinions. Similar processes can be executed in a more contemporary fashion online [115].

The Delphi technique is, however, just one possibility for the elicitation process among many, and is presented here as an example of a highly structured process of eliciting experts' judgments. Expert informant based modeling does not need to follow the fairly rigid ideal of a Delphi process, and the author's personal opinion is that a less formal and more conversational approach, conducted in relatively small expert groups with an iterative format, is more viable. As this thesis focuses on questions related to the description of knowledge bases with *formal modeling languages*, the *computational transformations* on the knowledge bases, and the inference procedures made possible by these transformations, the best practices of elicitation and modeling group work facilitation, while important, are not elaborated further.

While the data-driven modeling approaches can rely on expert inputs as well, expert elicitation is often in an auxiliary role, and not the methodological focus. A modeling approach primarily intended for expert informant oriented modeling processes should provide a modeling language more suitable for this type of modeling than what is normally available in cases of using expert inputs in parameterization of data-driven models. Elicitation of structural equations relating system components to each other and describing the rules of their operation is possible in principle, but an approach unfeasible in practice for description of expert knowledge. A modeling language for this purpose should support the heuristic-logical mode of work, and be natural in use of an expert-oriented modeling process. Suitable proposals would operate on a less exact and more approximate precision in description of the relationships of model components than what is typical in a data-driven model, where the relationships can be parameterized on the basis of the available empirical data, using techniques like regression analysis. Section 3.5 discusses the preferable design characteristics of an approach with high intended fitness for modeling approaches using chiefly expert elicited inputs.

2.4 Probabilistic and causal reasoning

A *logic* is a *formal language* and a set of inference procedures [114]. The language of a logic is formal, consisting of a finite set of symbols or building blocks. This language can be used to describe knowledge in the domain the logic is intended for. Inference produces statements about "the unknown on the basis of the known" [54]. The inference procedures of a logic are more or less justified operations performed on a construct composed of the language symbols. They enable reasoning based on the knowledge described in the language. As the language is formal and the inference procedures well defined, the inference can be automated. The automation enables drawing inference from the knowledge base described with the language computationally in cases where the knowledge base is extensive and the network of relating rules complex.

Computational inference will in such cases permit reasoning that would not be possible by more intuitive human reasoning alone. The human informants used in building a formal knowledge base may concentrate on describing the knowledge with the formal language primitives, with a focus on atomic facts and their relationships. The computationally complex inference can be automated and performed with a computer. Classical propositional logic could be said to describe knowledge as atomic propositions and logical connectives. The logical connectives of classical propositional logic relate the propositions to each other in a deterministic way. The atomic propositions have a truth value, and the truth value of more complex statements made up from the atomic propositions is inferred by the rules defined for the logical connectives. Propositional logic can be extended [128] to consider *partiality* of truth and other additional layers of information about the propositions. Language of a probabilistic logic describes knowledge with consideration to uncertainty. A probabilistic logic can describe problem complexes, decision-making problems or possibly systems as a set of propositions and their relationships with additional information concerning probability: The facts can be assigned probabilities, as well as their relationships. This probability can be based on empirical observations, but it can also be elicited from expert informants, capturing the experts' *degree of belief* on the propositions and the rules describing the relationships.

Bayesian belief networks, formalized in the late 1980's [105] and established as a field of study thereafter, are an established, well researched and supported approach for description of knowledge bases in a probabilistic and causal way and providing means for reasoning with such descriptions. Given their wide use in decision support activities, they can be seen nearly as a *default case* of a probabilistic and causal logic, and former proposals, as well as new proposals, can be positioned against the Bayesian network approach and better understood in relation to it. A Bayesian belief network is a *graphical* representation of facts, and their causal relationships, specified in the language of probability. Figure 2.3 on page 22 illustrated the graphical representation of causal dependencies in a Bayesian belief network. Pearl [105] argues for the high fitness of a belief network in representation of causal theories. Linguistic descriptions of relationships and rules between facts, as humans express them, do not normally map to absolute, deterministic rules as per propositional logic. Causal rules are not specified by human informants as absolute rules, but rather in a language of probability, which is tolerant to unexplicated exceptions to these rules and imperfect information. This tolerance allows the description of knowledge bases to focus on the main issues of explaining causal domain rules, instead of considering all possible corner cases and imaginable exceptions. In the Bayesian interpretation of probability, probabilities encode degrees of belief about facts in the world or the domain reasoned about, and new information, or perhaps a set of assumptions in reasoning, updates these degrees of belief [1–3 105].

The interpretation of the concept of probability is a foundational problem in scientific thought, and several different interpretations are commonly employed in different application areas of the concept [53]. Generally, in application of a language of probability in description of beliefs, the probabilities encode expert informants' subjective estimates of strengths of the facts and rules of the discourse, making the relevant interpretation of probability in this context that of *subjective* probability. The uncertainty measured by the probabilistic characterizations of the domain of discourse is a combination of two kinds of uncertainty: *a)* epistemic, as in uncertainty about the *real* facts and rules of the modeled domain; *b)* expressive, as in uncertainty related to the partiality of the description of the explanatory framework of the domain. In the case of a model of beliefs elicited from human informants, practicality dictates that the modeling work must focus on a subset of considerations relevant for the modeling task, replacing the exhaustive description of the explanatory framework with a probabilistic, approximate description.

Several approaches for describing knowledge and beliefs of expert informants and performing reasoning based on the descriptions have been proposed in the foresight arena. Many of them pre-date the emergence of Bayesian approach as a relatively accepted formalism for knowledge representation and reasoning. A number of approaches relevant from this perspective are discussed in Chapter 3 and reviewed in detail in Publication I. Their modeling language will determine the level of detail and the nature of information in the expert informant sourced system model. Given a relatively simple modeling language, the system description may be very transparent, in comparison to the system description of the data-driven approaches. Expert informant oriented models are used to the same ends as all models discussed earlier in this chapter: to understand the system better, to support learning, and to make inferences based on the expert-sourced knowledge base captured in the model, often with a foresight or decision support aim. The processual ease of building knowledge bases in expert processes is often a trade-off against analytical possibilities and modeling power. For this reason, different modeling contexts and aims may call for using different approaches.

The chief contribution of this thesis is the two novel approaches for expert informant oriented modeling called EXIT [100, 101] and AXIOM [93, 98, 99]. The approaches are developed by the author, building on the previous work on cross-impact analysis, structural and morphological analysis, and Bayesian networks. A guiding idea has been that the slightly aged toolset of cross-impact thinking can be updated, improved and extended, and brought to have a level of interoperability with the matured Bayesian approaches. In modeling domains and fields of research that heavily rely on expert informants, better methodological alternatives are needed to promote the utilization of systems thinking and modeling in foresight, strategy work, decision support activities and perhaps social sciences research aiming to support planning in general. Both new approaches have been implemented as freely available software, and the work related to these implementations is ongoing. Further development will introduce a graphical user interface for the implementing software, lowering the barrier of adoption for audiences not versed in modeling and simulation activities.

Publication I reviews the approaches for probabilistic causal modeling with a relatively high fitness for modeling utilizing expert informant processes. It commensurates the approaches by formulating a clear presentation of their characteristics, using basic graph theory concepts, and maps out the analytical utility of the approaches by looking at what questions they can be used to answer. Bayesian belief networks are used as a base case, from which other approaches can be arrived at by making various trade-offs to ease the expert elicitation. EXIT is presented in Publication IV, and its use in modeling in a case of a high-level model of the future developments of the Finnish electricity system is illustrated in Publication V. EXIT is also summarized in Section 4.1 of this thesis, and positioned against structural cross-impact approaches such as MICMAC, ADVIAN, DEMATEL, and cognitive mapping and fuzzy cognitive mapping approaches. The proposal for AXIOM approach in modeling of complex systems is made in Publication II, focusing on the AXIOM modeling language and outlining the computational process. Publication III details the analytical possibilities of AXIOM models and illustrates the use of AXIOM in processing a compact causal model originally used by Weimer-Jehle [133] in presenting the Cross-Impact Balances approach. AXIOM approach is also discussed in Section 4.2 of this thesis, where it is positioned against other probabilistic cross-impact approaches and

Bayesian belief networks, and its use in conjunction with Bayesian models is considered.

3 EXPERT KNOWLEDGE BASE MODELING AND ANALYSIS

This chapter discusses proposed *logics* for knowledge description and reasoning, with fitness for generic modeling of systems outlined as interrelated facts. They share an intended fitness for usage in expert processes where the model design and parameterization is based on expert-sourced inputs or can be solely based on them. Given the definition "Expert system = knowledge base+inference engine" [126], the discussed modeling approaches are also techniques for creating *expert systems*, the system models being the *knowledge base*, and their associated *computational transformations* being the *inference engine*. Systematic representation of expert knowledge in decision support activities is especially useful [4, 91, 106] in cases that are poor on data or that have a "dimensionally poor" data coverage, in the sense that some important considerations about the system or problem domain are not well covered by or captured in the data.

The methods discussed in this chapter differ in their modeling languages, analytical aims and computational transformations, but they all have

1. a *formal modeling language* or a defined set of generic building blocks used for describing knowledge about the system, its relationships and its rules,
2. a *computational transformation* or a set of transformations, used to extract the higher-order, systemic or emergent information about the system, on the basis of the knowledge base concerning the system properties and rules described by the model, and
3. guidelines and recommendations for *inference*, analyzing the output of the computational transformation and drawing conclusions from it.

The computational transformation (or inference engine) is simply a process, more or less justified by some argumentation, to draw inferences, higher-order information, or recommendations from the models. A *generic modeling language* is important for making the expert based knowledge description feasible, as well as the transparency of the knowledge base. The language should make it relatively easy for participating experts to describe their knowledge base, and other experts involved in the modeling and the model end users to 'read' this knowledge base and understand it [72]. A generic modeling language for description of the system rules is an enclosed or bounded set of *primitives* or atomic modeling building blocks, that are expressive enough to provide means to describe a variety of different systems. At the same time, the modeling language should also limit the expressiveness of the modeling in a way that prevents the logical or mathematical complexity of the model from rising too high, making the model scrutiny difficult and eventually turning the model into a black box where the basis of the inference is no longer transparent. Often the transformations discussed in the method descriptions and documentation and provided by the software implementations are a subset of the possible transformations made possible by the information content of the model. These undocumented possibilities for analysis should also be considered when the modeling approaches are appraised, as they may be introduced into the analysis if the methodological specfications are changed and associated software implementation is extended or recreated.

The existing modeling approaches relevant for this work, comparable to the proposed novel modeling approaches, EXIT and AXIOM, share the idea of expert elicited information as, at the very least, an important, in most cases the sole source of model inputs. Although Bayesian belief networks, discussed in more detail in Section 3.1, do not necessarily rely on any expert elicitation in model parameterization, but can be algorithmically learned [14, 64, 71] from empirical data without any associated expert process, an often-mentioned selling point of Bayesian networks is the possibility to incorporate expert knowledge into the model through elicitation. Bayesian networks can also be completely based on expert inputs, fully parameterized in an elicitation process without any direct use of statistical data. Techniques for learning fuzzy cognitive maps from data have also been presented [38, 102, 119]. The other discussed approaches, in normal use cases, fully rely on expert elicited inputs in model parameterization. It is possible to envision techniques for valuating the normally expert-elicited inputs on the basis of empirical data instead, but processes aiming at that have not been defined. A possibly sensible use case for valuation of a normally expert-elicited input in a data-driven way would be a model where a small number of inputs, relative to the total number of input valuations in the model, could be derived from data in a justified way, but the great majority of inputs are such that they cannot be valuated on the basis of data. This primary reliance on subjective estimates in the case of the majority of inputs justifies using an expert informant-based modeling approach instead of a data-based approach in the first place.

The modeling approaches comparable to EXIT and AXIOM also are characterized by their degree of conceptual and functional overlap with Bayesian belief networks and *influence diagrams*, a generalization [105] of Bayesian networks. This overlap exists specifically in how Bayesian belief networks and other discussed approaches are used in systems modeling, decision support, representation of knowledge bases of experts, and on how analytical utility of various orientations is derived from them. Bayesian belief networks are probabilistic causal models. The other discussed approaches are causal and probabilistic as well, although this might not be immediately evident from the way these methods are described in their original sources.

Probabilistic models could be said to be, in comparison to deterministic models, a better fit for expert informant oriented modeling. This results from the fact that probabilistic models allow the modeling of the rules of the modeled systems in a way that accounts for the uncertainty and incompleteness associated with these elicited rules. The expert elicited descriptions of the system's rules are almost always approximate and incomplete. The probabilistic description of causalities can be thought to reflect the incomplete knowledge of the system. A deterministic model based on such description might be biased and more importantly, impractical. Probabilistic modeling of rules gives leeway in terms of abstraction level: the system does not need to be described to the tiniest details, but the model can focus on the considerations essential for the decision-making problem and context.

The modeling approaches discussed in this work could be classified, in an ordering where the conceptual distance from Bayesian networks is increasing, to the following groups:

1. **Bayesian belief networks** (BBNs) and **influence diagrams** (IDs) themselves.

2. **Cross-impact techniques aiming at explicitly probabilistic inference**, such as *cross-impact analysis* by Gordon and Hayward (GHCIA) [49, 50, 51] and *AXIOM* [98, 99].

3. **Cross-impact techniques aiming at morphological inference**, such as *BASICS* [56, 57] *JL-algorithm* [83], and *SMIC* [34, 45, 46, 47, 48].
4. **Structural analysis approaches**, such as *EXIT* [100, 101], *MICMAC* [6, 20, 45, 46], *ADVIAN* [41, 79, 80], *cognitive maps* [8, 35, 124] and *fuzzy cognitive maps* (FCMs) [38, 66, 103, 121].
5. **Morphological analysis approaches**, such as *General morphological analysis* [112, 113], *Field anomaly relaxation* (FAR) [110], and the *Cross-Impact Balances* approach [131, 133, 134].

As these approaches are to a large extent conceptually overlapping, it is not surprising that their analytical outputs overlap as well. Bayesian networks and influence diagrams, as well as the AXIOM approach, can analytically cover several aims other discussed approaches have. Probabilistic and causal reasoning approaches with foresight applications are discussed in Publication I, which positions them against Bayesian belief networks and each other and identifies their analytical aims. It also outlines the computational transformations of these approaches. The analytical aims of expert informant oriented causal modeling techniques fall into three classes that are not mutually exclusive: structural, morphological and probabilistic.

Structural analysis focuses on the structure of the causal network: Structural information is inferred from the structure of the network of causal influences. It can provide the analyst an improved understanding of the relationships of the model variables or descriptors, and their role in the system overall. The inference is based on indirect impacts. *Morphological* analysis deals with the compatibility, consistency or congruence of system states or partial system states. It is used to identify probable, viable, harmonious or logical *morphological configurations* of the system. By doing that, the alternative scenarios for the system or consistent solutions to a problem can be explored. Explicitly *probabilistic* analysis provides the greatest degree of direct decision support, as it allows for analytically simulating the functioning of the system, testing it under different conditions, and observing how interventions influence the facts' probabilities. The probabilistic information can be used in conjunction with *utility functions*, which map model states to utility valuations. Utility functions make the identification of an intervention set that is optimal according to some criteria straightforward, resulting in easy decision support use. Probabilistic models hold greater amounts of information than structural or morphological models, so the cost or difficulty of creating them is higher. They can, on the other hand, be used for structural and morphological analysis as well.

Explicitly probabilistic causal models need to describe the probabilistic dependencies the different system components have on the states of other system components, specifying quantified probability changes conditional to the dependencies. This work discusses two alternative approaches: the *Bayesian* approach and the *cross-impact* approach. In Bayesian belief networks, the probabilistic relationship of any fact on all of its causes is fully specified with a conditional probability table. The conditional probability table reports the probability of a fact in all possible combinations of the facts it is dependent on. The 'language' of a Bayesian belief network describes probabilistic *dependency* of an effect on its causes in an exact way. Cross-impact language describes the probabilistic *impact* of a cause on its effect, in a more approximate and heuristic way. These different ways of specifying the probabilistic impacts have their strengths and weaknesses, but no matter which one is used, from the perspective of eliciting model inputs in an expert process, the probabilistic data is an additional layer of information to be elicited.

Structural and morphological information can be inferred *without* an exact description of dependencies of facts in terms of probability. The causal influences need to be described by their magnitude only in relation to other influences in the model, and these influences do not need to map to quantified changes in probability values: the structural or morphological information can be extracted from such *relative* influence valuations. For this reason, structural and morphological modeling is clearly easier for eliciting experts, as they need to supply a smaller amount of information to create a fully valued model, but also as the additional layer of conceptual complexity in the form of quantified probability is not involved in the modeling. While the modeling process is easier, the models are of higher abstraction level compared to *explicitly* probabilistic models, and their direct decision support use is more difficult.

To better position EXIT and AXIOM among the Bayesian approach, cross-impact approaches, and structural and morphological modeling approaches, they are next discussed in more detail. Publication I reviews a number of related approaches with applications in the foresight domain and commensurates them using graph theory concepts, and outlines their analytical functionalities. Graphical concepts are also used here in description of the methods to facilitate the understanding of the differences in the modeling languages.

3.1 Bayesian belief networks

Bayesian belief networks are models for probabilistic causal reasoning under uncertainty [26]. They are widely used in several areas, with numerous scientific, industrial, and decision support applications [55, 108]. The small model of Figure 2.3 in Chapter 2 was presented as a minimal example of a Bayesian network; typically Bayesian networks are more complex, consisting of a much greater number of nodes. Bayesian network, as a knowledge base representation, captures a causal structure of a collection of related facts and presents their probabilistic dependency with regard to the causal structure with full precision: a full joint probability distribution for any fact, given that all of its causes are included in the model, can be derived from the representation. The basic use case for the representation in decision support is inferring the change in the probability distributions of the states of the node descriptors in the network, when other nodes are set to be in a known state, to represent a decision-making context, or a set of assumptions to be tested for their effect on the system. Alternatively changes can be made to the probability distributions of nodes of interest, to capture different assumptions about the rules and relationships, aiming at observing the effects of those assumptions. The probabilistic inference in a Bayesian network can be *predictive*, dealing with probability changes of effects given information about their causes, but also *diagnostic*, inferring the likely causes based on the observed effects [18, 71].

The common graphical representation of a Bayesian network is a directed acyclic graph, Causal dependencies are denoted by directed edges between variables or descriptors denoted by graph nodes. The parent nodes are causes to the child nodes, their effects. The causes of a node can themselves be effects of other nodes higher up in the causal hierarchy. The Bayesian network nodes are probabilistic random variables and can represent almost any types of system properties. They often represent mutually exclusive discrete states, but nodes can also represent continuous quantitative system properties. Same model can hold both node types.

For influence diagrams, a special case of Bayesian belief network, also decision nodes and utility nodes are available as modeling primitives [64]. Decision nodes affect the state of at least one of the random nodes: the decision node states are alternative decisions or policies. Decisions that can potentially be implemented in parallel are given nodes of their own. Utility nodes receive information from random or decision nodes of the system, and model the *positive or negative utility*, benefit or harm, gain or cost, of their dependencies. In essence, they are used to compose a utility function. The decision making criteria is modeled with decision nodes, and these criteria are used in comparison and assessment of alternative decisions or sets of decisions. For a model containing several decision nodes, a combination of policy elements or interventions can be discovered by search of maximum expected utility (which can also be minimization of negative utility, harm) [64, 78].

The graph edges represent causal dependency relationships of the head nodes on tail nodes, or as the Bayesian network is a directed acyclic graph, dependency of child nodes on their parent nodes. The relationships are defined by populating the node-specific *conditional probability tables* with probability valuations conditional to each possible configuration of the states of the parents or explanatory variables, the causes. The parent nodes are causes and their child nodes are effects, which can in turn be causes for other effects further down the causal hierarchy. For defining the dependencies numerically, several methods can be applied: using learning algorithms on empirical or statistical data [1, 111], deterministic or probabilistic simulations [31, 109], and expert elicitation [62, 76, 91], or some combination of these. It is common to augment a data-based Bayesian model with expert informant sourced information, as Bayesian networks are well suited for that.

Modeling using Bayesian networks is well supported by software implementations such as Netica [89] and Hugin [70] that enable versatile analytical outputs, well beyond the basic output of Bayesian probability updating in a graph given some assumptions about the node states: if a Bayesian network representation of the system can be fashioned, the mature software tools and analytic processes enable very flexible and multipurpose examination of it. Bayesian networks, however, specifically in systems modeling relying chiefly on expert elicited inputs, can be problematic as the number of required inputs, in cases of structurally complex models, easily becomes unmanageably high. Structural complexity in this context means a high number of node states and a high number of dependency links. As structural complexity in the model increases, the amount of information required by the conditional probability table representation of the relationships grows exponentially. The number of conditional probabilities to be elicited for an effect e, in a case of n dependencies for e, is $\prod_{i=1}^{n} s(c_i) \times s(e)$, where $s(c_i)$ is the number of possible states a specific cause c_i can have, and $s(e)$ is the number of possible states of the dependent effect. An effect node with three possible states, and three dependencies, each also with three possible states, requires 81 conditional probabilities to have its relationship defined. An extensive model may have tens or hundreds of such dependency descriptions. 4-state node with 5 dependencies having 4 possible states each would require elicitation of 4096 conditional probabilities: This is certainly unfeasible to directly elicit, and some auxiliary technique would have to be employed to valuate the model. Such dependency structures are, in the experience of the author, based on the initial experiments of modeling with EXIT and AXIOM, not uncommon in the way an expert group might want to model a system.

For cases where the probability tables are elicited, the amount of input information can be managed by the following approaches

1. The structural complexity of the model is sufficiently limited to keep the number of elicited values manageable. This is suboptimal from a conceptual perspective of modeling, as possibly important considerations have to be pruned from the model, and the conceptual contents of the nodes might become highly abstracted or convoluted, in the sense that a single node will represent multiple aspects of the system or decision-making context.

2. The elicitation can aim at extracting parameters for probability distributions instead of the distributions directly, and this may reduce the work load, but this approach is normally applicable only for continuous variables, or discrete distributions where the states can be placed in a logical ordering: examples would be a discretized continuous variable or a node indicating whether or not a quantity or degree of something is decreasing, stable, or increasing. Still, even when distribution parameters are elicited instead of individual probability valuations for states, the number of distributions can remain unfeasibly high in complex cases.

3. For discrete distributions without a logical ordering, a technique of eliciting a smaller amount of information, from which the actual conditional probability table valuations are inferred, can be employed [30, 32]. An auxiliary approach will add additional complexity to the modeling process, but for complex cases relying on elicited inputs such approaches are undoubtedly necessary. AXIOM can be used as an auxiliary technique in valuation of a Bayesian belief network.

A Bayesian network graph is acyclic, thus the method does not allow modeling of cyclic interaction. The temporal aspect of the system, in cases where the system is modeled as a Bayesian network, is tightly coupled with the graph structure. There can be no ambiguity about the cause-effect relationship between nodes, and structural inference loops are not normally possible. This characteristic cannot be seen as a drawback in a general sense, it is simply a byproduct of the Bayesian reasoning rules. A strength of the acyclic form of a normal Bayesian network is that the probability updates are computationally fast as there is no need for a sampling process, and no error introduced by the random element of it to the results. For some application domains, however, it does impose limitations on the expressive power of the modeling language. Modeling of societal, political or technological developments, typical in foresight, benefits from a possibility to specify ambiguous causal structures.

Strengths of Bayesian networks in expert elicited systems modeling include the versatile analysis the approach provides, and the well-established and efficient techniques to incorporate statistical data or simulation results into the model, which can then be augmented with expert elicited inputs. For many decision support contexts, Bayesian networks are a highly fit approach for knowledge representation and reasoning. In a case where most of the model parameterization relies on expert informants, Bayesian network-based system models are problematic as the number of required inputs can become unfeasibly high, given a sufficiently complex model structure. Strategic, foresight-oriented probabilistic and causal reasoning largely relies on information that is expert sourced, and the decision support utility of models based on expert inputs is the ability to formally represent them with sufficint granularity and to automate reasoning on these complex knowledge bases. Limiting the structural complexity of the knowledge base description easily results in system descriptors being overloaded with non-aligned conceptual content which muddies the causal structure. Modeling in foresight does not typically aim at making predictions in the most efficient and data-economical way possible but rather at systematic and conceptually clear representations of the interaction of systemic drivers and forces. These characteristics of the modeling niche call for consideration of other proposals for alternative expert knowledge representations and inference mechanisms.

3.2 Probabilistic cross-impact languages

The early experiments with modeling the causal relationships on the basis of expert elicited inputs in the context of futures studies and foresight were performed in the late 1960's [49, 50]. The motivation for these modeling experiments was to be able to provide an auxiliary technique for forecasting and foresight work done utilizing expert panels, especially the Delphi technique. T. Gordon and Hayward [49] called the approach augmenting the Delphi technique by incorporating consideration of the interaction between the future events *cross-impact analysis*. The next two decades saw a lot of discussion [12, 13, 16, 17, 29, 47, 49, 50, 59, 60, 67, 68, 85, 88, 90, 127] on the methodological details of cross-impact techniques and applications of and incremental amendments to the cross-impact technique proposed by Gordon and Hayward have been published with lower frequency since [3, 10, 11, 19, 24, 45, 46, 51, 65, 86, 92, 123, 133].

The techniques normally referred to as cross-impact analysis are the Gordon-Hayward cross-impact analysis [49, 50, 51], henceforth referred to as GHCIA, and the SMIC approach by Godet and Coates [46]. GHCIA and SMIC are both probabilistic binary descriptor models resolved in a discrete event simulation. In a graphical representation of GHCIA and SMIC models, the graph nodes are system descriptors, presenting a hypothesis or a postulate about the state of the system in the future, also called an event by T. J. Gordon [51]. This state is assigned an initial or *prior* probability of occurrence, which is an estimate of the probability of the hypothesis, assuming no available information about the system, meaning that the states of the other descriptors are unknown. This kind of 'independent' initial probability for *all* random variables is one aspect where a cross-impact language differs from a Bayesian language, where only root nodes (or nodes without parents or causes) have independent priors. Unlike a Bayesian network, the graph is cyclic, and models bidirectional interaction with the interpretation of such bidirectional interaction that the temporal ordering of the random variables is unclear: whichever of two bidirectionally interacting variables should occur first will exert its probabilistic influence on the one occurring later. The graph is also fully connected, as can be seen in the example model presented in Figure 3.1. The model descriptor events take place in an unstructured temporal space *'the future'*, and have no temporal or causal ordering, only omnidirectional interaction.

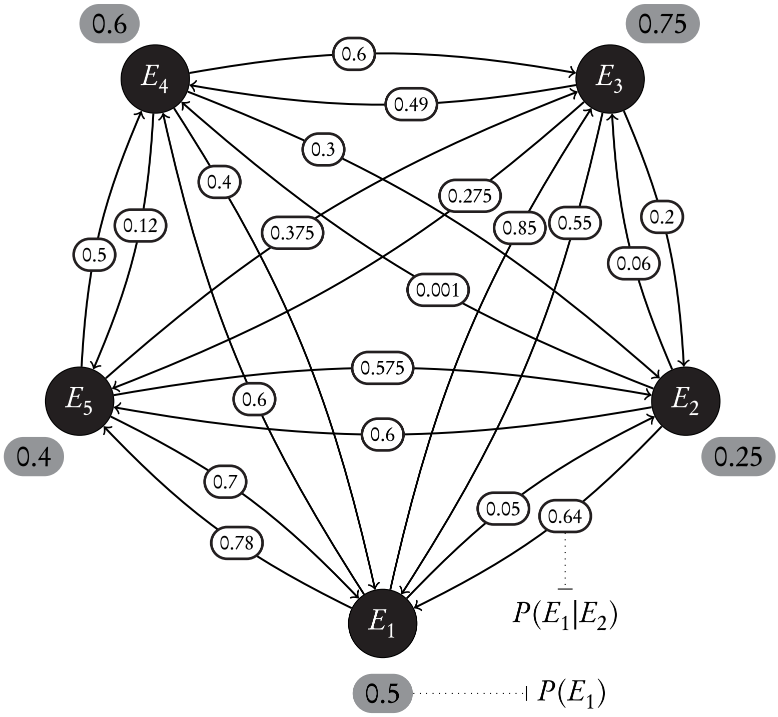


Figure 3.1 A Gordon-Hayward cross-impact model with five events.

The edges in the graphical representation of GHCIA carry information about the occurrence probability of the head node hypothesis, conditional to the occurrence of the tail node hypothesis. In the SMIC approach, the edges additionally carry information about the occurrence probability of the head node hypothesis, conditional to the non-occurrence of the tail node hypothesis [34, 46]. In GHCIA, the probability of the head hypothesis conditional to the non-occurrence of tail hypothesis is inferred [51, p. 8] from the probabilities conditional to the occurrence of the tail hypothesis.

The expert-elicited conditional probabilities are, in the case of GHCIA, checked for compliance with the standard probability axioms. The following conditions should be met:

1. $0 \leq P(i) \leq 1$
2. $0 \leq P(i|j) \leq 1$
3. $\frac{P(i)-1+P(j)}{P(j)} \leq P(i|j) \leq \frac{P(i)}{P(j)}$

If the initial conditional probabilities do not fall within permissible bounds, it is the task of the expert group to resolve the inconsistency by changing either the conditional probabilities or the initial a priori probability valuations. In the case of SMIC, the emphasis is much more in discovering a valuation for the initial and conditional probability valuations that are consistent by the SMIC criteria: the initial probabilities should meet the following conditions:

1. $0 \leq P(i) \leq 1$
2. $P(i|j)P(j) = P(j|i)P(i) = P(i,j)$
3. $P(i|j)P(j) + P(i|\neg j)P(\neg j) = P(i)$

The initial valuations are further computationally corrected to find a consistent set of valuations. The software implementation features a linear optimization function [46, pp. 144–146], which corrects the initial expert-sourced valuations into permissible bounds [34], aiming at keeping the corrected valuations as close to the original expert valuations as possible. The focus of SMIC on consistent valuation scheme heavily limits the number of nodes that can realistically be incorporated in the model. Godet and Coates [46, p. 149] recommend that the number of descriptors should not exceed 6. Any real modeling effort struggles to describe the domain with such a limited number of descriptors, and the abstraction level in the model easily becomes very high.

When the conditional probabilities have been defined, model evaluation can be performed. The evaluation process is a Monte Carlo process, where truth values are assigned to model descriptors in random order, according to the defined probabilities. When a descriptor is assigned a truth value, the probabilities of other descriptors are updated, using the *odds ratio technique* described by T. J. Gordon [51, pp. 7–9]. When all descriptors have been evaluated, the system of the model has a fully resolved state, which is saved. This saved state can be thought of as a scenario. The probabilities of the descriptors are reset to the initial values. The evaluation is repeated a large number of times.

The cross-impacted *posterior* probabilities are computed simply as the occurrence frequency of descriptors in the set of generated scenarios: the simulation-generated set of worlds is treated as a sample. The posterior probabilities reflect the influence of the impact network and capture the influence of longer impact chains. In GH-CIA, the recommended inference procedure is to test various assumptions with the model by changing the initial probability valuations, for instance to simulate interventions: different initial setups are compared in terms of posterior probabilities. In the case of SMIC, the aim is to identify the most probable scenarios for further examination with other futures methods [46]. For a system model of n hypotheses, SMIC outputs the probabilities for 2^n scenarios, ordered by their probability. Godet also recommends deriving an elasticity matrix for the variables by means of performing sensitivity analysis on the initial probability valuations of the variables.

As illustrated by Figure 3.1, every descriptor event is conditionally dependent on every other event in the model. A Bayesian network-esque conditional probability table description of the interactions, assuming that our modeling approach would allow the bidirectional interaction described in the graph, would require $(2^4 \times 2) \times 5 = 160$ conditional probability values. Only five initial probability values and 20 conditional probabilities are defined in the example model. How are the probability updates performed in the discrete event simulation? Equation (3.1) presents the odds ratio technique, the probability update logic of the Gordon-Hayward approach.

$$P_u(P, P_i, P_c) = \frac{\frac{P}{1-P} \times \frac{\frac{P_c}{1-P_c}}{\frac{P_i}{1-P_i}}}{1 + \frac{P}{1-P} \times \frac{\frac{P_c}{1-P_c}}{\frac{P_i}{1-P_i}}} \tag{3.1}$$

In Equation (3.1), P is the current probability to be adjusted; P_i is the initial probability; P_c is the probability conditional to a single cause; and P_u is the updated probability. The basic idea is to reason about the magnitudes of the probability impacts based on the differences of initial probabilities of events and the conditional probabilities. In the course of a single model evaluation, the first probability update always updates the probability equal to the conditional probability defined for the effect conditional to the cause. The subsequent probability updates need to take into account the fact that the probability has already been updated: the odds-ratio technique is one way to do that. Figure 3.2 plots the updating function with the initial probability P_i fixed at 0.5. Using this approach, the order of updates is not significant. The probability updating is *contextual*, dependent on the value of the updated probability at the time of the adjustment. This is the essence of a *cross-impact language* description of probabilistic interaction, and the same contextual updating logic is present in other probabilistic cross-impact techniques, such as BASICS or AXIOM. As a consequence of the hazier, contextual approach to the updates, in comparison to the exact description of a Bayesian belief network, a much smaller number of input values suffice to valuate the model.

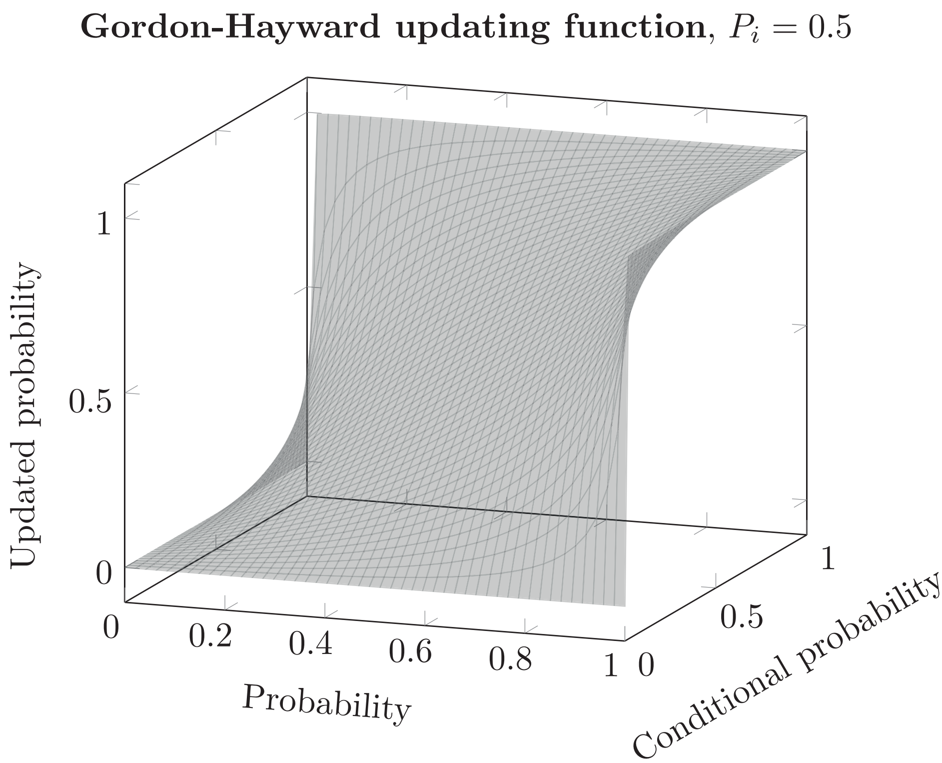


Figure 3.2 Probability updating function in Gordon-Hayward cross-impact analysis.

The GHCIA descriptors, as they are defined in the method descriptions, are binary. Mutually exclusive relationship between facts A and B can be modeled by defining $P(B|A) = P(A|B) = 0$, but this requires that the initial probability valuations for both A and B are such that the probability constraints discussed in page 47 are met. A mutually exhaustive state set cannot be modeled at all: there is no way to guarantee that the sum of the probability distribution of an intendedly exhaustive fact set remains equal to 1 in the course of the model evaluation. GHCIA and SMIC also have no built-in way to express a time dimension in models: all the system descriptors exist in a single temporal space. The lack of temporal depth means that the modeling of interventions, policies and other such influences remains quite vague: If fact I is intended to represent a policy action, there is no way to guarantee that I will actually be resolved in the model evaluation *before* the variables representing policy outcomes are resolved, and have the chance to propagate its influence on the intended target variables. These features limit the modeling power and practicality of the approaches, and their usability in systems modeling.

A later proposal in the cross-impact analysis genre, BASICS, takes the idea of contextual probability updates further. BASICS discards the information about the initial probabilities in probability updating, as well as the probability theory-inspired bounds for the initial probabilities and update magnitudes. The BASICS probability updates could be thought to be, instead of conditional probabilities, signals or messages, that update the probabilities in a fully contextual fashion. This approach to expressing the conditional probability effects in a cross-impact model has been discussed by Enzer [37] and implemented in the BASICS approach [56] and later by Luukkanen [83] in the JL-algorithm with incremental improvements over BASICS.

The BASICS approach is described by Honton, Stacey and Millett [56]. In the BASICS modeling language, descriptors can have an arbitrary number (greater than one) of possible states, which are assigned prior probabilities, whose sum is equal to 1. The probabilistic interactions that the model components have on each other are expressed as references to probability updating functions in a fixed set of such functions. BASICS updating functions take a probability to be updated as an argument and return an updated probability, altering the descriptors' probabilities contextually: a probability update by the same function will result in a different amount of probability change in the influenced descriptor, depending only on the value of the adjusted probability at the time of the adjustment. The probability updates ensue when the descriptor state causing the updates is evaluated to be true. The BASICS updating function set is graphed in Figure 3.3.

This further reduces the difficulty and workload of describing the relationships between the system components, especially in a model with a high descriptor count and complex dependencies. Instead of specifying conditional probabilities, the update logic is made fully contextual. The elicited experts may simply invoke an update capturing the approximate magnitude and direction of the probability change, without consideration to the initial probability valuation. As the function references are conceptually 'causal signals' instead of conditional probabilities, the need to consider logical bounds for conditional probabilities present in GHCIA disappears. The fixed set of updating functions is quite coarse: A degree of precision is undoubtedly lost, but gains are made in the ease and speed of the model valuation. The saved time and

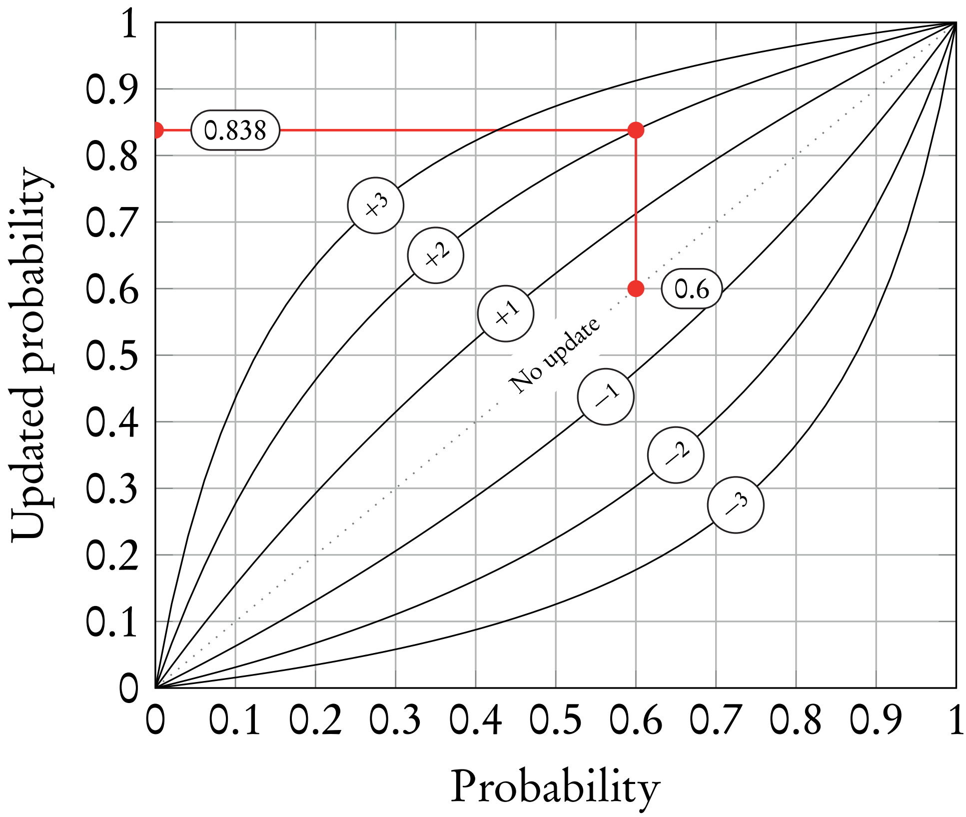


Figure 3.3 BASICS probability updating function set. Update of probability with value 0.6 by function '+2' alters the value to 0.838.

cognitive power can hopefully be used in more thorough consideration of the actual rules and logic of the modeled system, and how these considerations are captured in the model. The BASICS updating logic is the fundamental template of the AXIOM approach to probability updating, but the approach is developed further, as discussed in Section 4.2.

BASICS does not employ a Monte Carlo process in its model evaluation, and does not produce a posterior probability distribution for the states of the system descriptors. Instead, it employs a deterministic process, where the model is evaluated twice for each possible state of all of its descriptors, assuming the state in question to 'be true' or occur, then 'be false' or not occur. In the evaluation of descriptors, the most probable state is selected, making the model evaluation deterministic. Each model evaluation produces a set of descriptor states occurring in that evaluation, and this set can be interpreted as a scenario. A model with 10 descriptors, with 3 states each, results in $10 \times 3 \times 2$ scenarios.

The motivation is to find scenarios that are "probable and consistent" [56], in the light of the supplied prior probabilities and interactions. The scenarios that emerge from multiple different evaluations are interpreted to be probable and consistent, warranting further study with other analytical techniques. In this sense, the output produced by BASICS is analytically serving a similar purpose as morphological analysis, discussed in Section 3.4. JL-algorithm [83] is derived from BASICS, and proposes changes to the model evaluation procedure to eliminate effects of the ordering of the descriptors in the user input, as they are significant at least in some BASICS implementations.

BASICS and JL-algorithm make it possible to identify morphologically consistent scenarios, but they do not support simulation-style use of the model for testing the effect of interventions or other changes to the system that can be observed from posterior probabilities resulting from different initial conditions. The analytical output is limited to identifying sets of system descriptors that are probable with the given description of prior probabilities and interactions, inferred by the BASICS evaluation process.

3.3 Structural analysis

The term "Structural analysis" has been used by Godet [48] to refer to a process studying "systems consisting of interrelated elements". The analytical focus is strictly on the structure of the relationships of these elements, or the influence network. Generalizing the analytical aim of Godet's structural analysis, approaches enabling structural analysis are MICMAC [45, 46] and its fuzzified version FCMICMAC [130], ADVIAN [41, 52, 79, 80], cognitive maps [8, 35, 124] and fuzzy cognitive maps [72, 122], DEMATEL [44, 77], and EXIT [95, 96, 100, 101]. Structural analysis attempts to reveal the structure of *higher-order* influences, meaning the indirect connections between the model components: the higher-order influences effectuate over *chains* of causal links. Analysis of these higher-order connections through some computational transformation aims at revealing the 'hidden' structure of the influence network. Indirect influences are discovered from the model of the direct impacts given as input.

Structural causal models can be represented as directed cyclic graphs. The nodes represent concepts, trends, and driving forces. Their description is normally in a form of a hypothesis or a postulate about the state of the system. The graph edges are directed, and represent the *direct* causal influence the descriptors have on each other. Direct causal influence of cause variable V_c on effect variable V_e, in the context of structural analysis, means that there are no intermediary, mediating elements in between V_c and V_e which are included in the model: the model elements could be further broken down into sub-elements, or the model could be expanded in some other way to have more variables, so that the causal mediating elements would be included in the model or *made visible*. This would then change the structure of the direct causal influences so that they would be routed through these now-visible, newly modeled mediating elements. The direct influence on model level is not necessarily *conceptually* direct, but the model represents the system at a certain level or resolution and detail, and at any precision such a description will abstract away some mediating causal components.

The structural model edges may or may not be weighted. Unweighted edges can be thought of as a Boolean indicator of influence. The edge weight is an indicator of the strength or magnitude of the causal impact. The indicator can additionally hold information about the direction or 'sign' of the causal effect, whether or not the influence is promoting (positive) or obstructing (negative). The magnitudes of the influences can be expressed with a number, or with linguistic or ordinal valuations, which in practice are mapped to numeric values in the computational processes of the structural approaches.

Structural analysis approaches generally rely on a matrix representation of the model for some parts of their inference. As somewhat of a convention, the causes or impacting variables are placed as row variables and the effects or impacted variables are placed as column variables. In a case where the causal influence magnitudes are indicated as numeric values, the absolute row sum reflects the overall systemic *influence* of the row variable, how much influence it commands over the rest of the model variables. The absolute column sum reflects the overall systemic *dependence* of the column variable, or to what extent it is driven and influenced by the other model variables. This straightforward analysis technique [129] has been the outset for more elaborate proposals for analysis of models with similar information content. Most of these proposals rely on some form of iterative multiplication of the impact matrix to reveal the indirect impacts.

The MICMAC and ADVIAN approaches aim at ordering the variables based on their systemic influence or dependence, on the basis of the direct influences and the indirect influences [80]. The applications of the DEMATEL approach often have a similar aim of classification of the factors into several, typically four clusters based on relative influence and dependence [116, 117, 137]. In the MICMAC and ADVIAN approaches, the ordering based on the magnitudes of the *direct* systemic influence or dependence is the initial ordering. It is compared to the ordering based on indirect influences, once it is computed. The discovery of the indirect influences is based on the matrix multiplication approach. The starting point is the direct impact matrix ($\mathbf{D}$) given as input. In MICMAC, usually this direct impact matrix only contains values 0 and 1. Squaring the direct impact matrix ($\mathbf{D} \times \mathbf{D}$) reveals the indirect influences of 2$^{\text{nd}}$ order, or the indirect influences between variables with one intermediary variable. Multiplying this result matrix $\mathbf{R}$ with the initial matrix ($\mathbf{R} \times \mathbf{D}$) reveals the 3$^{\text{rd}}$ order influences, and repeating this matrix multiplication operation reveals the further higher-order indirect influences. For each iteration, a new ordering of the variables, based on either influence or dependence, can be produced by ranking by sum of row or column values. In MICMAC, the terminating condition for the iteration is when this ordering no longer changes. For some impact matrices, it is possible that this terminating condition is never satisfied and the process is non-terminating; the ADVIAN approach proposes a solution to this problem [79]. This *MICMAC ordering* is thought to reflect the higher-order interactions and the differences between the direct initial ordering and the MICMAC ordering are the analytical focus of the MICMAC approach. In ADVIAN, the row and column sums for each iteration are saved and the process yields a total sum reflecting the influence or dependence of each variable [79]. This enables some level of quantification of the magnitude of the overall direct and indirect influences, but does not consider pairwise relationships between the variables, or the direction or 'sign' of the influences. The development of the EXIT approach [95, 96, 100, 101] was motivated by the aspiration to extract more detailed and useful information about the relationships between the structural model variables, compared to MICMAC and direct derivatives of it. The EXIT approach is detailed in Publication IV and discussed in Section 4.1 of this thesis.

The DEMATEL method [44] uses the matrix multiplication approach in a way that produces outputs more comparable to EXIT than MICMAC or ADVIAN. In

DEMATEL, the direct impact matrix $\mathbf{D}$ is first normalized as $\mathbf{D} \times \frac{1}{m}$, where m is the maximum of the absolute row and column sums of $\mathbf{D}$, to yield the normalized impact matrix $\mathbf{N}$. The total impact matrix is then obtained by first multiplying $\mathbf{N}$ by itself to yield matrix $\mathbf{R}$, and then repeating $\mathbf{R} = \mathbf{R} \times \mathbf{N}$ until $\mathbf{R}$ converges to the null matrix, and summing each $\mathbf{R}$ to yield the total impact matrix $\mathbf{T}$. The result can normally, but not always [77], be obtained as $\mathbf{T} = \mathbf{N}(\mathbf{I} - \mathbf{N})^{-1}$, where $\mathbf{I}$ is the identity matrix. The DEMATEL total impact matrix quantifies the pairwise systemic influences, and considers the influence direction (sign), providing much more information from a structural model than MICMAC or ADVIAN. The logic is however quite different, and this difference is discussed more in Section 4.1.2.

The above-discussed approaches explicitly identifying as methods for structural analysis are conceptually and functionally somewhat related to cognitive maps and their fuzzified versions, fuzzy cognitive maps. Early on, cognitive maps have been proposed by Tolman [124] and Axelrod [8]. Cognitive maps are *signed* directed graphs, in which the nodes represent variable concepts: the node descriptions are formulated so that they carry information on the state of the concept or its development direction with them, not just the concept itself. Directed edges represent causal influences. Positive edges are interpreted to causally support or strengthen the head node concept. Negative edges indicate causal antagonism of the tail node concept on the head node concept. Causal propagation of variables on each other is inferred by means of reachability matrices. The aim is to infer what is the *nature* of the causality of a cause on an effect. This is done by investigating the direct and indirect connections of the cause on the effect, or all possible causal paths connecting them. A single indirect causal effect is negative if the number of negative causal edges in the path is odd, positive if the number is even. The total causal effect is interpreted to be positive if all indirect effects are positive, negative if all indirect effects are negative, and indeterminate otherwise. In practical modeling cases, this often leads to indeterminacy dominating in the total effects [72].

Extending on the ideas of cognitive maps, Kosko [72] proposed *fuzzy cognitive maps* and a computational process to draw inferences from such maps. The original ideas have been greatly elaborated since [38, 103, 135]. Fuzzy cognitive maps are often considered as a type of recurrent artificial neural networks [125]. The graphical system representations in FCM form consist of variable concept nodes and weighted edges. The concept nodes normally have an activation level value in the range $[0, 1]$.

This activation level value reflects their fuzzy truth value: in the lines of fuzzy set theory [72, 138], a value close to 1 indicates a strong fuzzy membership of the concept in the category ‘true’, and conversely a value close to 0 indicates the concepts strong fuzzy membership in the category ‘false’, or weak membership in the category ‘true’. The edge weights are in the range $[-1, +1]$. They reflect the magnitudes and directions of causal impacts the model nodes have on each other.

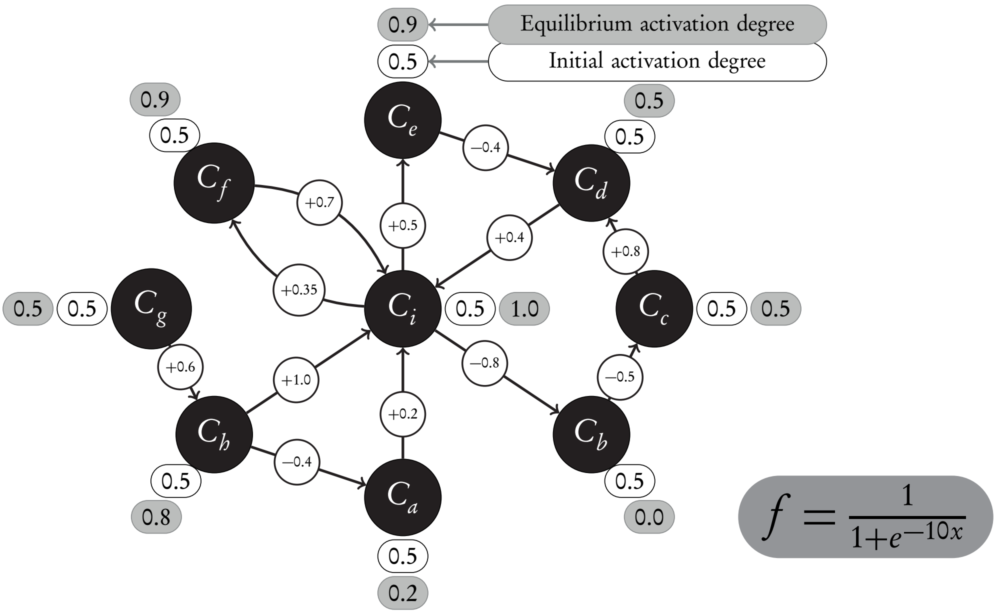


Figure 3.4 Fuzzy cognitive map with 9 concepts. The iterative evaluation process yields an equilibrium state for the system, and the activation degrees in this state are one important object of interest in FCM modeling.

Figure 3.4 shows an example of a FCM model. The process of model evaluation consists of successive steps, where the concept activation degrees are iteratively changed based on the influences described by the impact matrix. The network often, but not always, reaches an *equilibrium* state, where the activation degrees cease changing. The halting condition is *a)* two consecutive identical activation degree vectors, *b)* consecutive activation degree vectors where the greatest absolute difference between identically indexed entries is equal to or smaller than a defined threshold value (such as 0.001), or *c)* cyclically repeated series of identical activation degree vectors (in cases where equilibrium is not reached). The behaviour can, depending on the used *threshold function* (see next paragraph), also be chaotic, never reaching equilibrium or meeting other halting condition.

The initial *activation vector* is multiplied by the weighted adjacency matrix (both objects can be derived from the information of the graph in Figure 3.4). The entry values of resulting vector are 'squashed' with a threshold function (also called *squashing* or *clamping* function), such as the sigmoid function presented in Figure 3.4, or a similar function with a codomain of [0,1], such as functions f_1, f_2 and f_3 in Equation (3.2). The result vector is multiplied with the adjacency matrix again, and squashed, until a stopping condition is met. In the case of the model of Figure 3.4, equilibrium is reached in the 6$^{\text{th}}$ iteration.

$$f_1 = \frac{1}{1+e^{-\lambda x}} \qquad f_2 = \frac{\tanh(x\lambda)+1}{2} \qquad f_3 = \begin{cases} 0 & x \leq -0.65 \\ \frac{5}{7}x + 0.5 & -0.65 < x \leq +0.65 \\ 1 & x > +0.65 \end{cases} \tag{3.2}$$

The resulting new activation degree vector reflects the influence of the impact network on the concepts: with the assumptions of the model, a certain set of concepts will end up active (with a high activation degree close to 1) and others will end up non-active, with their activation degrees closer to 0. In standard Koskoan inference[72], the initial activation degrees can influence the end result, but in many cases they only influence the number of iterations required to reach equilibrium. The exact behaviour of the model is highly dependent on the selection of the threshold function.

Properties of the FCM graph are proposed [135] as one possible way to reason about the knowledge base or system modeled as an FCM: the in- and outdegrees reflect the influence and dependence a concept has. Measures of centrality for the nodes can be used to assess the systemic role different concepts have. The dynamic behaviour of the model exhibited in the iterative concept activation updating process is perhaps the main analytical focus, and the most obvious output is the ultimate vector of concept states or their activation levels. The transient states of concept states and the number of iterations to reach equilibrium state are also proposed as analysis targets for FCMs [125, 135].

The idea of using a neural network in representation of a system is interesting and can be quite easily implemented in a computational sense. The analysis aim is to reason about the influence of the impact network, just as in MICMAC, ADVIAN and EXIT. The causal propagation of FCMs could be said to be closer to the EXIT method and DEMATEL than MICMAC or ADVIAN. The FCM approach does not seek to order or quantify the indirect impacts in any way, but their influence is rather accounted for by the dynamic process where the concept activation levels change. The equilibrium state is the output from which the inferences are mostly made. The generally high abstraction level of structural analysis modeling is by no means lower in the case of fuzzy cognitive mapping. The selection of the threshold function influences the results quite significantly, and cannot easily be rationalized by the nature of the system.

Structural analysis approaches provide a simple set of modeling primitives for mapping causal flows in a system with a relatively high level of abstraction. The modeling process is fast, as much less information needs to be elicited compared to approaches that deal with probability on an explicit, computational level. In the most complex case of structural analysis, where numeric values are assigned for all directed variable pairs, a 20-variable model requires supplying 380 impact values. The high abstraction level implies that the structural modeling approach can be useful in efforts to formulate understanding and theory about the complex causal interlinkages in the modeled system, but the analytical output is often not highly actionable in direct decision support use. Structural analysis can, however, deliver a more informed picture of the interactions of the system components, based on a systematic expert process. An example of structural analysis using the EXIT approach is presented in Publication V. Use of AXIOM approach for deriving structural analysis outputs is discussed in Publication III.

3.4 Morphological analysis

Morphological analysis aims at using system models or modeled decision problems for identifying logical, consistent or probable system states, or reducing the total *problem space* into a smaller, internally consistent *solution space* [112, 133]. Models used for morphological analysis must contain information about the pairwise 'agreement' of the system descriptors, in order to enable identification of system configurations where the states of the descriptors are 'in agreement' or 'harmonic'. This can be achieved by analyzing the joint probabilities of system configurations or partial configurations, if the model contains explicitly probabilistic information. In morphological analysis proper, however, the consistent solution space is discovered using other means than computing joint probabilities. Morphological models describe the consistency or agreement between system descriptors or states of system descriptors with Boolean flags indicating consistency (or inconsistency) as is done in general morphological analysis [112], or a numeric agreement magnitude indicator, as is done in the Cross-Impact Balances (CIB) approach [133]. These indicators can well be interpreted in probabilistic terms, meaning that two descriptors with a Boolean flag indicating consistency, or a positive agreement magnitude indicator, are likely to occur together. This probabilistic interpretation of morphological analysis is not normally mentioned when the approach is discussed [see 112, 133].

The general morphological analysis (GMA) approach to modeling is to define the most important dimensions of the system or the problem complex to be investigated [112]. For each of these dimensions, a set of possible values, or states, is defined. A *field configuration* or *morphotype* in the GMA terminology is designated by selecting a single value for each dimension: this combination represents a 'solution' within the problem complex, or more generally, the system in a particular state. Each possible dimension state in the model is assessed in terms of logical consistency against the possible states of other dimensions. The solution may or may not be logical or consistent, depending on whether or not there are pairwise logical inconsistencies in the solution.

Mapping the pairwise inconsistencies enables eliminating the system configurations, which are inconsistent given some assumption of the states of other dimensions in the model. The viable solution space, the possible combinations of the system states that have not been *bound* or given a state in the initial assumptions, can now be presented to the analyst. The model can be asked questions in the format "assuming these states for these dimensions, what states are possible for the rest of the dimensions".

Cross-Impact Balances approach (CIB) also aims at "identification of plausible configurations of qualitatively defined impact networks" [133]. The degree of promoting or restricting influence the possible states of system descriptors have on other descriptors is expressed with more granularity than in the GMA approach, using a qualitative judgment scale, normally positive or negative integers. The CIB algorithm explores the configuration space and identifies a set of configurations which exhibit a balanced combination according to the CIB criteria.

Morphological analysis can be very useful in identification of internally consistent system configurations or scenarios, and finding solutions to problems with complicatedly entangled considerations. The modeling process is, in relation to probabilistic models, easier and the model evaluation process is relatively simple, both conceptually and computationally. Morphological modeling can also be a realistic approach in cases where the expert informants are not expected to be able to assess interactions between the system descriptors in terms of probability changes, but only on a more intuitive-heuristic level. However, the analytical outputs of the morphological approach can be approximated with probabilistic approaches, which in turn enable outputs which are not possible to extract from a morphological model. An example of deriving morphological outputs from AXIOM models is given in Publication III.

3.5 Ideal modeling approach for expert elicitation

The methodological niche of modeling systems or decision-making problems on the basis of expert elicited inputs has particular characteristics that are important to consider, when techniques for modeling work in this niche are assessed. These include at least the following:

1. *Limited time and expert informant resources call for limiting the number of required inputs.* Requesting too great a number of input valuations from the expert informants will likely make them unwilling to partake in the modeling altogether, as the modeling effort is thought to be unfeasible. Even with a highly motivated expert informant group, the time allocated for modeling is always limited. A high level of required inputs per system descriptor can often mean that the model complexity, in terms of number of system descriptors or the structure of dependencies, has to be limited. This might lead to a very high abstraction level and reduce the usefulness of the model in knowledge representation or decision support.
2. *A trade-off exists between the number of inputs and contemplation of what the valuations are supposed to capture about the system.* Less time in specifying atomic input valuations, such as conditional probability table values, means more time used in contemplation of the actual system rules and properties

being modeled. The level of scrutiny concerning individual valuations will be low in a case of high number of elicited inputs. There is less time for discussion among the expert group, and discussion and consensus seeking is the validation mechanism for expert elicited models. This will negatively impact the quality of the model, and obviously the quality of the eventual results.

3. *Expert informant have varying levels of technical modeling expertise.* The expert informants can in some cases be well versed in formal modeling, but this is not always the case. As the expert informant based modeling approach is often used to model domains that are typically not formally modeled, the experts of said domain often do not have technical modeling expertise. If such expert informants are directly exposed to a great deal of technical complexity of the modeling approach, they may be discouraged from the idea of using formal modeling as a research strategy. The technical details of the method should be quickly conveyed to the expert informants and easily learned.

4. *Expert inputs are approximate in nature.* Expert valuations are hazy, approximate and of limited precision. The modeling approach should not needlessly require inputs of higher precision than what the expert valuators are capable of providing. In some cases, however, the valuations can be of higher precision: evidence or theory may exist that warrants defining a specific relationship in the model with higher precision than other relationships. Ideally the modeling approach should be able to provide a way to model these higher-precision valuations too, but the method should not insist on precise valuations by default.

5. *Cognitive capacity of experts is limited.* The experts are not able to keep all the details of the model in mind simultaneously. Experts can be expected to be able to consider pairwise interaction, and the more complicated multilateral dependencies should ideally be derived by the computational transformation from these modeled pairwise interactions. The modeling style made possible by the modeling language should be efficient in breaking the description of the system rules into smaller parts, dividing the modeling problem into manageable segments. High technical complexity of the modeling language might also be a serious distraction for the actual cognitive work of thinking of the modeled system. A modeling language should add to the cognitive load as little as possible.

6. *Model input elicitation often takes place in group work setting.* Modeling systems based on expert inputs can be based on inputs received from just one single expert. This is not the standard case, however: expert groups are often involved in the modeling and the inputs are elicited in a group work process. Different experts will use different concepts and different abstractions about the system. The process of modeling may in some cases lead to convergence of the concepts and abstractions, a synthesis that can be validated by general acceptance among the expert group. This kind of conceptual convergence might require iterative modeling work. Different experts can also be used for valuation of different parts of the model. The valuations made by one group of experts should be easy to "read" by other experts, focused on a different part of the model.
7. *Domain concepts are difficult to identify and formulate.* The conceptual system model, which is the foundation for building a formal system model, can be unclear and ambiguous in the start of the modeling process. If the modeling process is successful, the 'correct', expressive, and collectively accepted concepts and abstractions are found. This might require several iterative rounds of modeling, discarding some parts of the model and redesigning the model structure. The abstractions and concepts derived from the conceptual model are subject to change during any attempt to formally model a system. Finding concepts and abstractions that are 'fit', descriptive and for which a consensus among the expert group can be found, is difficult. Identifying them may require iterative work.

With this argumentation and understanding of the special nature of the modeling niche, combined with the overview of the strengths and weaknesses of probabilistic, structural and morphological modeling, and their relatedness to each other, the desirable properties for better expert informant oriented systems modeling approaches can be outlined as follows:

1. The modeling language should be feasible for the expert elicitation work mode. It should be simple and relatively easy to understand for domain experts not well versed in modeling. The modeling language should "hide" technical, mathematical or algorithmic complexity, where that complexity is unessential to the aim of describing the system rules. The language primitives should be ef-

ficient in capturing the essential characteristics, rules, and operating logic of the system, at the precision that the expert informants can be expected to be able to provide. A higher precision level should not be required. Ideally, for the cases where the expert informants are able to model specific model components with greater precision, the language should support varying levels of precision for parameterization.

2. The modeling language should be easy to understand for 'readers' of the model. The readers of the model can be participating expert informants, who have not been involved in the modeling of a specific part of the model, but which they need to understand to better perform the modeling tasks assigned to them. Readers can also be model end-users, for whom the transparency of the model is important for understanding how the model works, why the model outputs are what they are, as well as having enough trust in the model to agree with the conclusions drawn from it.

3. The modeling language should enable making relatively easy changes to the formal model, as the underlying conceptual model is subject to change during the modeling process. Ideally such changes would result in minimal revaluation in the model parts that are not changed themselves. Reformulation of the model in the course of the expert process can be seen as a very important benefit and outcome of modeling, so the modeling approach should not be antagonistic to it.

4. The computational transformations associated with the approach should support deriving different analytical outputs from the modeling effort. Expert informant oriented techniques often focus in delivering either structural, morphological or simulation-type analytical outputs. Ideally the modeling approach could deliver all of these types of information. The model should be able to answer a range of different questions about the system, enabling as versatile, detailed, and actionable output as possible with the information content of the model.

5. The approach should provide a clear and practical mechanism for testing interventions on the system. These interventions should have a counterpart in reality and should not be too abstract. Interventions that are too abstract at the model level may be difficult to translate into actionable strategic or policy

recommendations.

6. The approach should support combined use with data-driven models. Several modeling domains are such that some modeled details or system aspects are well captured and represented by statistical data, or empirical data can be collected about them. Other modeled system characteristics, in turn, might not have any empirical data available. Ideally the expert informant based modeling approach could somehow integrate model parts parameterized on the basis of data, and model parts parameterized purely on expert informant sourced inputs.

7. The approach should have a free, well documented, open source software implementation. An implementation of an approach should be freely available and its usage documented. The source code should also be free, for transparency and for the case when the analysts might want to make changes to the method or extract something surprising. Documentation of some methods is somewhat obscure and makes it difficult to reproduce the implementation of the method, without filling the gaps in the method descriptions by experimentation and guesswork.

The various modeling approaches reviewed in Chapter 3 can be compared along several dimensions of design choices. These include the nature and the information content of the descriptors, the way relationships are described and what they mean, general graphical properties of the models, the computational transformations performed for the models and the way analysis is facilitated in the approach. These design characteristics are discussed in Publication I.

4 METHODOLOGICAL PROPOSALS OF THIS WORK

4.1 EXIT approach for structural analysis

EXIT falls in the category of approaches for structural analysis discussed in Section 3.3. As such, it can be most meaningfully compared to MICMAC, ADVIAN, FCMICMAC, and DEMATEL approaches, but also cognitive maps and fuzzy cognitive maps. MICMAC and ADVIAN models, as well as EXIT models, are normally presented as impact matrices. Cognitive maps and fuzzy cognitive maps are typically presented as graphs. These representational details are conventional, and both representations can be used for all models in the structural analysis category. If the graphical representation of the model is a dense graph, meaning that the number of edges is close to the maximal number of edges, the matrix representation is likely more practical and informative for an analyst. For a model with few connections between the variables, the graph representation is easily more informative. A detailed methodological description of the EXIT approach is given in Publication IV, and a use case is presented in Publication V, where the near-future change trends of the Finnish electricity system are related to each other as an EXIT model.

4.1.1 Overview of the approach

The EXIT modeling language consists simply of *hypotheses* and direct causal *impacts*. The hypotheses are the system descriptors, representing the events, driving forces, trends and phenomena of the modeled domain. They are formulated as postulates of possible facts about the system. Conceptually, the hypotheses have an unknown truth value, which can be thought to be found out "as the future unfolds", or as the modeled uncertainties are resolved in the real system or world. Hypotheses are

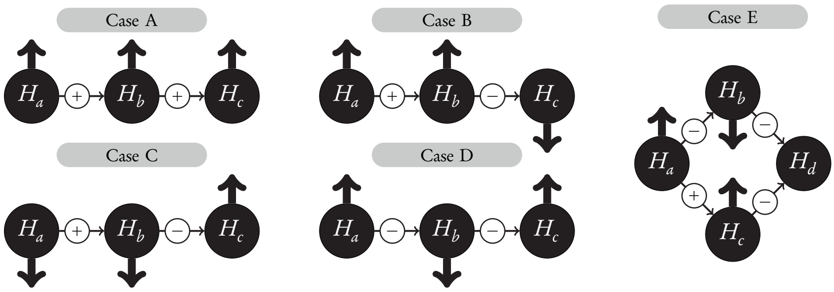


Figure 4.1 Logic of impacts' influence in EXIT. H_a, H_b, H_c and H_d are hypotheses in an EXIT model. The vertical arrows indicate the direction of probability change of a hypothesis: an upwards arrow signifies probability increase, downward arrow probability decrease.

ideally formulated in a precise, unambiguous way. Examples of hypotheses can be found in Figure 4.2.

Impacts are directed probabilistic relationships of causal nature between the hypotheses. In an impact, one hypothesis is the cause and the other hypothesis the effect. In a different impact, the direction can be reversed: cycles are allowed in the graph representation of an EXIT model. Hypothesis H_a can be both a cause of and an effect of the same hypothesis H_b. An impact carries an impact value in the range $[-1, +1]$. Impact value indicates the magnitude and sign of the probabilistic influence the impact represents. The basic interpretation is that information about the cause hypothesis changes the probability of the effect hypothesis. In the case of a positive impact value, knowing that the cause hypothesis is true, the probability of the effect hypothesis increases. Information about the cause hypothesis being false decreases the probability of the effect hypothesis. In the case of a negative impact value, the probability changes in the effect hypothesis are reversed. The information about the cause hypothesis can be thought of in a more general way: changes in the probability of the cause change the probability of the effect in a way described by the impact value. This reasoning is illustrated in Figure 4.1 and Table 4.1.

Normally impact values are expressed as integers in range $[-\text{maxValue}, \text{maxValue}]$ for convenience, as integers are easier to use in the elicitation process than decimals in the $[-1, +1]$ range. Using this approach means that a maximum impact value has to be defined for the model before assigning the impact values. The maximum impact value does not mean a fully determining probabilistic influence, it is simply the greatest magnitude for an impact in the model. The strengths of the other used impact values are interpreted in a linear fashion: impact with a value of $+2$ repre-

$\Delta P(H_a)$	$H_a \xrightarrow{+} H_b$	$H_a \xrightarrow{-} H_b$
$P(H_a)$ increases	$P(H_b)$ increases	$P(H_b)$ decreases
$P(H_a)$ decreases	$P(H_b)$ decreases	$P(H_b)$ increases

Table 4.1 EXIT direct impacts and their interpretation in terms of probability change of the impacted hypothesis.

sents an influence of half the strength of impact with value +4. While the impacts are understood to mean probability-changing influences, the impact values do not map to specific, quantified changes in the probabilities of the impacted hypotheses. The impact values simply relate the magnitudes of the impacts to the magnitudes of other impacts in the same EXIT model. Description of the probabilistic influences between the system descriptors at this level enables structural analysis of the system, with a very simple modeling language and low conceptual complexity.

On the basis of the modeled information about the direct impacts, the indirect impacts can be discovered. Indirect impacts are captured by *impact chains*, impacts connecting the elements in ordered sets of model hypotheses. The set of indirect impacts of hypothesis H_a on hypothesis H_b in an EXIT model with n hypotheses is the set of permutations of the hypotheses starting with H_a and ending with H_b, of lengths 3 to n. For instance, in a model with hypotheses H_a, H_b, H_c and H_d, the influence of hypothesis H_a on H_b effectuates through the causal chains $H_a \rightarrow H_b$ (the direct impact), $H_a \rightarrow H_c \rightarrow H_b$, $H_a \rightarrow H_d \rightarrow H_b$, $H_a \rightarrow H_c \rightarrow H_d \rightarrow H_b$, and $H_a \rightarrow H_d \rightarrow H_c \rightarrow H_b$. The *relative impact* of a single impact chain is simply the product of the impact values of the impacts in the chain, given they are in the range $[-1, +1]$; If the maximum impact defined for the model is not equal to 1, each impact value is divided by the defined maximum impact. The *total relative impact* of a cause on an effect is the sum of all the relative impacts of the impact chains from the cause to the effect.

Computing the total relative impacts for all directed hypothesis pairs yields a *summed* or *total impact matrix*. The total relative impact values represent the impacts cause or row hypotheses have on column or effect hypotheses, when flows of causal influence through all possible routes in the system are considered. The values are relative quantifications of influence magnitude, and relate the influences to the other influences in the same system model. The hypotheses can thus be compared to each other, in terms of their significance for a particular effect hypothesis of interest, their important dependencies, or their overall systemwide influence or dependence.

The summed impact matrix values are *normalized* by dividing each matrix entry by the mean of the absolute entry values of the summed impact matrix. This brings the matrix into a scale, where the unit is the so-called *cross-impact unit*, the average impact on an average cause on an average effect. Similarly, the direct impact matrix can be normalized by the mean of its absolute entry values, and after these transformations, the summed impact matrix and the direct impact matrix can be meaningfully compared. The time complexity of computing the relative impacts of the impact chains possible in the model grows exponentially as the hypothesis count grows, so an estimation strategy for the total relative impacts is needed. The estimation strategies are discussed in Publication IV. To summarize, the EXIT implementation uses a combination of full computation for short impact chains, the definition of 'short' being dependent on the hypothesis count, and an estimation of relative impacts of longer chains by stratified sampling. Given the approximate nature of the expert-sourced input valuations, this approach should provide more than sufficiently accurate estimates.

The EXIT model of Figure 4.2 exemplifies the inference logic related to indirect impacts. The direct impact of hypothesis H_a ("Electricity price increases") influences hypothesis H_b ("Wind and solar capacity increases") in a promoting way, with the impact value $\frac{+3}{4}$. Hypothesis H_e ("Renewable energy subsidies increase") promotes H_b with equal strength as H_a. However, impact of H_a on H_e is negative, valued $\frac{-3}{4}$. Indirect impact of H_a through H_e on H_b is therefore negative as well, as the promoting influence of H_e on H_b is impeded by H_a if H_a 'occurs'. If H_a was known to be true, it would directly promote H_b by $\frac{+3}{4}$, but the indirect influence through H_e mitigates this influence by some extent. H_a's total relative impact on H_b is $\frac{+3}{4} + \frac{-3}{4} \times \frac{+3}{4} = \frac{+3}{4} + \frac{-9}{16} = \frac{+3}{16} = +0.1875$.

Hypothesis H_a has directly no influence on hypothesis H_c ("Electricity storage capacity increases"). The influence effectuates through hypotheses H_b and H_d. As discussed in the previous paragraph, H_a influences H_b both directly, in a probability-increasing way, and through H_e in a probability-decreasing way. The indirect impact of H_a on H_c through H_d is valued $\frac{+1}{4} \times \frac{-1}{4} = \frac{-1}{16}$, and through H_b, based on what was already computed, $\frac{+3}{16}$, so the total relative impact of H_a on H_c is $\frac{+3}{32} + \frac{-1}{16} = \frac{+1}{32} = +0.03125$: the indirect influences largely cancel each other out in the system.

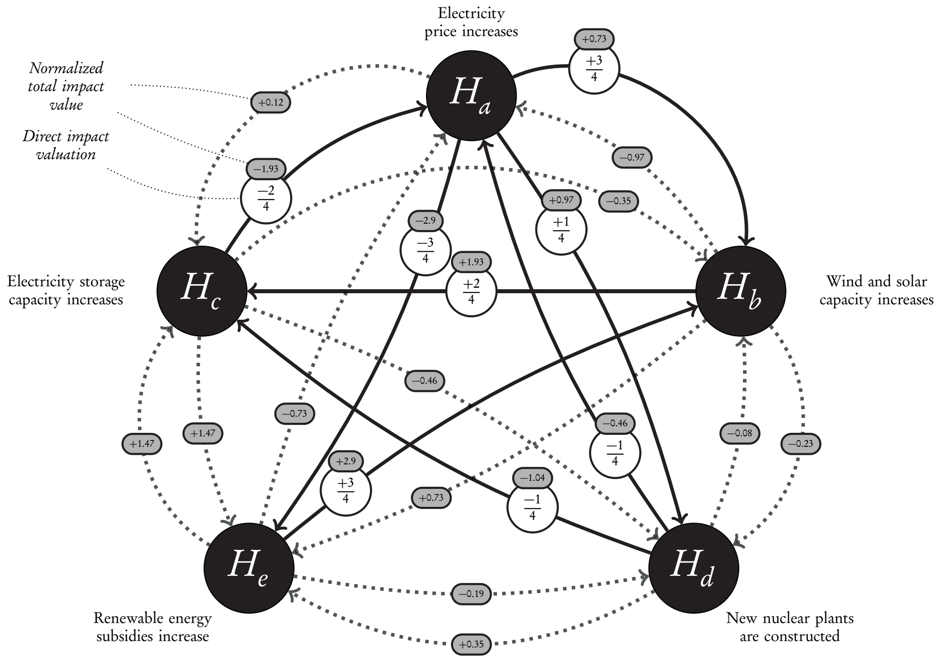


Figure 4.2 An illustrative EXIT model with five hypotheses (H_a–H_e). Hypotheses describe possible developments in the Finnish energy system. Impact valuations assigned by the author. Adapted from Panula-Ontto et al. [101].

This small example illustrates how the picture of the systemic relationships is formed by inference based on the impact network. In a small model, such as the example model of Figure 4.2, the results are easy to confirm, and the indirect impacts can be effortlessly observed from the graph representation of the model. In a large EXIT model, dense with impacts, the EXIT transformation becomes useful and may reveal unexpected and counter-intuitive relationships. The expert informants can be used to partition the contemplation of the relationships of the system elements to pairwise interactions, and the synthesis of this information is discovered with the EXIT transformation. Publication V shows a real modeling example utilizing EXIT.

EXIT can structure the discussion about important events, driving forces and trends. Once the causal network has been modeled, the EXIT transformation can commensurate the complex interactions between the system elements and relate them to each other in terms of magnitude. This enables the analyst to form a better understanding about the relationships between the system elements and the importance of each element on others. As the modeling language is of minimal conceptual complexity, grasping the basic idea of EXIT modeling is easy for expert informants, at least on the basis of the initial experiments with expert groups [73, 74, 101]. The modeling process is also fast, and leaves time available for discussion within the expert group, as the number of elicited inputs remains low. In large system models representing complex, densely connected systems, the analysis can give surprising insights that cannot be made available by intuitive-heuristic means without a similar computational transformation. A software implementation of EXIT is available at `https://github.com/jmpaon/EXIT`.

4.1.2 Relationship to other approaches for structural analysis

Short descriptions of MICMAC, ADVIAN, DEMATEL, cognitive maps and fuzzy cognitive maps have been given in Section 3.3. All of these approaches use some form of iterative matrix multiplication as a means to infer about the indirect influences, the main object of interest in structural analysis. MICMAC and ADVIAN aim at providing an alternative ranking for the model variables based on either their general influence or dependence, and classifying the variables by their rankings along these two dimensions. If an expert panel is assembled to provide the valuations for a structural impact model, it is desirable to extract more analytical value from the modeling effort than mere alternative rankings, if the information content of the model permits that. The rankings and MICMAC-style classification can be produced by simple summation of row or column values, if pairwise indirect impacts are quantified by some means: the original aim of MICMAC is thus achieved, but the much more detailed information of the pairwise interaction is also made available. The development of the EXIT approach was motivated by this aim, and the method is positioned, in the Publication IV proposing it, mainly against the MICMAC approach.

Matrix multiplication can be used to give a reasonable quantification of the total influences of a structural model, when the initial direct impact matrix is suitably scaled so that a terminating condition for the iteration exists. This is exactly what is done in the DEMATEL approach: the direct impact matrix is normalized by the maximum value of the row and column sums, guaranteeing that any row sum does not exceed 1. Iterating $(((\mathbf{N} \times \mathbf{N}) \times \mathbf{N}) \times \mathbf{N}) \times \ldots$ with the normalized direct impact matrix $\mathbf{N}$ converges towards the null matrix, and the total impacts are obtained as the sum of the yielded matrices.

The results reflect a different way of thinking about the causal influences in the system, compared to EXIT. In the direct impact matrix multiplication approach, cyclic or recursive impacts are included in the results. The causal propagation can indirectly cycle back to the cause, but as a result of the way the direct impact matrix is normalized, the magnitude of the causal flow is weakened with each step as it flows in the causal cycle. As a result, iteration eventually produces the null matrix. In EXIT, the pairwise total impact represents the sum of the relative impacts of all possible impact chains, which themselves are acyclic. The aim is simply to relate all the extant causal paths between two model variables in terms of magnitude to each other, and DEMATEL-like 'dynamic' system behaviour is excluded from consideration.

For *acyclic* EXIT models with n variables, the total impact matrix can be obtained much more efficiently than with the used sampling-based approach by normalizing the direct impact matrix by the inverse of maximum impact value and iteratively multiplying the normalized matrix $n-1$ times. Based on the initial experiments with the EXIT approach, however, acyclic models are rare and more typically the graphical representations of EXIT models are dense, if not fully connected. From this perspective, the matrix multiplication approach is normally not applicable to get the EXIT results.

Should the recursive, cyclic influences be considered in computing the total impacts in a structural model? It would at least make the computation much simpler, as no combinatorics would be involved. The answer must depend on the exact interpretation of the meaning of model variables and the causal flows. EXIT defines the variables as hypotheses with an unknown truth value. The computation of total pairwise influence considers only the possible causal paths from cause to effect, but not the dynamics captured by cyclic impacts. The argumentation for disallowing cyclicity in the causal flow between two variables is that information about the cause being true (or false) cannot increase its own degree of being true or false, even indirectly. The EXIT reasoning about the structural relationship between two variables starts with those two variables and proceeds to form an image of the possible causal paths between them. A different interpretation of the meaning of the model variables would be required for allowing 'dynamic' causal flows indirectly returning to the cause and cycling in an ever-weakening fashion to make sense. The EXIT interpretation of the causal propagation is perhaps more 'Bayesian' than system-dynamical. Arguments can be made for allowing cyclic causal flow in a structural model–if those arguments are convincing, the DEMATEL approach is available for analysis of the same model that can be analyzed with EXIT. Conversely, EXIT can be used in analysis of any model created with the DEMATEL approach in mind. Ultimately, the two approaches perform transformations of quite different nature on the model.

A fuzzy cognitive map could, in theory, be derived from an EXIT model by simply assigning an initial activation value for each hypothesis and selecting an appropriate squashing function: Modeling languages of both approaches are, in terms of interactions, very similar. For many models, it would not be straightforward to map the EXIT variables formulated as hypotheses, more akin to binary random variables in nature, to the *variable concepts* of fuzzy cognitive maps. But with some reformulation of the EXIT hypotheses, an EXIT model could be analyzed as a fuzzy cognitive map as well. The aim of the fuzzy cognitive map computational transformation is to model the dynamic behaviour of the system. The dynamic behaviour obviously results from the structural properties of the system model, and in this sense the analytical focus is similar to that of EXIT. However, as the main output is the equilibrium state for the system, and the values of the activation state vector, the approaches produce a very different natured end result from largely similar information. As the purpose is so different, they cannot be reasonably assessed against each other in terms of fitness for a purpose. They could be seen as complementary computational transformations for very similar models, very much like EXIT and DEMATEL.

4.2 AXIOM approach

4.2.1 Overview

AXIOM is a probabilistic causal logic, and as such also a generic modeling approach, with a high intended fitness for expert elicitation based modeling and decision support use. It is suitable for modeling decision-making problems and systems involving uncertainty. While it can be applied in modeling of a wide range of planning and decision-making contexts, it has only low fitness for modeling non-changing, deterministic systems with well-known rules. The design choices of AXIOM are aimed at providing a modeling approach with a special fitness for using expert informant elicited inputs, with a focus on foresight applications. To achieve this goal, AX-

IOM combines aspects of cross-impact techniques, morphological analysis, structural analysis and Bayesian belief networks. AXIOM modeling language, the computational transformation, and analysis of modeled systems are the focus of publications II and III.

As a probabilistic causal logic with a modeling language capable of representing facts and rules with varying levels of precision or haziness, it has applications especially in the foresight domain. Future developments are uncertain, and they are related to other developments in an uncertain way. Essential considerations for foresight are often not captured in existing data, and as a result, reasoning about future developments has to rely on heterogenous data sources, especially the views of expert informants. A logic capable of encoding expert elicited information with formality and providing reasonable processes of inference can be useful in *synthesizing* the heterogenous viewpoints and reasoning about the possible developments and their consequences. Automated reasoning capabilities of a logic allow for compartmentalizing the complicately interdependent considerations and drawing higher level insights from combined descriptions of lower level details with less complexity. From a decision support perspective, the ultimate aim is to evaluate decisions, policies and strategies by simulating their outcomes with the model.

The modeling language of AXIOM has a *relatively* high fitness for modeling processes fully relying on expert elicitation for model inputs. This claimed fitness for the expert informant niche results from the probabilistic nature of the model rules, the relatively low number of inputs required, and the flexibility of the modeling language capable of representing system rules at varying levels of precision. The nature of the outputs lends to decision support easily, and cover many of the analysis aims of other modeling approaches discussed in this work. AXIOM is also suitable to be used as an auxiliary modeling approach in conjunction with Bayesian networks: its output can be an itemset which can be used for parameterization of a Bayesian network. This means that expert informant oriented modeling can be done in AXIOM and the results used together with empirical data in creation of a Bayesian network. This approach can bring highly expert oriented and data oriented modeling techniques in the same analytical framework.

4.2.2 Positioning and contribution

Functionally, and in terms of the basic nature of inference, the closest modeling approach equivalents for AXIOM are Bayesian belief networks and influence diagrams, though technically the approaches are different. In a sense, a Bayesian network becomes an AXIOM model, if

1. the posterior probabilities are estimated with a sampling process instead of being computed with the exact computational methods used in Bayesian networks in normal cases,
2. graph cycles are allowed in the model (bidirectional influence can be allowed, as the posterior probabilities are estimated via sampling), and
3. conditional probability table based description of the causal dependencies is replaced with one based on AXIOM updating functions.

As posterior probabilities in a Bayesian networks can be estimated by means of sampling as well, it is perhaps not impossible to think of AXIOM as a special case of a Bayesian belief network. The analytical use of an AXIOM model is very close to the use of a Bayesian belief network or an influence diagram. The same facilities of predictive and diagnostic inference are present in AXIOM, as they are in Bayesian networks, although these facilities are provided through different, and less efficient, means of computation. The decision support facilities of influence diagrams, such as decision nodes and utility nodes, can be approximated with AXIOM as well.

Technically, the computational process of AXIOM is a discrete event simulation [15, 23]. The process generates a sample of *possible worlds*, and the probabilistic reasoning is based on occurrence frequencies of facts in the generated sample or samples. In this sense, the computational process differs from the exact methods of Bayesian network significantly. It must be noted, however, that the computation in Bayesian networks has to resort to sampling-based estimation as well in cases of very complex models [21, 104, 105].

Computationally the sampling based on discrete event simulation is inefficient compared to the way probability updates are implemented in Bayesian networks. However, the Monte Carlo process based inference allows for things that would not be allowed in a Bayesian belief network (or a normal Bayesian belief network, if AXIOM is understood to be a special case of it). Graph cycles are allowed in a graph representation of an AXIOM model, as they are in many other cross-impact models. Cycles can be allowed for a Bayesian belief network as well if the posteriors are estimated by sampling. This is important in modeling with a foresight aim.

Bidirectional probabilistic interaction between possible developments or system states is a typical thing to be modeled as characteristics of systems, especially when the modeling has a foresight aim. The semantics of bidirectional interaction, in probabilistic terms, is that the causal and temporal positioning of bidirectionally dependent descriptors is unclear or uncertain: one might happen before or after the other. In a discrete event simulation process of model evaluation, a set of 'possible worlds' is created. In a single possible world, the temporal and causal ordering of the two descriptors is clear (one happens before the other), but in the next possible world generated, the order can be reversed. The posterior probabilities inferred from the generated sample of possible worlds reveal the results of the bidirectional interaction.

The AXIOM model gives control over the evaluation logic with the *timestep* property, and the temporal dimension of a system can truly be modeled with the modeling language, unlike GHCIA or BASICS approaches. At the model level, descriptors with equal timestep values are evaluated and their states resolved in random order, meaning that their sequence is subject to change between model evaluations. Semantically and in the analytic sense, they happen simultaneously or in the same temporal space. Descriptors with a lower timestep value are guaranteed to be resolved before the descriptors with a higher timestep value. Comparable cross-impact approaches do not provide ways to model time. In Bayesian belief networks, the causal and temporal logic is coupled with the model structure, and this imposes limitations to the modeling power. The timestep approach and the cyclicity of an AXIOM graph provide more leeway for the modeler in this regard. In an AXIOM model, the temporal positioning of descriptors can be changed without necessarily having to change anything else in the model. In a Bayesian belief network, relocating a descriptor in the causal structure, through which the time aspect is represented, would create the need to redefine some of the conditional probabilities. Such changes might involve a great deal of work for the expert informants.

The discrete event simulation nature of AXIOM also opens up other possibilities that are not available in Bayesian belief networks. The updates fired by the evaluation of descriptors and resolving their state normally update probabilities of yet-unknown model facts, mimicking Bayesian probability updating in face of new evidence. However, the updates can also be set to do more than just update probabilities: they may change the remaining evaluation sequence or logic, or they can do structural or valuational updates to the model. This does not strictly mean that similar things could not be modeled with Bayesian belief networks, but that the way such consequences are represented at the model level can be, from the perspective of the model user, more obvious and understandable. Considering that a use purpose of both Bayesian belief networks and AXIOM models is also knowledge representation, such clarity is a positive aspect of the approach, even if it does not analytically enable something that would not otherwise be possible at all.

Generally speaking, the sampling based computation and the consequent 'slowness' of the model evaluation is obviously negative. However, this inefficiency is, in the opinion of the author, largely unimportant for the typical use case of a cross-impact model in general or an AXIOM model in particular. The functional bottleneck in expert informant oriented modeling is the expert process, by a cosmological margin. The time used in any computational transformation of linear time complexity imaginable is going to be insignificant in the timeline of the modeling process. Once the model has been built, the inference can be performed as batch processing, already supported quite well by the intervention statement functionality of the AXIOM implementation currently in distribution [94]. More support for batch extraction of outputs will be provided in the implementation in the future. If real-time manipulation of the model and instant probability updating are necessary, the normal BN is vastly superior to any sampling based estimation strategy, but this computational efficiency comes at the cost of limited modeling expressiveness. It must also be noted that the computational process of an AXIOM model aiming at estimation of posteriors with a single setup can be performed in a matter of minutes in most cases even with the current implementation, where computational efficiency has not been a particular concern. The sampling process can be fairly trivially parallerized, and this alone will in the case of many a personal computer make the process 3-4 times faster. As the software implementation development proceeds, the efficiency of the implementation will be of higher concern in the development of the framework. Still, optimizations to the computational process might be in conflict with modeling language features to be introduced in the future, so it might be too early to optimize the sampling at this point.

From a modeling language standpoint, and specifically from a full expert elicitation based model valuation, the most important difference between AXIOM and Bayesian belief networks are the way interactions are described in the model. In AXIOM, the probabilistic relationships of model components are described, instead of conditional probability tables, as in Bayesian networks, with references to updating functions. This approach has been developed and utilized in the cross-impact analysis tradition [49, 50, 51, 56].

The motivation of describing the probabilistic dependencies of facts as a Bayesian network is to avoid the need to define full joint probability distributions. By adding information about the structure of the dependencies, the number of required conditional probabilities can be dramatically reduced, and the full joint probability distribution can be inferred from the graphical model [104]. If a Bayesian network is algorithmically learned from data with a full joint probability distribution, the conversion to a Bayesian network is, in practical cases, an information-lossy operation.

Analogously, the motivation to describe probabilistic dependencies of facts in the cross-impact analysis language, as strictly or predominantly pairwise probabilistic influences between facts, is the desire to avoid the need to define full conditional probability tables for all dependencies, as in a Bayesian network. The cross-impact language description is not particularly useful if the causal structure is well defined and the complexity of the structure, namely the number of dependencies of a variable and the number of states of the dependencies, is low. In such cases, the conditional probability table description is not more difficult, and can even be conceptually simpler for the informants. However, the cross-impact language description can be very useful for complex systems with a high number of causal dependencies between facts, especially when the model parameterization relies on expert informants. In a Bayesian network, the number of conditional probabilities grows exponentially as the number of dependencies grows: The number of conditional probabilities in a Bayesian belief network is $\sum_{i=1}^{N} s(n_i) \times p(n_i)$, where N is the number of nodes in the model, $s(n_i)$ is the number of states node n_i has, and $p(n_i)$ is the number of state combinations parents of node n_i have, or 1 if n_i has no parents.

Figure 4.3 shows three abstract models and compares the number of input valuations necessary for full model parameterization using a BBN description and a cross-impact language description. Models A and B have the same number of states, but the dependency structure is different between them. Model C has nodes with higher number of states. Comparison illustrates how the input valuation count grows fast

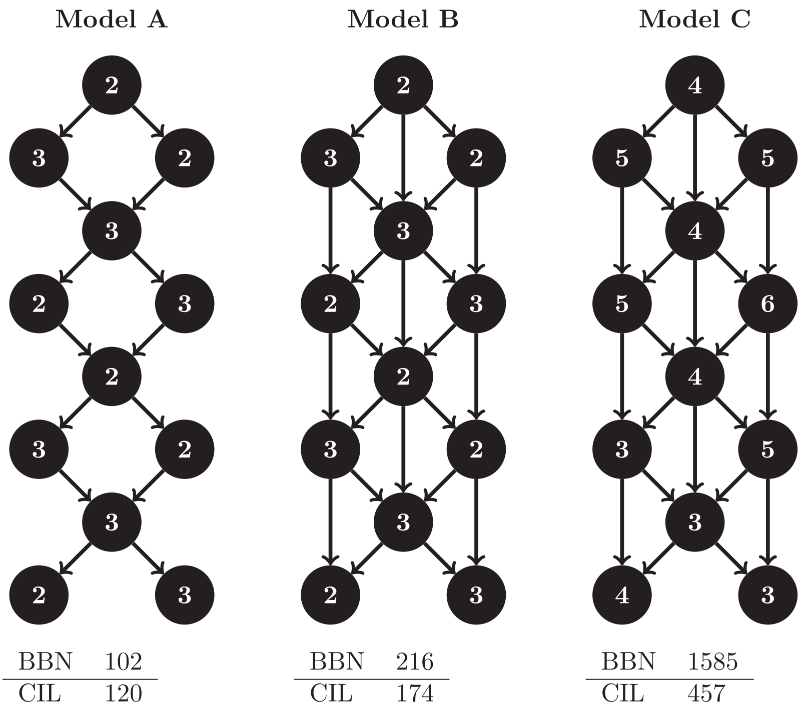
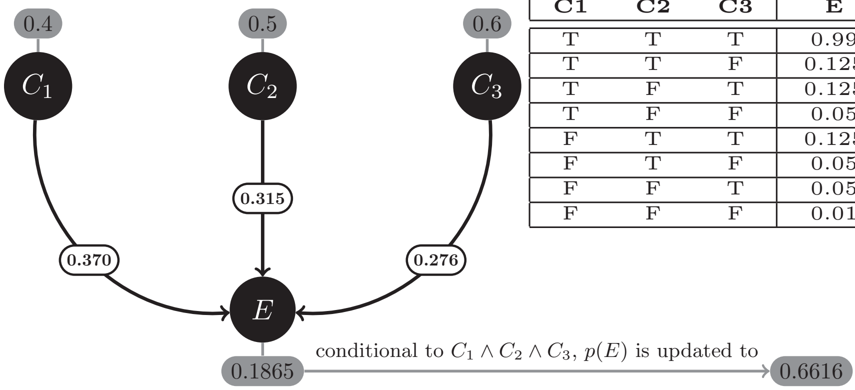


Figure 4.3 Number of inputs required for BBN and for a cross-impact language (CIL) representation. Node labels indicate the number of possible states the node has.

in the case of a BBN, as the dependency structure becomes more complex and state count for nodes increases. The input valuation counts in Figure 4.3 are very pessimistic for both approaches, but especially for cross-impact language description: the assumption is that a dependency is described with a value in all entries of the submatrix describing the influence of different states of the cause on the states of the effect. Normally, only half or less of these entries would be valuated.

Making expert elicitation a more feasible approach for input acquisition in the context of Bayesian networks is almost a research topic on its own [25, 30, 32, 33, 43, 62]. Auxiliary techniques are useful in easing the elicitation process, but they do bring an additional layer of complexity to the modeling. AXIOM is an alternative way to generate input material for Bayesian networks, and it has the advantage of being a causal reasoning and decision support tool on its own.

In the cross-impact languages, the number of inputs to be elicited grows only in a quadratic or subquadratic fashion, as the probability impacts are described mostly in a pairwise fashion, instead of for all possible configurations of the states of the dependencies of an effect. The cross-impact language description, if the language does not allow for multi-cause updates, is less expressive in the sense that *synergic influences*, conditional to the joint occurrence of several facts cannot be modeled at all. Figure 4.4 displays a synergic influence of three causes C_1, C_2 and C_3 on effect E, and shows how the strictly pairwise impact description of the influences runs into problems with such structural intricacies.



0.4 **C1**	*0.5* **C2**	*0.6* **C3**	*0.1865* **E**
T	T	T	0.99
T	T	F	0.125
T	F	T	0.125
T	F	F	0.05
F	T	T	0.125
F	T	F	0.05
F	F	T	0.05
F	F	F	0.01

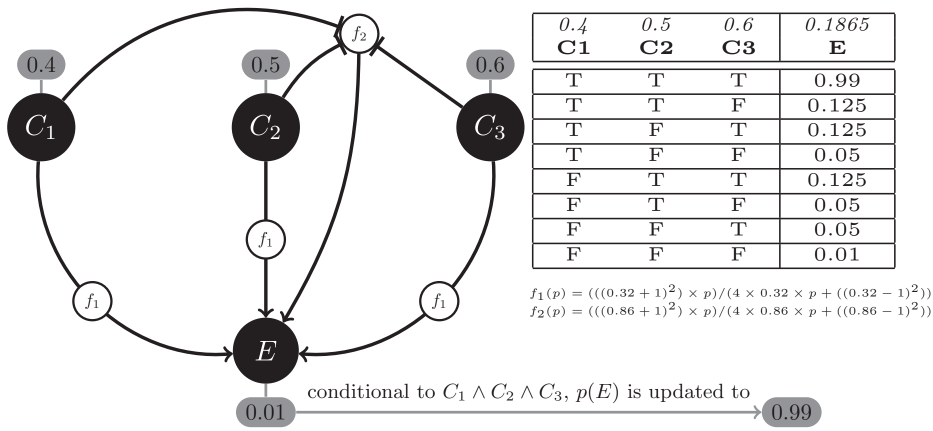
Figure 4.4 A synergic probabilistic influence, problematic in a GHCIA model. Occurrences of causes C_1, C_2 and C_3 update the probability of effect E.

All causes raise the probability of the effect E on their occurrence. The probability-elevating influence of the three causes is very high (raising the probability to 0.99) when all causes occur, but the individual impacts of the causes are much more marginal. This makes the GHCIA description of the nature of the dependency *structurally* very approximate. The joint influence could be divided to the three individual causes, but then the estimate of the probability of E would be very biased in cases where only one or two of the causes occur.

As discussed in Chapter 3, the BASICS approach uses a set of six updating functions to which determining the quantified probability change of the contextual probability update is delegated to. The BASICS probability updates are, equal to GHCIA, conditional to a single cause. As such, they are also unable to model structurally complex, synergic influences. The haziness in the BASICS cross-impact language description of interactions is both *valuational* and *structural*.

Valuational haziness is an inevitable consequence of the contextual probability updating logic. The informant providing a conditional probability, in the case of GHCIA, or referencing an updating function, in the case of BASICS or AXIOM, is unable to know the context in which the probability update happens and will there be further probability updates on the updated probability. Contextual updating is hazy and approximate–and that is its whole point, as it is means to the end of easing the model valuation. Valuational haziness, in cross-impact languages, could be said to be lowest in GHCIA, as at least the first update is exactly what the informant specified. BASICS is very high in valuational haziness, as the limited set of updating functions forces to model the impacts with low granularity. AXIOM is somewhere in between these approaches in valuational haziness, as it can have any number of updating functions.

Structural haziness, illustrated in Figure 4.4, is equally high in GHCIA and BASICS. In most cases it is not necessarily a significant limitation: many joint influences or several causes can mostly be conceptually decomposed into single-cause influences, and the situation described by Figure 4.4 is more of a special case. However, the structural haziness issue can be improved without much conceptual overhead by allowing the contextual probability updates to be conditional to an arbitrary number of causes.



0.4 **C1**	*0.5* **C2**	*0.6* **C3**	*0.1865* **E**
T	T	T	0.99
T	T	F	0.125
T	F	T	0.125
T	F	F	0.05
F	T	T	0.125
F	T	F	0.05
F	F	T	0.05
F	F	F	0.01

$f_1(p) = (((0.32 + 1)^2) \times p)/(4 \times 0.32 \times p + ((0.32 - 1)^2))$
$f_2(p) = (((0.86 + 1)^2) \times p)/(4 \times 0.86 \times p + ((0.86 - 1)^2))$

Figure 4.5 Multi-cause impacts in AXIOM.

Figure 4.5 shows how the influence structure of Figure 4.4 could be modeled with AXIOM by allowing multiple causes for impacts. It must be noted that the distributed version of AXIOM implementation does not yet support this functionality at the time of writing, but the expansion is trivially implemented and one possible way is outlined in Publication III as pseudocode. The possibility of modeling the multi-cause impacts does not in any way force using them, and in this sense there is no trade-off in terms of ease of model valuation.

BASICS uses an approach of delegating the probability updates to updating functions. The modeler simply describes the magnitude of a probability influence as a reference to an appropriate updating function, without any additional information. The BASICS approach has been the inspiration for AXIOM way of performing the updates. BASICS has a set of six updating functions, which update probabilities contextually, mapping a current probability to an updated probability. The probability updates could be thought of as signals or messages facts send to other facts to update their probability. This information flow between the facts is conditional to state changes in the model: When a statement is evaluated and resolved to a state, and something more is known about the system, the probability influences conditional to this new known fact are fired and update probabilities.

The BASICS approach to interaction description is simpler and more heuristic in comparison to GHCIA. In GHCIA, the magnitude of the probability updates is specified as conditional probabilities, and their values have defined bounds (see 3.2). In BASICS, the probability updates are not specified as conditional probabilities, and the system of prior probabilities and cross-impacts does not need to conform to any requirements imposed by probability axioms. The approach to updates is fully contextual. This could of course be seen as a drawback as well. If the GHCIA approach of the conditional probabilities being subject to constraints is seen as an important part of the modeling approach by the users of AXIOM, it warrants consideration of extending the GHCIA approach, or providing a more GHCIA-like updating function in AXIOM.

An extended, modernized version of GHCIA would have to be generalized for multi-state descriptors, and an AXIOM-like timestep property would need to be introduced to increase the modeling power of the original GHCIA approach. A modernized GHCIA approach could be used in conjuction with BBNs just like AXIOM, as a BBN could be derived from the output relatively unproblematically, or in a no more problematic fashion than from AXIOM output. The BASICS language has the upside to GHCIA language in that there is no need to define probability impacts between all descriptors. In GHCIA, all events have a defined probability impact on all other descriptors: The conditional probabilities need to be consistent according to the rules defined for a GHCIA cross-impact matrix. This might take some focus out of the heuristic expert process of defining system rules. Note that the conditional probabilities can be set equal to initial probabilities, representing a neutral impact. However, these neutral updates *might* violate the bounds defined for the GHCIA conditional probabilities, so in this sense, there is no 'neutral' update available in the case of GHCIA cross-impact language.

BASICS updating functions are equivalent to AXIOM simple updating functions. One difference is that in BASICS, the set of updating functions is fixed, but in AXIOM, there can be as many updating functions as are needed in the opinion of the modelers. This detail is of course implementation specific and BASICS could easily be amended to have a different set of updating functions.

AXIOM expands on the idea of updating functions in cross-impact languages. The AXIOM updating functions close over the entire model: The updates can be made conditional to *any* information in the model. As discussed above, this can mean any number of states of the model, i.e. a combination of several facts, or descriptor states. In addition to this, it could mean the current probability distributions of yet-unresolved statements, or structural information, such as the structure of the impact network. Making updates conditional to other information than resolved states is currently an experimental feature. The main issue is to provide a way for the modeler to describe such dependencies in a way that is simple to understand and results in model behaviour that is relatively easy to predict. Expanding the modeling language to this direction comes at a cost of increased complexity, and might run counter to the original idea of providing a conceptually simple logic for modeling with expert inputs.

Using probability distributions of unevaluated nodes could be used to model actor behaviour. The decision or strategy or an actor is often dependent on the outlook of future developments at the moment the decision is made. A descriptor or a set of descriptors would be set up to model the decisions of actor or actors, and the probability distribution would be made dependent on current probability distributions of other descriptors. No AXIOM models modeling actor behaviour though this mechanism currently exist, but the approach lends to modeling it.

The updates can also do more than update probability distributions. Most importantly, they could alter the evaluation logic in the sense of reordering the evaluation sequence. An important expansion to simple probability updates is to be able to model an impact to compel the occurrence or non-occurrence of a state immediately, to model a deterministic relationship, as per propositional logic. Such an update can be performed in two ways: The first option is to set the state of the target descriptor of the update, but fire its updates later, when the descriptor is taken up for normal statement evaluation. The second option is to perform the updates conditional to the state immediately. These two options are slightly different from a modeling semantics perspective. Updates could also change the model structurally, such as eliminate impacts or add them. These logic extensions can be useful in some cases, but for the most part, the author expects that simple updating functions performing probability updates are sufficient.

The AXIOM way, or the way of the cross-impact languages in general, of describing the interactions is more approximate and hazy, but reduces the number of inputs that need to be elicited, making full model parameterization based on expert informant elicited inputs much more feasible, especially in structurally complex models. The cross-impact approaches have introduced ways to do probability updates based on a limited number of inputs, compared to BBNs, although the motivation has hardly been to ease the parameterization of a BBN, as the cross-impact analysis tradition seems to have developed independently from the use of BBNs. Their shortcoming in the description of the probabilistic dependencies is the approximateness and lack of expressiveness for modeling multi-cause impacts. The AXIOM logic is a possible approach to do the expert informant based modeling with a more realistic number of inputs, and use the output to arrive at a BBN representation of the system. Another important difference is the causal structure of the model, where AXIOM allows more freedom for modeling. This flexibility is important for the most obvious use cases of AXIOM, namely foresight applications and other decision problems where causal hierarchies are not obvious.

Despite the differences, the basic utility of both Bayesian networks, influence diagrams and AXIOM models is the same: Assuming specific parts of the system to be in specific, known states, and observing how the probabilities of states for other system parts change as a result. This can mean observing how effects behave as assumptions are made about their causes, or conversely, observing what are the likely states of the causes, given certain states for the effects. Specifying utility valuations for the model states and their combinations enables identifying combinations of decisions, policies and interventions to the system that would maximise utility or minimize harm.

AXIOM makes it possible to perform structural and morphological analysis as well, so the analytical aims of probabilistic logics in foresight can be covered quite well with it. Examples of structural and morphological reasoning with a small model are presented in Publication III. The structural analysis aim is to discover the 'real' influence a cause exerts on some effect of its, by consideration of the indirect influences mediated by other facts. In AXIOM, this can be accomplished simply by comparing the posterior probabilities of the effect in two different iterations: one where the occurrence of the cause is resolved probabilistically and one where it is set to be true. The difference between the posteriors indicates the impact of the cause on the effect over the impact network, measured as change in probability. An EXIT-like total impact matrix can be derived by generating n iterations for a system of n total states for descriptors, where in each iteration, a single state is assumed to occur. If analytically useful, this impact matrix can be normalized as is done in EXIT, by dividing the matrix entries with the mean of absolute values of the matrix. The morphological analysis can be performed by computing posterior probabilities for full system configurations or partial configurations. The fundamental meaning of morphological consistency of any set of facts is that they are "probable to occur together" or perhaps "not improbable to occur together". Therefore, configurations or morphologies of high probability, relative to other possible morphologies, can be interpreted to be morphologically consistent.

4.2.3 Modeling language, processing and inference

The modeling language of AXIOM is subject to some changes as the framework is developed further. Publication II describes a basic case of AXIOM model, with only simple updates. The AXIOM approach as discussed in Publication II is fully implemented with a 'user interface' in the sense that analysis can be performed by giving a text file with the model information as input. Publication III discusses further developments in the AXIOM framework, such as non-simple updates. It lays out the basic implementation logic for non-simple updates, that is easily applicable to multi-cause impacts. However, the best implementation of dependencies on 'partial facts', meaning, probabilistic states of unresolved statements, is slightly open for interpretation.

The system descriptors in AXIOM are called *statements*, and they have an arbitrary, but greater than one, number of possible states. These states are called *options* in the AXIOM nomenclature. Statements describe possible system or domain facts with their options. Options can be loaded with varying levels of descriptive information about the system. Conceptually, options can represent a very atomic, indivisible fact about the system, such as an occurrence of an event, or a numerical detail, such as an amount or a percentual share. They can also represent several closely related facts, akin to a mini-scenario about a particular part of the system or a subsystem. Options are mutually exclusive, and exhaustive: for each statement, exactly one option will 'occur' in a single model evaluation. Options have an initial or prior probability, as well as a mutable probability, that is subject to change during the model evaluation. The prior probabilities and the mutable probabilities for states of a statement are probability distributions, covering the probability space completely: sum of the probabilities is equal to 1 in both distributions.

The prior probability, in the context of cross-impact analysis, means the initial, independent probability valuation of a fact. The prior probabilities are assigned for the options assuming no information available about the state of the system, or at the model level, the states of the other statements. In a case of deriving an AXIOM model from a BBN, if there was a need to do that, the initial probabilities would be the BBN probabilities without evidence. The terminology, which in the case of AXIOM conforms to the terminology of GHCIA and BASICS, can be misleading for a reader familiar with Bayesian belief networks. A Bayesian prior probability means probability before acquiring some evidence. The information of the evidence, in Bayesian thinking, updates the probabilities, after which they are *posterior* to the new evidence. In the established cross-impact lingo, the posterior probability is probability posterior to accounting for the model cross-impacts, however that is performed.

The statements also have a timestep property, which indicates the temporal position of a statement in relation to other statements in the model. In a single model evaluation, statements with a lower timestep value are evaluated first. Statements with equal timestep property values are evaluated in random order. The timestep property gives the modeler arbitrary precision in control of the model evaluation logic.

The influence of known facts on other, unknown facts in the model is expressed with *impacts*. Impacts have conditions and consequences. Normally, the conditions are states of descriptors, and the consequence is a probability update. In a basic case, a single system state is the condition. As the single-cause condition is resolved to be true, its impacts occur. The impact is 'fired' or executed when the source option is evaluated to be true or occurs, in the course of model evaluation. Again, normally, the consequence that occurs is a probability update. The effect option undergoes a probability update, where its current probability is mapped to an updated probability with an updating function. This results in the complement probabilities in the statement, i.e. the probabilities of the other options, to be adjusted as well to preserve a valid probability distribution: The complement probability of the updated probability of the effect option is divided to the other options so that each option's share of the new complement probability remains equal to their share of the old (unupdated) complement probability. Determining the exact magnitude of the probability update is contextual and is delegated to a probability updating function.

Figure 4.6 shows a number of probability updating functions. They are used to map the probability of an effect option to an updated probability. The probability updating functions must have a domain of $[0,1]$ and a codomain of $[0,1]$. Additionally, probability updating functions are recommended to *a)* be symmetric about the line $y = -x + 1$, *b)* have the property $y(x_0) < y(x_1)$ when $x_0 < x_1$, and *c)* have the property $y(x) > x$ if the name of the function implies positive (probability-increasing) impact, and the property $y(x) < x$ if the name of the function implies negative (probability-decreasing) impact. However, these recommended properties are not required, and updating functions not having these properties are allowed, and can be used if seen fit by the modeler.

Figure 4.7 plots the graphs of some unusual probability updating functions. A case where the function 'Unusual A' could be used would be such that the modelers do not want the probability of some fact to climb over some value, such as 0.85, by the update. A similar motivation might explain the use of function 'Unusual B'. The function 'activates', upon first probability update with the function, a fact whose probability might be very close to zero: An extremely unlikely fact will become possible by the update, its probability elevated to ~ 0.1. Subsequent updates might

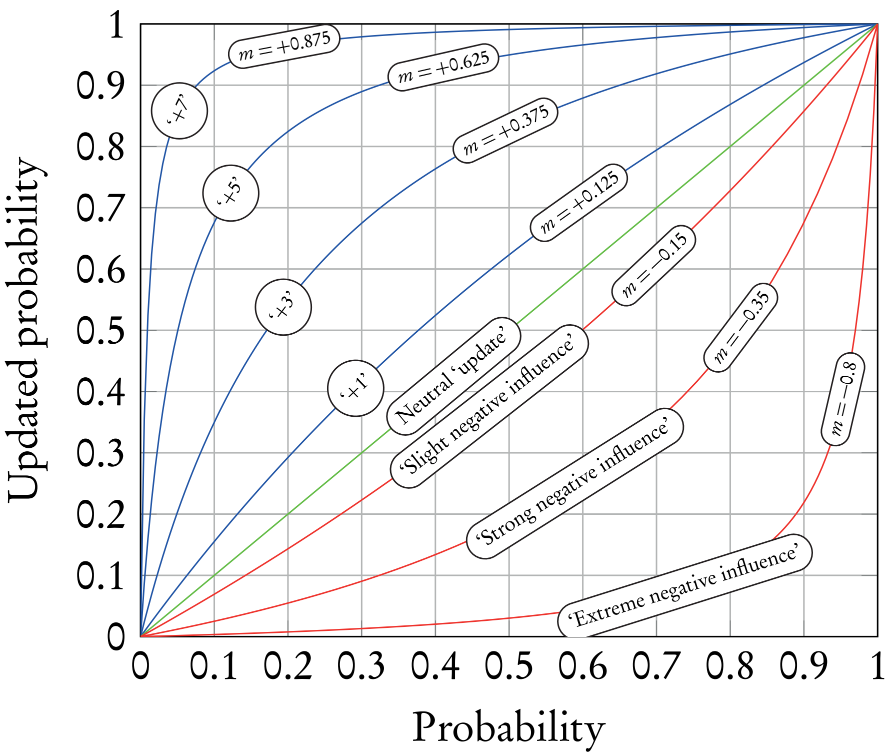


Figure 4.6 A set of *simple* AXIOM updating functions. Simple updating functions map probabilities subject to a probabilistic influence, conditional to occurrence of some cause of theirs, to updated probabilities. Functions plotted in this graph are parameterized with the m value, or the magnitude of the probabilistic impact, in the domain $[-1,+1]$. The m value can be placed in the binary function $u(p,m) = ((p \times (m+1)^2))/(4mp + ((m-1)^2))$ to get the plotted probability updating functions.

further elevate the probability by decreasing increments. However, updates by only this function guarantee that the probability will not climb past 0.433. To give a possibility for more predictable updates, in terms of absolute probability change, an updating function like 'Predictable decrease' might be used. It decreases, in cases where the probability to be updated is in range [0.2, 0.9], the probability by exactly 0.15.

While these features are not yet implemented in the distributed version of AXIOM implementation, it is also possible that the update does not change the probability distribution of the target statement. Instead, the update can force a statement to immediately be evaluated to a certain state, in turn firing the impacts associated with that state. This represents a deterministic influence a fact has on another. Ad-

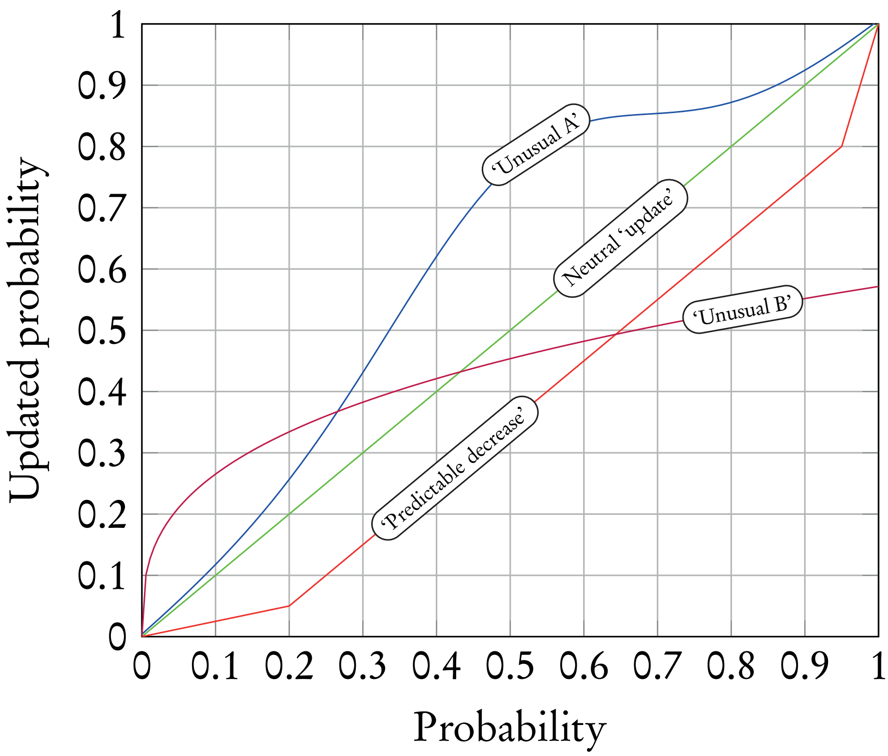


Figure 4.7 Alternative AXIOM probability updating functions.

ditionally, the updaters can perform any change in the model, such as a structural change, like removing or adding an option or an entire statement, or removing or adding an impact.

The model is evaluated by evaluating each statement of the model. The sequence of the evaluation is determined by the timestep property. Statements with a lower timestep property value are always evaluated before statements with a higher value. Statements with equal timestep are evaluated in random order. Conceptually this means that their temporal and causal ordering is ambiguous, and that they happen in unknown order or ‘simultaneously’, even when they do have a defined ordering within a single model evaluation. The timestep property values give the model its temporal structure.

Evaluation of a statement means assigning one of its options as its value. The probability of assignment of any option under a statement is equal to its current probability, which may have been updated several times already in the course of the model evaluation. Assignment of an option as the value of a statement fires all of its updates. These updates reflect the causal influences and possibly the altered situational awareness about the system, reflected in the probability updates on other statements. The model is fully evaluated when all of its statement have been assigned a state. This resolved model state is called configuration, and represents a possible world or a scenario. The configuration information is stored in an AXIOM *iteration* object. The model is reset to its initial state, meaning that all statements are again set to be in an unknown state, the option probabilities are reset to their initial values and the model structure is restored to the initial setup. The model evaluation process is performed again, a large number of times, saving the results to the iteration.

The iteration object, and sets of iteration objects, are the basis for inference. The posterior probability for any atomic fact is computed as its occurrence frequency in the iteration. The posterior probability for any compound fact, or a *morphology*, is computed as the occurrence frequency of its elements in the iteration. This is equal to computing the association rule learning (ARL) operation 'support' for an itemset. Similarly, the ARL operation 'Confidence' is an estimate of the probability of any atomic or compound fact conditional to another atomic or compound fact. Bayesian 'inverse logic' and 'mixed inference' can be performed with the itemset of the iteration object, given that it holds a sufficient number of configurations. Inferring the possible causes of a fact down in the causal hierarchy is achieved by selecting the rows in the itemset contained in the iteration where the fact occurs, and observing the probability distribution of the possible causes within this subset of configurations. The approach is rather inefficient compared to the Bayesian diagnostic inference, but nevertheless, such analytical outputs can be made available from AXIOM output.

The difference in initial or prior probabilities and the posterior probabilities computed from the iterations, in a case of no assumptions of interventions having been made, in the opinion of Gordon [49, 50, 51] reflect both *inconsistency* in the expert elicited valuation of initial probabilities and the influence of *higher-order* or indirect impacts. In the opinion of the author of this thesis, they mainly reflect inconsistency in the initial valuations, *assuming* that *all causes* for every effect are included in the model–which is of course not always true. Initial valuations that do yield probabilities posterior to the cross-impacts equal to the initial valuations can be composed for at least small AXIOM models. This, however, requires defining an information-dense setup of very precise impact valuations. The difference in the prior and posterior probabilities of any effect also reflects the absence of drivers and their influences on the effect in the model–things that have not been modeled.

With that, the main inference feature in a process like AXIOM is the comparison of the posterior probability distributions between several different iteration objects. Different iteration objects hold results of different AXIOM models, with the meaning that some details are changed for the evaluated model between different iterations. This can mean altering the model valuations, model structure or other details, but chiefly the use of *intervention statements*, a convenience feature provided by the current AXIOM implementation [94]. Statements flagged as intervention statements are not evaluated probabilistically, as in normal model evaluation, but are rather resolved to a predefined state when they are taken up for evaluation. Intervention statements can represent policy or some other intervention to the system. When a model has flagged intervention statements, the AXIOM implementation generates an iteration for each possible combination of the states of the intervention statements. This enables fairly easy comparison of different assumptions about the system and is the primary batch processing facility in the current implementation of AXIOM.

The intervention statements roughly correspond to *decision nodes* in influence diagrams. Conversely, any AXIOM model statement can be used as an utility node of an influence diagram. An utility function can be defined for desirable or undesirable states of statements, and be used for identification of optimal interventions or comparisons between different initial setups of the model. This is illustrated in the analysis part of Publication III.

As AXIOM can output full system configurations, it can generate an itemset-like dataset. A Bayesian belief network can be algorithmically learned from such data [1, 22, 42, 61, 64, 71]. As already discussed in Section 4.2.2, this provides a degree of interoperability with AXIOM and Bayesian approaches.

4.2.4 Significance and future work

AXIOM draws from the aged toolset of cross-impact analysis techniques, and the newer Bayesian approach for probabilistic reasoning, to propose a new probabilistic logic for foresight and decision support activities. In structurally complex models, the approach is much more feasible for full expert elicitation based valuation than Bayesian networks and influence diagrams. In comparison to cross-impact techniques such as Gordon-Hayward approach or BASICS, the new approach offers much more modeling power. Compared to several other logics proposed for foresight and systems analysis activities, such as structural and morphological analysis techniques, AXIOM can analytically cover most of their ambitions. The approach combines different orientations of analysis under the same framework. The straightforward way the output can be used to derive a Bayesian network representation of the knowledge base described as an AXIOM model connects the AXIOM modeling to Bayesian modeling. Deriving a Bayesian network from AXIOM output enables use of more extensive expert informant based knowledge bases with models based on empirical data.

The discrete event simulation nature of the AXIOM computational transformation is hopefully conceptually simple, or at least less obscure than the inference based on e.g. fuzzy cognitive maps seeking, but possibly never arriving in an equilibrium. The analytical transformation of Bayesian networks to derive the posteriors might also be conceptually more difficult than the AXIOM discrete event simulation. In the case of AXIOM, the computational transformation directly maps to a metaphor of the future unfolding, a great number of possible worlds being generated under the rules of the simulation, and treating this set of possible worlds as a sample, on which the inference is based on. This metaphor is especially viable in the case of foresight and futures.

The AXIOM approach can and will be developed further, especially in terms of the software implementation, but possibly also the methodological specification and modeling language. In terms of the modeling language, the following expansions would appear justified, as they would be backwards compatible and not increase the conceptual complexity much, but would enable more expressiveness.

1. *Probabilistic timestep values*. In addition to the normal timestep, the timestep could be random variable with a mean, standard deviation and skewness. The value for a random timestep would be defined for each model evaluation, in the beginning of the evaluation The evaluation sequence would be ordered in the beginning of each model evaluation.
2. *Probabilistic dependency of timestep values on model facts.* The timestep values could be made subject to change conditional to the occurrence of model facts.

The model arriving in specific states could reorder the evaluation sequence defined at the beginning of the model evaluation. The counterpart in real systems being modeled with AXIOM is any set of conditions that might make a development take place sooner (or later) than it is expected to take place without information about the relevant developments.

3. *Descriptors with continuous values.* Numerical descriptors can obviously be included in models in a discretizised form with normal AXIOM statements, but the possibility of modeling them in continuous form might be important in some modeling cases. They would, however, require the introduction of some other way of propagating their influence over the network than normal AXIOM updates, which occur only once upon the evaluation of statements. In this sense, the conceptual complexity continuous values introduce might defeat the modeling power they add.

For the software implementation, further development steps are discussed in Section 6.7. From the perspective of adoption of the method, by far the most important issue would be the development of a graphical user interface. After all, the approach is intended to support modeling in domains not normally modeled, and the relevant expert informants, as well as modelers, in these domains most likely expect not to be faced with a command line interface, let alone to be forced to compose their models as Java code using the implementation classes as a library.

5 CONCLUSIONS AND DISCUSSION

This thesis has described and reviewed a number approaches for modeling and analysis of collections of interrelated facts. The discussed approaches share the property that they can be understood as probabilistic logics. A logic is comprised of a modeling language and rules for inference. A modeling language is a finite, often a compact set of symbols. The symbols are are used to transform information (knowledge or data) into a model, which is a structured representation of the information, formal to the degree the modeling language itself is formal. While logics differ, often the symbols can be thought as facts and rules. The symbols of the modeling language themselves have the same meaning in different models representing different knowledge bases. The inference rules of a logic describe how higher-order constructs of reasoning are generated from the atomic model facts and rules. The approaches this work has discussed can also be understood as approaches for creating expert systems. An expert system, in turn, is said to comprise of a knowledge base and an inference engine. Understanding the approaches as expert systems perhaps gives a better cue on the type of information the approaches discussed model: information elicited from knowledgeable people or *experts* of the modeled domain. While empirical and statistical data can obviously be used as an information source for Bayesian networks and fuzzy cognitive maps, and ways to parameterize other models discussed in this thesis can be devised, this work has focused on the idea of using expert knowledge as the primary or sole source of model inputs.

Is modeling based on expert elicited inputs useful? After all, for many questions where an expert opinion exists to answer it, we can find a divergent or opposing expert view as well: experts can be, and often are, in disagreement about the facts and rules about almost any given system. This divergence in expert opinion, however, is not exhibited across the board in modeling systems: the views and opinions of experts are often in conflict only in the case of a subset of the properties and rules of the modeled system, and a solid concensus may exist for a majority of details concerning the modeled systems. For the areas where expert views diverge, a collaborative, iterative process of information exchange, reasoning and modeling may lead to convergence of positions, ultimately eliminating a lot of the conflicts in the 'source material' of such expert informant oriented modeling. If this does not happen, the effort to formally model a knowledge base still reveals the points of contention, and may direct the further information gathering towards the right direction. Formal modeling based on expert inputs may produce significant *processual* benefits, even when the end result from a perspective of using the model in direct decision support is that the source material is too ambiguous to be used.

For many modeling domains, incorporating expert knowledge into models could be seen as a very useful idea, as it may augment the modeling based on data in areas where the data coverage is poor, and incorporate decisively important aspects relevant to decision-making that are not necessarily covered by data at all. Such dimensionally poor data coverage is easily the case in many strategic considerations, which have to factor in the *change* of the systems reasoned about. From a modeling perspective, change in systems will introduce new variables and form new relationships between them. Existing data is, in most cases, unable to capture change in operating logic of a system, so reasoning beyond the apparent reasoning based on data is often required. Experts can obviously be used in modeling in various capacities no matter the approach, but different approaches have different levels of fitness for expert informant processes. Especially modeling work using inputs from expert panels requires, in practice, an approach with a modeling language where the expert views can be mapped to model inputs in a straightforward way and the number of those inputs is feasible. Structural equations, for example, would be quite unfeasible to elicit in high numbers, and the process of transforming hazy expert inputs into such representation is not easy. Graphical representations of dependencies between model components and valuations of those dependencies as degrees of belief are a substantially more realistic format of inputs for expert processes.

The fitness of a modeling language for expert processes of possibly great numbers of participants enables covering the modeled knowledge base with the joint expertise of a group of experts. If the modeling language is conceptually simple, the expert processes may involve domain experts with limited expertise on the technical aspects of modeling itself. This will, again, enable covering more ground analytically and incorporating views and knowledge bases in modeling that might otherwise be ignored. The comparative technical simplicity of expert informant oriented modeling approaches makes them also easy to be examined and understood by possible model users and other stakeholders. The only way models can influence decision-making is that the relevant decision-makers trust the models–and if understanding the model structure and valuations is made easier, no blind trust is required: the included considerations, choices made and the fundamental assumptions can be scrutinized without a high level of technical expertise also by people who have not been involved in the modeling.

Models in the service of foresight, be they based on data or expert inputs, cannot be validated in the same sense as models aiming at prediction of recurring phenomena. There is no empirical benchmark to assess the predictive power of foresight. As the future unfolds, the actual developments may or may not be aligned with the reasoning based on the models, but the actual development is only one possible world out of many that foresight seeks to reason about. Model validation, if one can speak of validation, comes from a wide exposure to experts of different fields, and seeking of consensus on the model structure and valuations through contemplation and argumentation. Compared to predictive statistical models, the modeling aim is not to predict recurring outcomes with the greatest accuracy and efficiency. The models created do not need to aim for using the minimum amount of data and the simplest possible structure. They should rather aim to model the knowledge in the domain comprehensively, and the structure can be complex if such complexity serves the reasoning about the domain and decision-making related to it.

Foresight processes, most of the time, rely on expert informants and collaborative work. The challenge is often to facilitate the expert work, structure the process and synthesize useful information from the outputs. Foresight activities relying on expert informants need structured processes which aim at formulating descriptions about the relationships and dependencies of new developments, events and forces, and the outcomes of policies and interventions.

The EXIT approach provides an alternative inference approach for structural modeling, which has not been previously proposed, perhaps because of the higher computational complexity involved, compared to the matrix multiplication based approaches. The matrix multiplication approach in structural analysis focuses on dynamic properties of a model that is defined to be causal, and can potentially be hard to interpret. The EXIT approach focuses purely on the structure of the causal network, eliminating dynamic behaviour from consideration, and is better aligned with normal interpretations of causality. It can be used in conjunction with matrix multiplication based structural analysis approaches and fuzzy cognitive maps to provide an alternative view on the causal structure. For modelers, the approach is of minimal complexity and provides a framework for a well structured process of foresight oriented systems thinking.

The AXIOM approach modernizes the slightly aged ideas of cross-impact languages and reformulates the cross-impact approach to be quite compatible with representing models as Bayesian networks. AXIOM models can interoperate with Bayesian networks as an auxiliary technique, as their output can be used as input for algorithmic generation of a Bayesian network. In the case of full expert elicitation, AXIOM is easily more feasible, and it can be used to represent system properties that are not easily represented in a Bayesian network. This work has identified the structural, morphological and probabilistic analysis aims of probabilistic reasoning, and the way AXIOM can be utilized for all of these analysis aims has been outlined. The comparatively high modeling power of AXIOM against other approaches has been illustrated.

More generally, this work has examined a number of approaches that are not often discussed in the same context. In their original sources, the approaches use disparate concepts, making comparison and positioning challenging. The methodological discussion on expert informant oriented modeling and probabilistic logics in systems analysis and strategic foresight remains factionalized and divided. Their conceptual and functional overlap may be difficult to perceive by the potential users. In addition to proposing novel approaches, this thesis has brought the alternatives under the same methodological discourse. The factional and disintegrated nature of the discussion stifles methodological development in the modeling niche. Comparative assessment of the alternatives and clearly identifying their analytical aims, strengths and weaknesses is a step towards mainstreaming their utilization in research and needed for the gradual betterment of the tooling for systems thinking, expert informant oriented modeling, and probabilistic reasoning.

6 PERSONAL CONTRIBUTION

The main contributions of this entire work are the two modeling approaches, EXIT and AXIOM, and their implementations. The approaches and their implementations are the sole work of the author. The methodological details of EXIT and AXIOM have been discussed earlier in this introduction in Sections 4.1 and 4.2, and are the focus of Publications II, III, and IV. A crucial point in proposing any analytic process involving non-trivial computation is to provide software implementations, which are also a part of the contribution of this thesis. The five publications included in this thesis describe the EXIT and AXIOM approaches methodologically, position them against comparable approaches, argue for their comparatively high fitness in systems modeling using expert informant processes, and illustrate their use in research, analysis and decision support. The publications and their role in the thesis are presented in Figure 6.1.

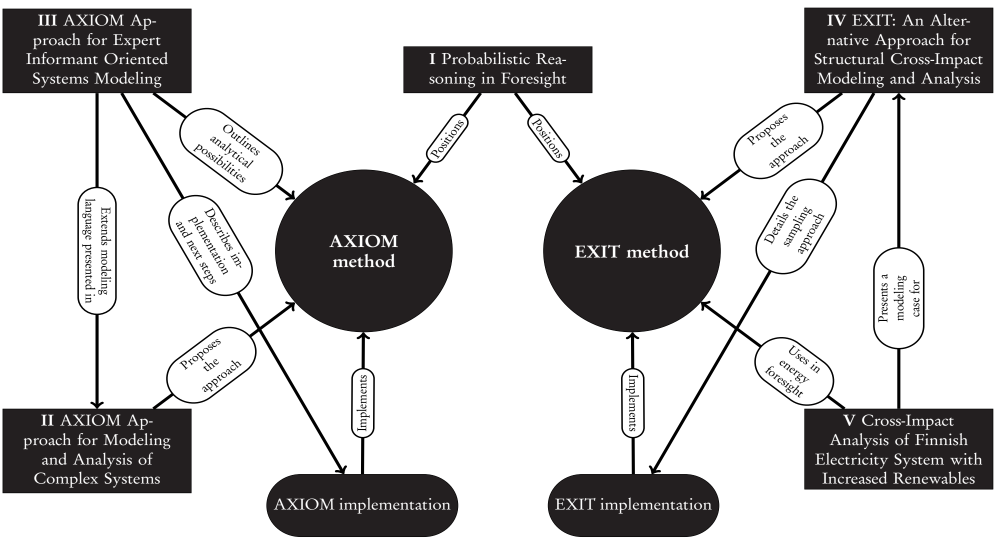


Figure 6.1 Publications and their role in the thesis.

6.1 Publication I: Probabilistic Reasoning in Foresight

Publication I reviews the most prominent methodological proposals for probabilistic reasoning, or *probabilistic logics*, with applications in the foresight domain. Over time, the interest and need of researchers and analysts to study various difficult-to-model and complex phenomena has resulted in the emergence of a number of techniques under the banners of structural analysis, morphological analysis, cross-impact analysis and probabilistic causal modeling. The original works documenting these techniques often do not reference to or discuss similar concepts and approaches, and positioning and comparison is difficult as a result of non-congruent terminology and framing. For this reason, a comparative review of relevant approaches is valuable for advancing the state of the art. The positioning of the approaches is done by starting from Bayesian networks and detailing what is given up, and possibly gained, in terms of expressive power of modeling languages and analytical outputs, as some aspects of the Bayesian approach are rethought from the perspective of more intuitive-heuristic modeling. The manuscript provides descriptions of Bayesian networks, BeNe-EIA approach, Gordon-Hayward cross-impact analysis, SMIC, the BASICS approach, JL-algorithm, AXIOM, MICMAC and ADVIAN, EXIT, cognitive maps and fuzzy cognitive maps, general morphological analysis, and the Cross-Impact Balances approach. The approaches are commensurated with basic graph theory concepts to assist the reader with interrelating them. These techniques are compared to each other in terms of amount or required input information, analysis possibilities and general properties.

Annukka Lehikoinen wrote, assisted in writing and commented extensively on the section about Bayesian networks, and provided important comments on the manuscript in general. Sakari Kuikka wrote the part describing the Bayesian link matrix approach (BeNe-EIA), and commented on the manuscript overall. The manuscript has been submitted to journal *Technological Forecasting and Social Change*.

6.2 Publication II: AXIOM Approach for Modeling and Analysis of Complex Systems

Publication II proposes the AXIOM modeling language and an associated discrete-event simulation process used in the analysis of AXIOM models. The argumentation for the method design choices made in AXIOM is presented by discussing other techniques in the cross-impact analysis cluster of methods. The focus is on the modeling language concepts, and their use in modeling is illustrated with a small semi-abstract model. Research related to Publication II has been presented in the conference "Futures of A Complex World" organized in Turku, Finland 12.6.2017–13.6.2017 and published in the conference proceedings.

6.3 Publication III: The AXIOM Approach for Probabilistic and Causal Modeling with Expert Elicited Inputs

Publication III elaborates on the AXIOM approach by relating it, in addition to the most prominent cross-impact techniques, to Bayesian belief networks. The methodological inheritance of AXIOM from Gordon-Hayward approach and the BASICS approach is discussed in detail. The utilization area of AXIOM against Bayesian networks is delineated. The analytical orientations typical for comparable methods are identified and the use of AXIOM in delivering outputs of these orientations are illustrated with a cross-impact model used in proposals for related methods, BASICS and the Cross-Impact Balances approach. The interoperability between AXIOM and Bayesian networks is discussed. The focus is on the novel modeling and analysis possibilities of the new approach.

Publication III has been published in journal *Technological Forecasting and Social Change*.

6.4 Publication IV: EXIT: An Alternative Approach for Structural Cross-Impact Modeling and Analysis

Publication IV proposes the EXIT modeling language and details the computational transformation used to extract the information about the higher-order influence between the EXIT model variables. EXIT is positioned against the matrix multiplication approach for analysis of similar expert-sourced information. The conceptual level interpretation of the model components is discussed at length. As the process proposed is computationally more costly than the matrix multiplication approach based solution, the possible estimation strategies are discussed and a feasible strategy is proposed.

Kalle A. Piirainen provided comments for the manuscript overall. Publication IV has been published in journal *Technological Forecasting and Social Change*.

6.5 Publication V: Cross-Impact Analysis of Finnish Electricity System with Increased Renewables: Long-run Energy Policy Challenges in Balancing Supply and Consumption

Publication V presents the process and results of a small-scale expert informant modeling exercise, where pivotal factors and drivers influencing the development of the Finnish electricity system in the timeframe 2018–2030 and their mutual interactions have been modeled using the EXIT approach. The aims were to formulate a specific, compact set of system descriptors relevant to the near-term future of the Finnish energy system, recognizing emerging challenges related to increasing wind and solar penetration, model the direct interactions based on an expert group process, discover the internal dynamics of the modeled system, and ultimately to identify the critical system drivers to increase understanding of the systemic relationships between the descriptors and the emergent system characteristics. The study was a trial of the EXIT approach, aiming at demonstrating the use of the EXIT approach in energy foresight domain, using a relatively small and high-level set of system descriptors.

J. Luukkanen, J. Kaivo-oja and J. Vehmas led the model design and the research process leading to model variable selection. S. Valkealahti, T. Björkqvist, T. Korpela, P. Järventausta, Y. Majanne, M. Kojo, P. Aalto, P. Harsia, K. Kallioharju, H. Holttinen and S. Repo were involved in the model valuation and provided feedback in the interpretation of the results. T. O'Mahony, J. Vehmas and J. Kaivo-oja provided comments on the manuscript overall. Publication V has been published in journal *Energy Policy*.

6.6 EXIT software implementation

The EXIT software implementation is a Java program for performing the computation of EXIT structural cross-impact analysis. The current implementation has a command line interface. A text file containing the model variable names and the initial direct impact matrix is passed as an argument, along with the maximum impact value and the sample size to be used in the sampling process. The release can be downloaded at `https://github.com/jmpaon/EXIT/releases` and the source code at `https://github.com/jmpaon/EXIT/tree/master/EXIT`.

6.7 AXIOM software implementation

The AXIOM software implementation available at `https://github.com/jmpaon/AXIOM/releases` implements all the functionalities described in Publication II. The expanded functionalities discussed in Publication III are not yet featured in a release of the AXIOM software implementation. These features will be added in the next version of the implementation, which is a Groovy application and will take more of a domain specific language approach to the modeling.

The software implementation of AXIOM will be further developed, with roughly with the following order of importance:

1. Direct support for multi-cause probability updating functions
2. Better support for batch processing of the model
3. Parallerization of computation
4. A Groovy DSL for AXIOM modeling

5. Direct support for 'complex' update processes
6. Graphical user interface
7. More efficient sampling process, if one can be developed

While the software will be significantly developed further in the future, the current distribution is a functional modeling and analysis tool with the initial ideas of the AXIOM approach fully implemented.

REFERENCES

[1] S. Acid, L. M. de Campos, J. M. Fernandez-Luna, S. Rodriguez, J. M. Rodriguez and J. L. Salcedo. A Comparison of Learning Algorithms for Bayesian Networks: A Case Study Based on Data from an Emergency Medical Service. *Artificial Intelligence in Medicine* 30.3 (2004). Bayesian Networks in Biomedicine and Health-Care, 215–232. ISSN: 0933-3657. DOI: https://doi.org/10.1016/j.artmed.2003.11.002. URL: http://www.sciencedirect.com/science/article/pii/S0933365703001325.

[2] H. J. Adèr. *Advising on Research Methods: A Consultant's Companion*. Johannes van Kessel Publishing., 2008.

[3] N. Agami, M. Saleh and H. El-Shishiny. A Fuzzy Logic based Trend Impact Analysis Method. *Technological Forecasting and Social Change* 77.7 (Sept. 2010), 1051–1060. DOI: 10.1016/j.techfore.2010.04.009. URL: https://doi.org/10.1016/j.techfore.2010.04.009.

[4] P. Aguilera, A. Fernández, R. Fernández, R. Rumí and A. Salmerón. Bayesian Networks in Environmental Modelling. *Environmental Modelling & Software* 26.12 (2011), 1376–1388. ISSN: 1364-8152. DOI: https://doi.org/10.1016/j.envsoft.2011.06.004. URL: http://www.sciencedirect.com/science/article/pii/S1364815211001472.

[5] J. Alcamo. *Environmental Futures: The Practice of Environmental Scenario Analysis*. Vol. 2. Elsevier, 2008.

[6] R. Alizadeh, P. D. Lund, A. Beynaghi, M. Abolghasemi and R. Maknoon. An Integrated Scenario-Based Robust Planning Approach for Foresight and Strategic Management with Application to Energy Industry. *Technological Forecasting and Social Change* 104 (2016), 162–171. ISSN: 0040-1625. DOI: http://dx.doi.org/10.1016/j.techfore.2015.11.030.

[7] E. Amanatidou, M. Butter, V. Carabias, T. Könnölä, M. Leis, O. Saritas, P. Schaper-Rinkel and V. van Rij. On Concepts and Methods in Horizon Scanning: Lessons from Initiating Policy Dialogues on Emerging Issues. *Science and Public Policy* 39.2 (2012), 208–221. DOI: 10.1093/scipol/scs017. URL: http://dx.doi.org/10.1093/scipol/scs017.

[8] R. M. Axelrod. *Structure of Decision: The Cognitive Maps of Political Elites*. Princeton University Press, 1976, 422. URL: http://www.jstor.org/stable/j.ctt13x0vw3.

[9] J. Banks, J. Carson, B. Nelson and D. Nicol. *Discrete-Event System Simulation*. Pearson, 2005.

[10] V. A. Bañuls and M. Turoff. Scenario Construction via Delphi and Cross-Impact Analysis. *Technological Forecasting and Social Change* 78.9 (2011), 1579–1602. DOI: 10.1016/j.techfore.2011.03.014. URL: https://doi.org/10.1016/j.techfore.2011.03.014.

[11] V. A. Bañuls, M. Turoff and S. R. Hiltz. Collaborative Scenario Modeling in Emergency Management through Cross-Impact. *Technological Forecasting and Social Change* 80.9 (Nov. 2013), 1756–1774. DOI: 10.1016/j.techfore.2012.11.007. URL: https://doi.org/10.1016/j.techfore.2012.11.007.

[12] A. W. Blackman. A Cross-Impact Model Applicable to Forecasts for Long-Range planning. *Technological Forecasting and Social Change* 5.3 (1973), 233–242. DOI: 10.1016/0040-1625(73)90002-4. URL: https://doi.org/10.1016/0040-1625(73)90002-4.

[13] M. F. Bloom. Time-Dependent Event Cross-Impact Analysis: Results from a New Model. *Technological Forecasting and Social Change* 10.2 (1977), 181–201. DOI: 10.1016/0040-1625(77)90044-0. URL: https://doi.org/10.1016/0040-1625(77)90044-0.

[14] P. Boets, D. Landuyt, G. Everaert, S. Broekx and P. L. M. Goethals. Evaluation and Comparison of Data-Driven and Knowledge-Supported Bayesian Belief Networks to assess the Habitat Suitability for Alien Macroinvertebrates. *Environmental Modelling & Software* 74 (Dec. 2015), 92–103. ISSN: 1364-8152. DOI: 10.1016/J.ENVSOFT.2015.09.005. URL: https://www.sciencedirect.com/science/article/pii/S1364815215300487.

[15] S. Brailsford, L. Churilov and B. Dangerfield. *Discrete-Event Simulation and System Dynamics for Management Decision Making*. John Wiley & Sons, 2014.

[16] J. Brauers and M. Weber. A New Method of Scenario Analysis for Strategic Planning. *Journal of Forecasting* 7.1 (1988), 31–47. ISSN: 1099-131X. DOI: 10.1002/for.3980070104. URL: https://doi.org/10.1002/for.3980070104.

[17] J. R. Burns and W. M. Marcy. Causality: Its Characterization in System Dynamics and KSIM Models of Socioeconomic Systems. *Technological Forecasting and Social Change* 14.4 (Sept. 1979), 387–398. DOI: 10.1016/0040-1625(79)90036-2. URL: https://doi.org/10.1016/0040-1625(79)90036-2.

[18] J. F. Carriger, M. G. Barron and M. C. Newman. Bayesian Networks Improve Causal Environmental Assessments for Evidence-Based Policy. *Environmental Science & Technology* 50.24 (Dec. 2016), 13195–13205. ISSN: 0013-936X. DOI: 10.1021/acs.est.6b03220. URL: http://www.ncbi.nlm.nih.gov/pubmed/27993076.

[19] A. Ceric. Analysis of Interactions between IT and Organisational Resources in a Manufacturing Organisation using Cross-Impact Analysis. *Journal of Enterprise Information Management* 29.4 (2016), 589–611. DOI: 10.1108/JEIM-04-2015-0027. eprint: https://doi.org/10.1108/JEIM-04-2015-0027. URL: https://doi.org/10.1108/JEIM-04-2015-0027.

[20] M. Chander, S. K. Jain and R. Shankar. Modeling of Information Security Management Parameters in Indian Organizations using ISM and MICMAC Approach. *Journal of Modelling in Management* 8.2 (2013), 171–189.

[21] M.-H. Chen, Q.-M. Shao and J. G. Ibrahim. Basic Monte Carlo Methods for Estimating Posterior Quantities. *Monte Carlo Methods in Bayesian Computation*. Springer New York, 2000, 67–93. ISBN: 978-1-4612-1276-8. DOI: 10.1007/978-1-4612-1276-8_3. URL: https://doi.org/10.1007/978-1-4612-1276-8_3.

[22] J. Cheng. Learning Bayesian Networks from Data: An Efficient Approach Based on Information Theory. *WWW 1999*. 1999.

[23] B. K. Choi and D. Kang. *Modeling and Simulation of Discrete Event Systems*. John Wiley & Sons, 2013.

[24] C. Choi, S. Kim and Y. Park. A Patent-Based Cross Impact Analysis for Quantitative Estimation of Technological Impact: The Case of Information and Communication Technology. *Technological Forecasting and Social Change* 74.8 (Oct. 2007), 1296–1314. DOI: 10.1016/j.techfore.2006.10.008. URL: https://doi.org/10.1016/j.techfore.2006.10.008.

[25] S. L. Choy, R. O'Leary and K. Mengersen. Elicitation by Design in Ecology: Using Expert Opinion to Inform Priors for Bayesian Statistical Models. *Ecology* 90.1 (2009), 265–277.

[26] R. G. Cowell, P. Dawid, S. L. Lauritzen and D. J. Spiegelhalter. *Probabilistic Networks and Expert Systems: Exact Computational Methods for Bayesian Networks*. Springer Science & Business Media, 2006.

[27] M. Culka. Uncertainty Analysis using Bayesian Model Averaging: A Case Study of Input Variables to Energy Models and Inference to Associated Uncertainties of Energy Scenarios. *Energy, Sustainability and Society* 6.1 (Mar. 2016). ISSN: 2192-0567. DOI: 10.1186/s13705-016-0073-0. URL: https://doi.org/10.1186/s13705-016-0073-0.

[28] N. Dalkey. Analyses from a Group Opinion Study. *Futures* 1.6 (1969), 541–551. ISSN: 0016-3287. DOI: https://doi.org/10.1016/S0016-3287(69)80044-3. URL: http://www.sciencedirect.com/science/article/pii/S0016328769800443.

[29] N. C. Dalkey. An Elementary Cross-Impact Model. *Technological Forecasting and Social Change* 3 (1971), 341–351. DOI: 10.1016/s0040-1625(71)80022-7. URL: https://doi.org/10.1016/s0040-1625(71)80022-7.

[30] B. Das. Generating Conditional Probabilities for Bayesian Networks: Easing the Knowledge Acquisition Problem. *arXiv preprint cs/0411034* (2004).

[31] S. Dorner, J. Shi and D. Swayne. Multi-Objective Modelling and Decision Support using a Bayesian Network Approximation to a Non-Point Source Pollution Model. *Environmental Modelling & Software* 22.2 (Feb. 2007), 211–222. ISSN: 1364-8152. DOI: 10.1016/J.ENVSOFT.2005.07.020. URL: https://www.sciencedirect.com/science/article/pii/S1364815205001817.

[32] M. J. Druzdel and L. C. Van Der Gaag. Building Probabilistic Networks: "Where do the Numbers come from?": *IEEE Transactions on knowledge and data engineering* 12.4 (2000), 481–486.

[33] M. J. Druzdzel and L. C. Van Der Gaag. Elicitation of Probabilities for Belief Networks: Combining Qualitative and Quantitative Information. *Proceedings of the Eleventh conference on Uncertainty in Artificial Intelligence*. Morgan Kaufmann Publishers. 1995, 141–148.

[34] J. C. Duperrin and M. Godet. SMIC 74–A Method for Constructing and Ranking Scenarios. *Futures* 7.4 (1975), 302–312. ISSN: 0016-3287. DOI: `https://doi.org/10.1016/0016-3287(75)90048-8`.

[35] C. Eden. On the Nature of Cognitive Maps. *Journal of Management Studies* 29.3 (May 2007), 261–265. ISSN: 00222380. DOI: `10.1111/j.1467-6486.1992.tb00664.x`. URL: `http://doi.wiley.com/10.1111/j.1467-6486.1992.tb00664.x`.

[36] S. Enzer. Delphi and Cross-Impact Techniques. *Futures* 3.1 (1971), 48–61. ISSN: 0016-3287. DOI: `http://dx.doi.org/10.1016/S0016-3287(71)80006-X`.

[37] S. Enzer. Cross-Impact Techniques in Technology Assessment. *Futures* 4.1 (1972), 30–51. ISSN: 0016-3287. DOI: `http://dx.doi.org/10.1016/0016-3287(72)90023-7`.

[38] G. Felix, G. Nápoles, R. Falcon, W. Froelich, K. Vanhoof and R. Bello. A Review on Methods and Software for Fuzzy Cognitive Maps. *Artificial Intelligence Review* (2017), 1–31.

[39] N. Fenton and M. Neil. *Risk Assessment and Decision Analysis with Bayesian Networks*. CRC Press, 2012.

[40] D. N. Ford and J. D. Sterman. Expert Knowledge Elicitation to Improve Formal and Mental Models. *System Dynamics Review* 14.4 (1997), 309–340. DOI: 10.1002/(SICI)1099-1727(199824)14:4<309::AID-SDR154>3.0.CO;2-5.

[41] A. Fried and V. Linss. *Towards an Advanced Impact Analysis of Intangible Resources in Organisations*. Tech. rep. 2. Technische Universität Chemnitz, 2005. URL: `http://hdl.handle.net/10419/55390`.

[42] N. Friedman, I. Nachman and D. Peér. Learning Bayesian Network Structure from Massive Datasets: The Sparse Candidate Algorithm. *Proceedings of the Fifteenth Conference on Uncertainty in Artificial Intelligence*. Morgan Kaufmann Publishers Inc. 1999, 206–215.

[43] L. C. van der Gaag, S. Renooij, C. L. Witteman, B. M. Aleman and B. G. Taal. How to Elicit Many Probabilities. *Proceedings of the Fifteenth Conference on Uncertainty in Artificial Intelligence*. Morgan Kaufmann Publishers. 1999, 647–654.

[44] A. Gabus and E. Fontela. *World Problems, an Invitation to Further Thought within the Framework of DEMATEL*. Tech. rep. Battelle Geneva Research Center, Geneva, Switzerland, 1972.

[45] M. Godet, F. Bourse, P. Chapuy and I. Menant. *Futures Studies: A Tool-box for Problem Solving*. Futuribles. GERPA Prospective, 1991.

[46] M. Godet and J. Coates. *From Anticipation to Action: A Handbook of Strategic Prospective*. Future-oriented studies. Unesco Publishing, 1994. ISBN: 978-92-3-102832-8.

[47] M. Godet. Scenarios of Air Transport Development to 1990 by SMIC 74–A New Cross-Impact Method. *Technological Forecasting and Social Change* 9.3 (1976), 279–288. DOI: `10.1016/0040-1625(76)90012-3`. URL: `https://doi.org/10.1016/0040-1625(76)90012-3`.

[48] M. Godet. Introduction to la prospective: Seven Key Ideas and One Scenario Method. *Futures* 18.2 (1986), 134–157. ISSN: 0016–3287. DOI: `https://doi.org/10.1016/0016-3287(86)90094-7`. URL: `http://www.sciencedirect.com/science/article/pii/0016328786900947`.

[49] T. Gordon and H. Hayward. Initial Experiments with the Cross Impact Matrix Method of Forecasting. *Futures* 1.2 (1968), 100–116. ISSN: 0016-3287. DOI: `http://dx.doi.org/10.1016/S0016-3287(68)80003-5`.

[50] T. J. Gordon. Cross-impact matrices: An illustration of their use for policy analysis. *Futures* 1.6 (1969), 527–531.

[51] T. J. Gordon. *Cross Impact Method*. Tech. rep. United Nations University Millennium Project, 1994.

[52] B. Guertler and S. Spinler. Supply Risk Interrelationships and the Derivation of Key Supply Risk Indicators. *Technological Forecasting and Social Change* 92 (2015), 224–236. ISSN: 0040-1625. DOI: `https://doi.org/10.1016/j.techfore.2014.09.004`. URL: `http://www.sciencedirect.com/science/article/pii/S0040162514002741`.

[53] A. Hájek. Interpretations of Probability. *The Stanford Encyclopedia of Philosophy*. Ed. by E. N. Zalta. Winter 2012. Metaphysics Research Lab, Stanford University, 2012.

[54] S. I. Hayakawa and A. R. Hayakawa. *Language in Thought and Action*. Houghton Mifflin Harcourt, 1990.

[55] D. Heckerman, A. Mamdani and M. P. Wellman. Real-World Applications of Bayesian Networks. *Communications of the ACM* 38.3 (1995), 24–26.

[56] E. J. Honton, G. S. Stacey and S. M. Millett. *Future Scenarios: The BASICS Computational Method*. Economics and policy analysis occasional paper. Battelle Columbus Division, 1984.

[57] W. R. Huss and E. J. Honton. Scenario planning–What style should you use?: *Long Range Planning* 20.4 (1987), 21–29. ISSN: 0024-6301. DOI: `http://dx.doi.org/10.1016/0024-6301(87)90152-X`.

[58] International Council on Systems Engineering (INCOSE). *What is Systems Engineering?* 2017. URL: `http://www.incose.org/AboutSE/WhatIsSE`.

[59] M. Ishikawa, M. Toda, S. Mori and Y. Kaya. An Application of the Extended Cross Impact Method to Generating Scenarios of Social Change in Japan. *Technological Forecasting and Social Change* 18.3 (Nov. 1980), 217–233. DOI: `10.1016/0040-1625(80)90024-4`.

[60] J. E. Jackson and W. H. Lawton. Some Probability Problems associated with Cross-Impact Analysis. *Technological Forecasting and Social Change* 8.3 (1976). ISSN: 0040-1625. URL: `https://doi.org/10.1016/0040-1625(76)90004-4`.

[61] P. Jackson. *Introduction to Expert Systems*. Addison-Wesley Longman Publishing, 1998, 542. ISBN: 0201876868. URL: `https://dl.acm.org/citation.cfm?id=521024`.

[62] A. James, S. L. Choy and K. Mengersen. Elicitator: An Expert Elicitation Tool for Regression in Ecology. *Environmental Modelling & Software* 25.1 (Jan. 2010), 129–145. ISSN: 1364-8152. DOI: `10.1016/J.ENVSOFT.2009.07.003`. URL: `https://www.sciencedirect.com/science/article/pii/S1364815209001704`.

[63] F. V. Jensen. *An Introduction to Bayesian Networks*. Springer, 1996, 178. ISBN: 0387915028. URL: https://dl.acm.org/citation.cfm?id=546868.

[64] F. V. Jensen and T. D. Nielsen. *Bayesian Networks and Decision Graphs*. Springer, 2007, 447. ISBN: 9780387682815.

[65] G. H. Jeong and S. H. Kim. A Qualitative Cross-Impact Approach to Find the Key Technology. *Technological Forecasting and Social Change* 55.3 (July 1997), 203–214. DOI: 10.1016/s0040-1625(96)00209-0.

[66] A. J. Jetter and K. Kok. Fuzzy Cognitive Maps for Futures Studies–A Methodological Assessment of Concepts and Methods. *Futures* 61 (2014), 45–57. ISSN: 0016-3287. DOI: https://doi.org/10.1016/j.futures.2014.05.002.

[67] J. Kane. A Primer for a New Cross-Impact Language–KSIM. *Technological Forecasting and Social Change* 4.2 (1972), 129–142. ISSN: 0040-1625. DOI: http://dx.doi.org/10.1016/0040-1625(72)90010-8.

[68] Y. Kaya, M. Ishikawa and S. Mori. A Revised Cross-Impact Method and its Applications to the Forecast of Urban Transportation Technology. *Technological Forecasting and Social Change* 14.3 (Aug. 1979), 243–257. DOI: 10.1016/0040-1625(79)90080-5.

[69] R. A. Kelly, A. J. Jakeman, O. Barreteau, M. E. Borsuk, S. ElSawah, S. H. Hamilton, H. J. Henriksen, S. Kuikka, H. R. Maier, A. E. Rizzoli, H. van Delden and A. A. Voinov. Selecting among Five Common Modelling Approaches for Integrated Environmental Assessment and Management. *Environmental Modelling & Software* 47 (2013), 159–181. ISSN: 1364-8152. DOI: https://doi.org/10.1016/j.envsoft.2013.05.005. URL: http://www.sciencedirect.com/science/article/pii/S1364815213001151.

[70] U. B. Kjærulff and A. L. Madsen. *Bayesian Networks and Influence Diagrams: A Guide to Construction and Analysis*. Springer New York, 2013.

[71] K. B. Korb and A. E. Nicholson. *Bayesian Artificial Intelligence*. CRC Press, 2011, 463. ISBN: 9781439815915.

[72] B. Kosko. Fuzzy Cognitive Maps. *International Journal of Man-Machine Studies* 24.1 (Jan. 1986), 65–75. ISSN: 0020-7373. DOI: 10.1016/S0020-7373(86)80040-2. URL: https://www.sciencedirect.com/science/article/pii/S0020737386800402.

[73] T. Kuhmonen, I. Ahokas, M. Ahvenainen, P. Pohjolainen, J. Panula-Ontto, A. Kirveennummi, B. Auffermann and V. Kinnunen. *Suomen proteiinijärjestelmän vaihtoehtoiset tulevaisuudet*. Tech. rep. Tulevaisuuden Tutkimuskeskus, 2017. URL: `http://www.utu.fi/fi/yksikot/ffrc/julkaisut/tutu-julkaisut/Documents/Tutu-julkaisuja_1-2017.pdf`.

[74] T. Kuhmonen, K. Hyvönen, J. Panula-Ontto, R. Saarimaa, I. Ahokas, J. Kaskinen and T. Nurmi. *Paikallisen ruuan tulevaisuudet ja yhteiskunnalliset vaikutukset*. Tech. rep. Tulevaisuuden tutkimuskeskus, 2016. URL: `http://www.utu.fi/fi/yksikot/ffrc/julkaisut/tutu-julkaisut/Documents/Tutu-1-2016.pdf`.

[75] P. M. Kuhnert, T. G. Martin and S. P. Griffiths. A Guide to Eliciting and Using Expert Knowledge in Bayesian Ecological Models. *Ecology letters* 13.7 (2010), 900–914.

[76] S. Kuikka and O. Varis. Uncertainties of Climatic Change Impacts in Finnish Watersheds: A Bayesian Network Analysis of Expert Knowledge. *Boreal Environment Research* 2.1 (1997), 109–128.

[77] H.-S. Lee, G.-H. Tzeng, W. Yeih, Y.-J. Wang and S.-C. Yang. Revised DEMATEL: Resolving the Infeasibility of DEMATEL. *Applied Mathematical Modelling* 37.10-11 (2013), 6746–6757.

[78] A. Lehikoinen. Bayesian Network Applications for Environmental Risk Assessment. PhD thesis. University of Helsinki, 2014.

[79] V. Linss and A. Fried. *Advanced Impact Analysis: The ADVIAN method–an Enhanced Approach for the Analysis of Impact Strengths with the Consideration of Indirect Relations*. Tech. rep. Chemnitz University of Technology, 2009.

[80] V. Linss and A. Fried. The ADVIAN Classification–A New Classification Approach for the Rating of Impact Factors. *Technological Forecasting and Social Change* 77.1 (2010), 110–119.

[81] H. A. Linstone and M. Turoff. *The Delphi Method: Techniques and Applications*. Addison-Wesley, 1977. URL: `http://is.njit.edu/pubs/delphibook/`.

[82] Long Tien Truong, G. Currie and M. Sarvi. Analytical and Simulation Approaches to Understand Combined Effects of Transit Signal Priority and Road-Space Priority Measures. *Transportation Research Part C: Emerging Technolo-*

gies 74 (2017), 275–294. ISSN: 0968-090X. DOI: https://doi.org/10.1016/j.trc.2016.11.020. URL: http://www.sciencedirect.com/science/article/pii/S0968090X16302455.

[83] J. Luukkanen. Role of Planning Philosophy in Energy Policy Formulation. PhD thesis. Tampere University of Technology, 1994.

[84] S. Makridakis, S. C. Wheelwright and R. J. Hyndman. *Forecasting: Methods and Applications*. John Wiley & Sons, 2008.

[85] J. P. Martino and K.-L. Chen. Cluster Analysis of Cross Impact Model Scenarios. *Technological Forecasting and Social Change* 12.1 (July 1978), 61–71. DOI: 10.1016/0040-1625(78)90035-5.

[86] E. Medina, R. D. Arce and R. Mahía. Barriers to the investment in the Concentrated Solar Power sector in Morocco: A foresight approach using the Cross Impact Analysis for a large number of events. *Futures* 71 (2015), 36–56. DOI: 10.1016/j.futures.2015.06.005.

[87] Merriam-Webster Online. *Merriam-Webster Online Dictionary*. 2018. URL: http://www.merriam-webster.com.

[88] I. I. Mitroff and M. Turoff. On the Distance between Cross-Impact Models: A Set of Metric Measures for Cross-Impact Analysis. *Technological Forecasting and Social Change* 8.3 (1976), 275–283. DOI: 10.1016/0040-1625(76)90005-6.

[89] Norsys Software Corporation. *Netica 4.08*. 2008.

[90] E. Nováky and K. Lóránt. A Method for the Analysis of Interrelationships between Mutually Connected Events: A Cross-Impact Method. *Technological Forecasting and Social Change* 12.2-3 (Aug. 1978), 201–212. DOI: 10.1016/0040-1625(78)90056-2.

[91] A. O'Hagan, C. E. Buck, A. Daneshkhah, J. R. Eiser, P. H. Garthwaite, D. J. Jenkinson, J. E. Oakley and T. Rakow. *Uncertain Judgements: Eliciting Experts' Probabilities*. Chichester, UK: John Wiley & Sons, July 2006. ISBN: 978-0-470-03331-9. DOI: 10.1002/0470033312. URL: http://doi.wiley.com/10.1002/0470033312.

[92] M. Pagani. Roadmapping 3G Mobile TV: Strategic Thinking and Scenario Planning through Repeated Cross-Impact Handling. *Technological Forecasting and Social Change* 76.3 (Mar. 2009), 382–395. DOI: `10.1016/j.techfore.2008.07.003`.

[93] J. Panula-Ontto. AXIOM Method for Cross-Impact Modeling and Analysis. MA thesis. University of Tampere, Nov. 2016. URL: `https://tampub.uta.fi/handle/10024/100041`.

[94] J. Panula-Ontto. *AXIOM: Advanced Cross-Impact Option Method*. 2017. URL: `https://github.com/jmpaon/AXIOM`.

[95] J. Panula-Ontto. *EXIT: Express Cross Impact Technique*. 2017. URL: `https://github.com/jmpaon/EXIT`.

[96] J. Panula-Ontto, J. Luukkanen, J. Kaivo-oja, Y. Majanne and J. Vehmas. Complex Energy Futures. The Use of Express Cross-Impact Technique (EXIT) with Participatory Expert Workshops to Analyse Complex Systems and Interactions. *Conference proceedings of 2016 International Conference on Advances on Clean Energy Research, ICACER 2016, At Bangkok, Thailand*. 2016.

[97] J. Panula-Ontto, S. Kuikka and A. Lehikoinen. Probabilistic Reasoning in Foresight: Aims and Approaches. *Technological Forecasting and Social Change* (2018). Submitted to journal 12.11.2018.

[98] J. Panula-Ontto. AXIOM Approach for Modeling and Analysis of Complex Systems. *Proceedings of the conference "Futures of A Complex World"*. Ed. by R.Saarimaa and M.Wilenius. 2018, 72–90. ISBN: 978-952-249-499-3.

[99] J. Panula-Ontto. The AXIOM Approach for Probabilistic and Causal Modeling with Expert Elicited Inputs. *Technological Forecasting and Social Change* 138 (2018). DOI: `10.1016/J.TECHFORE.2018.10.006`.

[100] J. Panula-Ontto and K. Piirainen. EXIT: An Alternative Approach for Structural Cross-Impact Modeling and Analysis. *Technological Forecasting and Social Change* 137 (2018). DOI: `10.1016/J.TECHFORE.2018.06.046`.

[101] J. Panula-Ontto, J. Luukkanen, J. Kaivo-oja, T. O'Mahony, J. Vehmas, S. Valkealahti, T. Björkqvist, T. Korpela, P. Järventausta, Y. Majanne, M. Kojo, P. Aalto, P. Harsia, K. Kallioharju, H. Holttinen and S. Repo. Cross-Impact Analysis of Finnish Electricity System with Increased Renewables: Long-run

Energy Policy Challenges in Balancing Supply and Consumption. *Energy Policy* 118 (2018). DOI: 10.1016/J.ENPOL.2018.04.009.

[102] E. Papageorgiou, C. D. Stylios and P. P. Groumpos. Active Hebbian Learning Algorithm to Train Fuzzy Cognitive Maps. *International Journal of Approximate Reasoning* 37.3 (2004), 219–249.

[103] E. I. Papageorgiou and J. L. Salmeron. A Review of Fuzzy Cognitive Maps Research during the Last Decade. *IEEE Transactions on Fuzzy Systems* 21.1 (2013), 66–79.

[104] J. Pearl. *Causality: Models, Reasoning and Inference*. 2nd. New York, NY, USA: Cambridge University Press, 2009. ISBN: 9780521895606.

[105] J. Pearl. *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. Elsevier, 2014.

[106] J. Pitchforth and K. Mengersen. A Proposed Validation Framework for Expert Elicited Bayesian Networks. *Expert Systems with Applications* 40 (2013), 162–167. ISSN: 0957-4174. DOI: 10.1016/J.ESWA.2012.07.026.

[107] C. A. Pollino, O. Woodberry, A. Nicholson, K. Korb and B. T. Hart. Parameterisation and Evaluation of a Bayesian Network for Use in an Ecological Risk Assessment. *Environmental Modelling & Software* 22.8 (2007), 1140–1152.

[108] O. Pourret, P. Naïm and B. Marcot. *Bayesian Networks: A Practical Guide to Applications*. Vol. 73. John Wiley & Sons, 2008.

[109] M. Rahikainen, I. Helle, P. Haapasaari, S. Oinonen, S. Kuikka, J. Vanhatalo, S. Mäntyniemi and K.-M. Hoviniemi. Toward Integrative Management Advice of Water Quality, Oil Spills, and Fishery in the Gulf of Finland: A Bayesian Approach. *AMBIO* 43.1 (Feb. 2014), 115–123. ISSN: 0044-7447. DOI: 10.1007/s13280-013-0482-7. URL: http://link.springer.com/10.1007/s13280-013-0482-7.

[110] R. Rhyne. Technological Forecasting within Alternative Whole Futures Projections. *Technological Forecasting and Social Change* 6 (1974), 133–162. ISSN: 0040-1625. DOI: https://doi.org/10.1016/0040-1625(74)90014-6.

[111] C. Riggelsen. Learning parameters of Bayesian networks from incomplete data via importance sampling. *International Journal of Approximate Reasoning* 42.1-2 (May 2006), 69–83. ISSN: 0888-613X. DOI: 10.1016/J.IJAR.2005.10.005. URL: https://www.sciencedirect.com/science/article/pii/S0888613X05000654.

[112] T. Ritchey. Problem Structuring using Computer-Aided Morphological Analysis. *Journal of the Operational Research Society* 57.7 (2006), 792–801. ISSN: 1476-9360. DOI: 10.1057/palgrave.jors.2602177.

[113] T. Ritchey. Principles of Cross-Consistency Assessment in General Morphological Modelling. *Acta Morphologica Generalis* 4.2 (2015).

[114] S. J. Russell and P. Norvig. *Artificial Intelligence: A Modern Approach*. Pearson Education Limited, 2016.

[115] S. E. Seker. Computerized Argument Delphi Technique. *IEEE Access* 3 (2015), 368–380. ISSN: 2169-3536. DOI: 10.1109/ACCESS.2015.2424703.

[116] Y.-C. Shen, G. T. Lin and G.-H. Tzeng. Combined DEMATEL Techniques with Novel MCDM for the Organic Light Emitting Diode Technology Selection. *Expert Systems with Applications* 38.3 (2011), 1468–1481.

[117] J.-I. Shieh, H.-H. Wu and K.-K. Huang. A DEMATEL Method in Identifying Key Success Factors of Hospital Service Quality. *Knowledge-Based Systems* 23.3 (2010), 277–282.

[118] J. A. Sokolowski and C. M. Banks. *Principles of Modeling and Simulation: A Multidisciplinary Approach*. Wiley, 2009. ISBN: 9780470289433. URL: https://books.google.fi/books?id=wOOikQEACAAJ.

[119] W. Stach, L. Kurgan, W. Pedrycz and M. Reformat. Genetic Learning of Fuzzy Cognitive Maps. *Fuzzy Sets and Systems* 153.3 (2005), 371–401.

[120] P. A. Steenhof and W. Fulton. Factors affecting Electricity Generation in China: Current Situation and Prospects. *Technological Forecasting and Social Change* 74.5 (2007), 663–681. ISSN: 0040-1625. DOI: https://doi.org/10.1016/j.techfore.2006.09.005. URL: http://www.sciencedirect.com/science/article/pii/S0040162506001806.

[121] C. D. Stylios, P. P. Groumpos et al. Mathematical Formulation of Fuzzy Cognitive Maps. *Proceedings of the 7th Mediterranean Conference on Control and Automation*. 1999, 2251–2261.

[122] R. Taber. Knowledge Processing with Fuzzy Cognitive Maps. *Expert Systems with Applications* 2.1 (1991), 83–87. ISSN: 0957-4174. DOI: `https://doi.org/10.1016/0957-4174(91)90136-3`. URL: `http://www.sciencedirect.com/science/article/pii/0957417491901363`.

[123] D. Thorleuchter, D. V. den Poel and A. Prinzie. A Compared R&D-Based and Patent-Based Cross Impact Analysis for Identifying Relationships between Technologies. *Technological Forecasting and Social Change* 77.7 (Sept. 2010), 1037–1050. DOI: `10.1016/j.techfore.2010.03.002`.

[124] E. C. Tolman. Cognitive Maps in Rats and Men. *Psychological Review* 55.4 (July 1948), 189–208. ISSN: 0033-295X. URL: `http://www.ncbi.nlm.nih.gov/pubmed/18870876`.

[125] A. K. Tsadiras. Comparing the Inference Capabilities of Binary, Trivalent and Sigmoid Fuzzy Cognitive Maps. *Information Sciences* 178.20 (2008), 3880–3894.

[126] E. Turban. *Decision Support and Expert Systems: Management Support Systems*. 3rd. Upper Saddle River, NJ, USA: Prentice Hall PTR, 1993. ISBN: 0024216917.

[127] M. Turoff. An Alternative Approach to Cross Impact Analysis. *Technological Forecasting and Social Change* 3 (1971), 309–339. DOI: `10.1016/s0040-1625(71)80021-5`.

[128] K. S. Van Horn. From Propositional Logic to Plausible Reasoning: A Uniqueness Theorem. *International Journal of Approximate Reasoning* 88 (Sept. 2017), 309–332. ISSN: 0888-613X. DOI: `10.1016/J.IJAR.2017.06.003`.

[129] F. Vester. Der Papiercomputer. *Management Wissen* 10 (1987), 48–57.

[130] P. J. Villacorta, A. D. Masegosa, D. Castellanos and M. T. Lamata. A New Fuzzy Linguistic Approach to Qualitative Cross Impact Analysis. *Applied Soft Computing* 24 (2014), 19–30. ISSN: 1568-4946. DOI: `https://doi.org/10.1016/j.asoc.2014.06.025`. URL: `http://www.sciencedirect.com/science/article/pii/S1568494614002993`.

[131] S. Vögele, P. Hansen, W.-R. Poganietz, S. Prehofer and W. Weimer-Jehle. Building Scenarios for Energy Consumption of Private Households in Germany using a Multi-Level Cross-Impact Balance Approach. *Energy* 120 (2017), 937–946. DOI: `10.1016/j.energy.2016.12.001`.

[132] W. Watthayu, Y. Peng et al. A Bayesian Network Based Framework for Multi-Criteria Decision Making. *Proceedings of the 17th International Conference on Multiple Criteria Decision Analysis*. 2004.

[133] W. Weimer-Jehle. Cross-Impact Balances: A System-Theoretical Approach to Cross-Impact Analysis. *Technological Forecasting and Social Change* 73.4 (May 2006), 334–361. DOI: `10.1016/j.techfore.2005.06.005`.

[134] W. Weimer-Jehle, J. Buchgeister, W. Hauser, H. Kosow, T. Naegler, W.-R. Poganietz, T. Pregger, S. Prehofer, A. von Recklinghausen, J. Schippl and S. Vogele. Context Scenarios and their Usage for the Construction of Socio-Technical Energy Scenarios. *Energy* 111 (2016), 956–970. ISSN: 0360-5442. DOI: `http://dx.doi.org/10.1016/j.energy.2016.05.073`.

[135] B. S. Yoon and A. J. Jetter. Comparative Analysis for Fuzzy Cognitive Mapping. *Portland International Conference on Management of Engineering and Technology: Technology Management For Social Innovation, Proceedings*. 2016, 1897.

[136] B. P. Zeigler, H. Praehofer and T. G. Kim. *Theory of Modeling and Simulation: Integrating Discrete Event and Continuous Complex Dynamic Systems*. Academic press, 2000.

[137] X. Zhou, Y. Shi, X. Deng and Y. Deng. D-DEMATEL: A New Method to Identify Critical Success Factors in Emergency Management. *Safety science* 91 (2017), 93–104.

[138] H.-J. Zimmermann. Fuzzy Set Theory. *Wiley Interdisciplinary Reviews: Computational Statistics* 2.3 (2010), 317–332.

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Probabilistic Reasoning in Foresight: Aims and Approaches

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Probabilistic Reasoning in Foresight: Aims and Approaches

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Abstract

This paper discusses probabilistic modeling approaches in foresight applications. Foresight often relies on inputs elicited from experts, and probabilistic logics are well suited for participatory expert processes. They are used for inference about future developments with consideration to causally linked factors, likely consequences of policies and interventions, identifying the best combinations of policies, and identifying consistent scenarios. Bayesian belief networks are an established modeling approach for probabilistic knowledge representation and inference. Certain characteristics of the Bayesian approach limit its utilization in foresight. Several other probabilistic logics with conceptual and functional overlap with Bayesian belief networks have been proposed in the foresight field. These approaches can be related to Bayesian belief networks in terms of the trade-offs they make to ease the expert elicitation and offer more flexibility in modeling, with the cost of losing some precision in the description of the modeled domains and sacrificing some of the analytical possibilities. This paper positions these approaches to Bayesian networks and each other, outlines the research questions they can be used to answer and evaluates their strengths and weaknesses.

Keywords: Probabilistic reasoning, Expert elicitation, Belief networks, Decision support, Expert systems, Probabilistic logic, Cross-impact analysis, Modeling
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1. Introduction

This paper discusses probabilistic modeling approaches with high fitness for expert elicitation processes and strategic foresight applications. Probabilistic modeling is especially suited for foresight applications dealing with uncertain future events and developments, as it is able to consider the high level of epistemic uncertainty involved in foresight activities. Foresight often relies on inputs elicited from expert informants [1,2,3,4,5,6], and the modeling languages of probabilistic logics are relatively well suited for participatory expert processes aiming at elicitation of model inputs.

Probabilistic logic can be used for several foresight-oriented inference aims: reasoning about the likely future developments with consideration to a number of factors, also causally linked to each other, reasoning about the likely consequences of policies and interventions, identifying best combinations of actions to maximize utility or minimize harm, identifying consistent options or scenarios, and forming an understanding of relationships of factors in complex networks of interdependencies. These analytical aims are not mutually exclusive and can be pursued with different models and inference procedures.

Bayesian belief networks are the most established modeling approach for representation of knowledge in a probabilistic way and providing the means for inference for that knowledge base. While Bayesian belief networks are widely used in decision support activities in a multitude of applications [7,8,9,10,48], some characteristics of the approach limit its utilization in foresight. Several other probabilistic logics using expert informants as the information source, with conceptual and functional overlap with Bayesian belief networks, have been proposed in the literature, especially in the foresight field. These approaches can be related to Bayesian belief networks in terms of the trade-offs they make to ease the expert elicitation and to offer more flexibility in modeling, with the cost of losing some precision in the description of the modeled domains and sacrificing some of the analytical possibilities. This paper positions these approaches to Bayesian networks and each other, outlines the research questions they can be used to answer, and evaluates their strengths and weaknesses.

Modeling approaches such as flow charts and cognitive maps aiming only at non-formal, conceptual-level modeling fall outside the scope of this paper. The review does not focus on the substance-oriented case studies, but the approaches are reviewed from the perspective of their characteristics and fitness for expert elicited modeling process. The contribution is to inform the readers on the availability, characteristics and potential uses of the methods in the category, especially in foresight applications.

While narrower methodological reviews of analysis techniques of interest in this paper such as cross-impact analysis [11,12,13], morphological analysis [14], and Bayesian belief networks [15,16,17] have been presented before, their mutual applicability to formulating models in expert processes and analytical possibilities have not been compared using congruent concepts and terminology. We describe the reviewed approaches using basic graph theory concepts (even when the original descriptions of the approaches use some other set of concepts or way of representation), and identify the analytical outputs they are able to deliver. The aim is to commensurate and position the probabilistic reasoning approaches against each other and assist the readership in forming an understanding of the available methods. The publications reporting the various methods in this modeling niche often position the presented method against a few very similar approaches, but a broader and more comprehensive look into the properties, similarities and differences, and relative fitness for modeling, research and decision support uses has been lacking. This review aims to fill this gap, and facilitate further methodological discussion and development in this specific realm of modeling.

2. Expert Elicitation and Probabilistic Reasoning

A *logic* is a formal language and a set of inference procedures[18]. The language of a logic is *formal*, consisting of a finite set of symbols or building blocks. This language can be used to *describe knowledge* in the domain the logic is intended for. The *inference procedures* of a logic are more or less justified operations performed on a construct composed of the language symbols. They enable reasoning based on the knowledge described in the language. As the language is formal and the inference procedures systematic, the inference can be *automated*. The automation enables drawing inference from the knowledge base described with the language computationally in cases where the knowledge base is extensive and the relating rules complex.

Classical propositional logic could be said to describe knowledge as atomic, indivisible propositions and logical connectives. The logical connectives relate the propositions to each other in a deterministic way. The atomic propositions have a truth value, and the truth value of more complex statements made up from the atomic propositions is inferred by the rules defined for the logical connectives. Propositional logic can be extended in different ways[19] to consider partiality of truth and other additional layers of information about the propositions.

Language of a *probabilistic logic* describes knowledge with consideration to uncertainty[20]. A probabilistic logic can describe problem complexes, decision-making problems, or systems of interconnected considerations as a set of propositions and their relationships with additional information concerning probability. In a probabilistic language, the facts, as well as their relationships, can be assigned probabilities. These probabilities can be based on empirical observations, but they can also be elicited from expert informants, capturing a *degree of belief* of the experts on the propositions and the rules describing the relationships.

More or less formal and reductive descriptions of reality are called models[21], and the practice of representing reality with such formalizations *modeling*. Formal modeling is traditionally understood to be strongly data-driven[21], meaning that the properties of modeled elements of reality and the definitions of their relationships are derived from statistical data. Normally, these formal descriptions of relationships are presented in the form of mathematical equations, and the parameterization of the relationships relies on statistical techniques such as regression analysis. While the empirical data drives the modeling, such modeling still aims at "formal representation of theory"[22], and the structure and the rules of the models are based on theoretical-level understanding of reality.

Data-driven modeling is bounded by data availability[21]. This is due to costs of acquiring the data, but also difficulties in quantification of important or interesting aspects of the system. The scope of modeling is limited by data unavailability, as only systems, domains, and problems with ample available data will be modeled, but also in the sense that important system drivers and features, for which data is not available, wind up simply not represented in models. As models are often used in policy or strategy formulation concerning future decision options and decision support, data unavailability in modeling also limits policy scope and strategic perspective in decision-making[23].

Expert elicitation is an alternative to the data-driven approach for getting the inputs required for modeling[24,25,26,27]. In cases where data for modeling is available, data-driven modeling may result in higher predictive performance, but models integrating expert knowledge are often of higher relevance for decision support[28]. Expert knowledge may cover parts and aspects of modeled reality for which statistical data is unavailable, but are still understood in some level of detail. This knowledge may be needed in order to support the analysis of such future decision options, for which there is no historical data[(23)]. This is almost inevitably the case in many strategic considerations. Foresight-oriented modeling, especially in the context of complex, weakly quantified systems with high abstraction level, such as socio-techno-economic systems, often has to rely, at least partly, on expert elicitation for model structure and parameters. Modeling changing systems and operating logics cannot rely on existing statistical data for parameterization of the model, as these derived characterizations reflect the current logic of the system, but not necessarily how this logic will change in the future, as a result of new developments and policies that create new dependencies between variables.

While many modeling approaches can be used in conjunction with expert elicitation processes, most modeling techniques are not well suited to be used with inputs elicited from experts, making the process more or less difficult. Modeling work relying on expert informant sourced inputs can only be feasible with a modeling language suitable for the expert-oriented work mode. Such languages should offer a way to describe model relationships in a way that is practical for the purpose, typically less precise than specifying mathematical equations directly. Probabilistic logics have a high fitness for describing expert knowledge bases. They can model both the epistemic uncertainty related to the modeled domain, but also the uncertainty and haziness of the expert inputs. The conceptual simplicity and the relatively low amount of elicited information typical for modeling reality in the language of probabilistic logics mean that the elicitation process is much more feasible than a similar expert process aiming at parameterization of normally data-driven models.

3. Approaches for probabilistic reasoning

This section gives a description of the most prominent probabilistic modeling approaches with foresight applications. The approaches are commensurated using basic graph theory concepts. The models of some approaches are not represented as graphs in their original descriptions, but they can be represented as graphs, and this representation is useful in helping the reader to understand the *information content* of the models. For models that are, in their graphical form, *dense* or *fully connected*, the graphical representation is often not practical for presenting actual models, but it serves the purpose of making the approaches more comparable in the context of this review.

Understood as probabilistic logics, the modeling languages of approaches discussed in this paper need to provide facilities for description of the *facts* and the *rules* of the modeled domain. In graphical representations of the discussed models, nodes are *descriptors*, representing *facts* or propositions about the modeled domain. Depending on the approach, the descriptors can hold the following information:

a) A continuous value, with a probability distribution.

b) Two or more mutually exclusive values or possible states of the descriptor. These mutually exclusive values are also, at the model level, thought to be exhaustive, fully covering all the possible states of the descriptor. The set of states may or may not have a probability distribution.

c) Binary truth-valued concepts, capable of having true and false as their states. Binary concepts may or may not have a probability.

d) Variable concepts, with a defined direction of change, such as 'population grows' or 'wind power capacity increases'. This is distinct from binary truth-valued concepts as variable concepts are never resolved to a state.

The edges connect the graph nodes, and represent information about the relationships, causal influences and dependencies between the descriptors, or more generally, *rules*. Edges can be directed, meaning that one of the nodes connected by the edge is a head node and one a tail node, and the direction is meaningful. The significance is often the direction of influence, the tail node being the influencer or *cause* and the head node being the influenced or *effect*. Edges can also be undirected, with the interpretation that the causal direction of the relationship between the connected nodes is not specified: the facts represented by the nodes are simply, in probabilistic terms, probable or improbable to occur together. The nature of their causal connection is left undefined in a structural sense. *Hyperedges* can also be used in graphical descriptions of models: a hyperedge connects an arbitrary number of nodes, in a directed or undirected fashion.

Edges carry information describing the relationship between the connected nodes. This information can be the following:

a) A conditional probability, expressing the probability of the head node or effect conditional to a single tail node or cause (see Section 3.2), or a set of tail nodes, or all of its causes (see Section 3.1). In a case of a set of tail nodes or causes, the edge is a hyperedge.

b) A reference to an probability-updating function, to which the conditional probability updates of the effect are delegated to. Graphically, these edges can be normal directed edges in cases of single tail nodes or causes (see Section 3.3), or directed hyperedges in cases of multiple tail nodes or causes (see Section 3.4).

c) A relative magnitude indicator of the probabilistic influence. The relative magnitude indicators do not map to any quantified changes in probabilities, but rather simply express the magnitudes of the influences *in relation* to other relative influences in the model.

The graphs themselves can be cyclic or acyclic. Cyclic models are able to represent bidirectional interaction and ambiguous causality. Acyclic models are in this sense more limiting from modeling perspective. In acyclic graphs, the tail nodes can also be called *parents* and the head nodes *child nodes* or *children*. The acyclic form of graph makes for computationally more efficient inference. In some cyclic models, the computational transformation on which the inference relies on is an estimation process based on sampling, such as a Monte Carlo process. Sampling based estimation is computationally slow compared to the inference made possible by the acyclic form of a model: the cyclicity is a trade-off between modeling power and computational efficiency, if it results in a need to estimate the results by sampling. On the other hand, acyclic models, in structurally complex cases, may also need to resort to sampling based estimation instead of exact computational methods [20].

3.1. Bayesian belief networks and influence diagrams

A Bayesian belief network, henceforth BBN, is a graphical model for probabilistic causal reasoning under uncertainty. The graphical representation of a BBN is a directed acyclic graph, describing relationships, denoted by directed edges, between random variables, denoted by nodes. The nodes are normally multi-state descriptors, but in many implementations of bayesian networks the nodes can also hold continuous values. The relationships are defined by populating node-specific conditional probability tables (CPTs) with conditional probability distributions (CPDs) [20,29,30].

A CPD contains information on the probability of a variable (child node, effect) being in a certain state depending on the state of its explanatory parent variables (causes). For defining the numerical dependencies, a wide variety of methods can be applied, beginning from the simulations of either deterministic [31] or probabilistic nature [32] or the direct use of data by utilizing different learning algorithms [33,34]. Under the belief that future events are exchangeable with earlier observations, the statistical frequency distributions can be utilized as well [35]. In data- or resource-poor cases, eliciting the degrees of belief of the experts, is widely used [16,26,36,37,38] In elicitation of inputs, conditional probability tables can be elicited directly or parameters for distributions can be asked from experts. In direct elicitation of conditional probability tables, the dependency structure of the model has to remain relatively simple to keep the number of elicited values manageable. Eliciting distribution parameter values instead of 'naked' conditional probabilities may reduce work load for elicited experts, but this approach is normally used only for continuous variables.

Normally, the BBN nodes are probabilistic random variables and can represent several different kinds of system properties. The random nodes can represent mutually exclusive discrete states, but also continuous quantitative system properties, and both types can be used in the same model. For an *influence diagram*, a special case of Bayesian belief network, also *decision nodes* and *utility nodes* are available as node types [29]. Decision nodes affect the state of at least one of the random nodes: the states of a decision node are mutually alternative decisions or policies. Decisions that can be potentially implemented in parallel, are given nodes of their own. Utility nodes receive information from one or more nodes of the system (both random nodes and decision nodes). A utility node defines the utility, harm, gain, or cost for all the possible output combinations of interest. Utility nodes of the model define the decision making criteria, against which the model evaluates the ranking order of the mutually alternative decisions. If the model includes several decision nodes, an influence diagram can suggest policy optimization, meaning that a search for the combination of the decision alternatives that maximizes the expected utility or minimizes the expected harm, or find the most cost-effective solution, can be performed [39].

Unlike most models discussed in this review, a Bayesian network graph is acyclic, and does not allow for structural inference loops. This imposes limitations on the expressive power of the model, as cyclic interactions or ambiguous causal structures cannot be modeled. This limitation can, to some extent, be overcome by applying 'time-slicing', i.e. duplicating the model and this way creating dynamic and adaptive time-steps [40,41,42]. For complex systems, however, this solution is not very sustainable, as the size of the model easily grows beyond human perception capacity.

The inference in a BBN follows the so-called Bayes' theorem stating that the posterior probability of fact B given fact A represents what is known about how likely fact B is to be true given the *observation* or occurrence of fact A. The Bayesian logic can also be called 'inverse logic', as it can be used not only for predicting events given the causing factors, but also in an omnidirectional fashion, for inferring the likely causes based on the observed effects [43,44]. As a consequence, a BBN can be used for three types of inference: a) predictive inference, meaning forward direction–from parent to child node), b) diagnostic inference, meaning backward direction–from child to parent node, and c) mixed inference, meaning forward and backward at the same time [45,46].

Of the discussed approaches, BBNs are the most widely used, with many scientific, industrial and decision support applications [47,48]. They are used in planning and management activities [7,9,49,50] with a limited foresight aim, and they have been applied in technology foresight [51], but their utilization in e.g. scenario work typical to long range foresight is not yet common. Analytically, BBNs can be used for delivering many outputs similar to other approaches discussed in this section, with certain limitations, mainly resulting from the acyclic form of the model prohibiting loops and modeling of bidirectional interaction. Analysis based on BBNs is well supported with mature software implementations such as Hugin [52] and Netica [53].

From the perspective of utilization in foresight applications, normal BBNs could be said to have the following problems:

a) The acyclic form of the model means that bidirectional interaction between descriptors cannot be modeled, and the causal structure is unambiguous. In foresight applications, the causality structure is often ambiguous: occurrence of event A before event B might causally influence B, but it might often be reasonable to expect a causal influence in the other direction, should B occur before A.

b) The temporal logic of a foresight-oriented model is tightly coupled with the structure of the Bayesian network. A temporal dimension can be modeled to some extent by the time-slicing approach, but the nodes themselves carry no information about their temporal positioning in relation to other nodes. This limits the description of the temporal dimension of models to some degree.

c) The number of required inputs, in cases of structurally complex models, easily becomes unmanageably high. As the structural complexity of the dependencies in the model increases, the amount of information required by the conditional probability table representation of the relationships grows exponentially. The number of conditional probabilities to be elicited for an effect e, in a case of n dependencies for e, is $(\prod_{i=1}^{n} s(c_i)) \times s(e)$, where $s(c_i)$ is the number of possible states a specific cause c_i can have, and $s(e)$ is the number of possible states of the dependent effect. While the probabilistic interaction between nodes can be accurately described with this approach, it limits modeling by expert elicited inputs as the structural complexity has to be kept relatively low to keep the elicitation process feasible. Limiting the structural complexity heavily will result a high abstraction level for the descriptors and possible omission of considerations that might be important.

There are solutions [16,27,54,55,56,57] to the problem of exponentially growing input information in a Bayesian network, but the basic problem has to be considered in their use in chiefly expert elicited model parameterization. While BBNs undoubtedly can be a very useful approach in foresight applications as well, their problematic aspects may warrant consideration of other probabilistic modeling approaches. The use of Bayesian approaches in expert elicitation processes has inspired methdolological proposals aiming at providing more intuitive-heuristic model valuation, such as the approach by Varis [58,59]. This approach differs substantially from conventional BBN models, aiming at modeling of probabilistic influences between continuous variables with a discretized representation at the model level. The discrete states of the nodes are assigned prior probabilities, and they are updated with information linked from other parts of the network, yielding the posterior probability distribution. The posteriors are calculated by using two independent likelihood messages. The updated belief is obtained as the product of them and the prior probability, i.e. what is known without the model structure and how much more is learned when looking at the state of all variables. A link transfers information from one node to another and is described by a link matrix. In a standard BBN, only nodes without parents can have an independent prior probability distribution.

The analysis starts from a 'tabula rasa' model, in which all model variables are technically connected with all other variables, but these connections are non-informative: a change in one variable does not influence the other variables. Also the variables are, at the outset, empty of all information. In Bayesian terms, they are represented by a uniform, non-informative probability distribution. In the modeling process, the tabula rasa is being filled with information on the variables and their interconnections, typically via an expert informant elicitation process [(58)]. The knowledge in the other parts of the model is taken into account by the information flow through the links and other variables. Several parent nodes can have an impact on one node, and the strength of these dependencies is influenced by the link values and computed by matrix multiplication. From statistical point of view, link values are equal to R^2. Techniques for estimating the belief network valuations [(59)] have been presented. This approach is especially suitable for directive and strategic analysis. The modeling power of the approach is limited in cases of non-linear dependencies, which can be well represented in a standard BBN model, and is suitable for cases where the modeled domain can be represented with continous variables. However, it offers many useful features for combined use of statistical, deterministic and other types of models. In addition to basic analyses, comprehensive sensitivity analyses for causal thinking can be carried out in the approach [(59)].

3.2. Gordon-Hayward cross-impact analysis and SMIC

The cross-impact approach [(60,61)] predates Bayesian models, and has been introduced with an explicit foresight aim and full expert-based model valuation in mind. The Gordon-Hayward cross-impact analysis [(60,61,62)], or GHCIA, and the SMIC approach [(63,64)] are probabilistic binary descriptor cross-impact modeling approaches. There appears to be no link from existing literature on Bayesian approaches to the cross-impact techniques or the other way around. While the cross-impact analysis comes from a quite different research tradition than the BBN approach, and approaches probabilistic reasoning from a different technical standpoint, the basic ambition is similar: to observe probability changes in a probabilistic network, posterior to some evidence or assumptions.

The GHCIA and SMIC nodes are binary descriptors with probabilities. They present a hypothesis or a postulate, or a fact, about the state of the system in the future. The facts are assigned an initial probability of occurrence, which is the expert estimate of the probability of the fact when no other information about the system is available.

The edges carry information about the conditional occurrence probability of the fact of the head node (effect), given the occurrence of the fact of the tail node (cause) [(62)]. In SMIC, the edges additionally carry information about the occurrence probability of the head node fact, conditional to the non-occurrence of the tail node fact [(63,64)]. In GHCIA, the non-occurrence conditional probability is inferred from the occurrence conditional probability, instead of being specified by the expert informants [(62)].

The initial and conditional probabilities are supplied by a single expert or an expert group, preferably a group. In the case of GHCIA, the probability valuations $P(i)$ and $P(j)$ for any two facts i and j in the model and the conditional probability valuation $P(i|j)$ are checked for compliance with the following conditions:

1. $0 \leq P(i) \leq 1$
2. $0 \leq P(i|j) \leq 1$
3. $\frac{P(i)-1+P(j)}{P(j)} \leq P(i|j) \leq \frac{P(i)}{P(j)}$

The last condition specifies the allowed bounds for the conditional probability of fact i given the occurrence of fact j. If the expert-sourced probabilities do not fall within permissible bounds, it is the task of the expert(s) to resolve the inconsistency by changing either the conditional probabilities or the initial probability valuations [(62)]. In the case of SMIC, the acceptable conditional probability bounds are reasoned [(65)] to be different and more strict than what is acceptable in GH-CIA. The software implementation provides a linear optimization function [(64)], which corrects the initial expert-sourced valuations into the permissible bounds, while keeping the corrected valuations as close to the original expert valuations as possible. The emphasis is on the discovery of a consistent system of conditional probability valuations.

When the interactions and dependencies of the model facts have been described as a system of conditional probabilities, model evaluation can be performed. Evaluation consists of assigning a truth value, meaning that the state of the variable is known after assignment, for all the model descriptors in random order, according to their probabilities. When a descriptor is assigned a truth value, the probabilities of the other descriptors are updated according to the relationship described by the system of conditional probabilities. This is done according to the *odds ratio technique* [(62)], described by Eq. (1).

$$P_u(P, P_i, P_c) = \frac{\frac{P}{1-P} \times \frac{\frac{P_c}{1-P_c}}{\frac{P_i}{1-P_i}}}{1 + \frac{P}{1-P} \times \frac{\frac{P_c}{1-P_c}}{\frac{P_i}{1-P_i}}} \tag{1}$$

Equation (1) presents the probability update logic of the Gordon-Hayward approach. P is the current probability to be updated, P_i is the initial probability, P_c is the probability conditional to a single cause, and P_u is the updated probability. The idea is to reason about the magnitudes of the probability impacts based on the differences of initial probabilities of facts and the conditional probabilities. The first probability update a node undergoes brings its probability equal to the conditional probability defined in the update. For the subsequent probability updates, it is necessary to take into account that that the probability has already been updated, and the updating technique of Eq. (1) is one possible way to do that. Function presented in Eq. (1) is plotted in Fig. 1 with the initial probability fixed at 0.5.

The model is evaluated when all of its descriptors have been assigned a truth value. This system state can be thought as a scenario and is the result of a single model evaluation. This result is saved, the probabilities of the descriptors are reset to their initial a priori values, and the evaluation is performed again, “a large number of times”: the computation is a Monte Carlo process [(66)]. After a number of evaluations deemed sufficient have been performed, the cross-impacted posterior probabilities for the possible states of the descriptors (true or false) can be computed as the frequency of occurrence of these states in the set of generated scenarios. The operation of the modeled system can now be tested under various assumptions by changing the initial probability valuations or the conditional probabilities and comparing how the a posteriori probabilities change under different setups. For example, the likely impacts of implementing a certain value for a decision node can be evaluated with the model.

A SMIC model is evaluated in a process similar to GHCIA, but the aim is to identify the most probable scenarios, or combinations of node states, for further examination with other futures methods [(63,64)]. For a system of n hypotheses, SMIC produces the probabilities for 2^n scenarios, ordered by their probability. Godet also recommends [(64)] deriving an elasticity matrix for the variables of model by means of performing sensitivity analysis on the initial probability

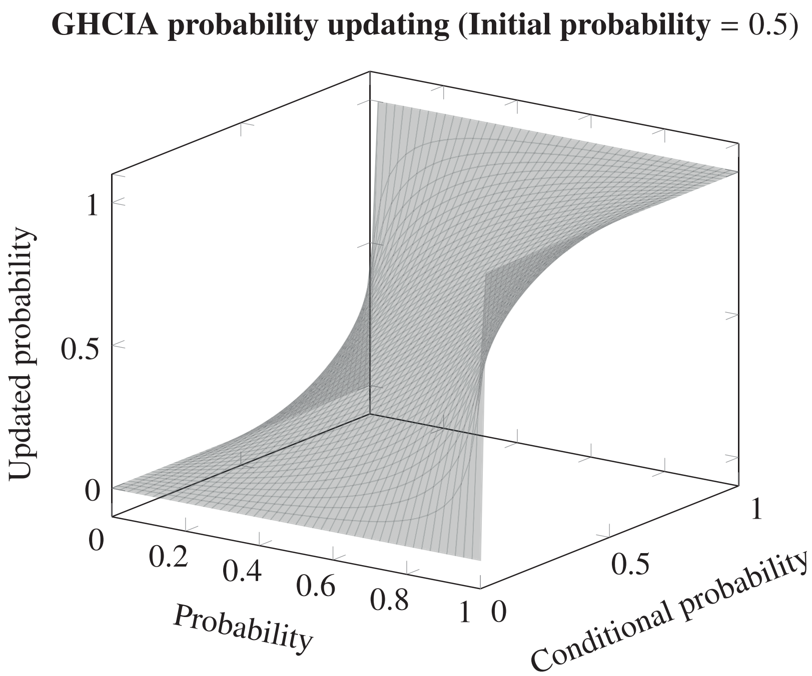


Figure 1: Gordon-Hayward approach probability updating function graphed. Graph is plotted with the initial probability fixed at 0.5.

valuations of the variables.

Comparing GHCIA to a BBN, the inference is of similar nature: a system of conditional probabilities is defined, and the changes in the probabilities of facts in the model are observed when the probabilities of nodes representing decisions, policies, or other variables of interest are changed by the analyst. Technically, the approaches differ significantly, as the GHCIA approach uses a sampling process to arrive at *estimates* of the posterior probabilities, whereas a Bayesian network normally uses exact computational methods to yield the posterior probability distributions (although in complex networks sampling may be used to estimate posteriors)[20]. The basic analytical aim, however, is similar. An utility function can be defined for the model, and used to identify an optimal combination of policies and interventions, represented as a set of decision nodes.

The modeling power of GHCIA is limited compared to BBN, as the descriptors are binary and the model has no structure in the same sense as a BBN: all events represented by nodes occur at the same time, in an analytical sense. Temporal dimension cannot be modeled with the GHCIA approach. The binary nature of descriptors means that mutual exclusivity of facts cannot be reliably modeled, and exhaustiveness of facts cannot be modeled at all: there is no way to guarantee that at least one of random variables, in a set supposed to represent an exhaustive set of facts, will be evaluated true.

p	C_1 0.4	C_2 0.6	C_3 0.7	E ***0.5475***
0.168	T	T	T	0.95
0.072	T	T	F	0.72
0.112	T	F	T	0.68
0.048	T	F	F	0.39
0.252	F	T	T	0.55
0.108	F	T	F	0.35
0.168	F	F	T	0.3
0.072	F	F	F	0.2
1				

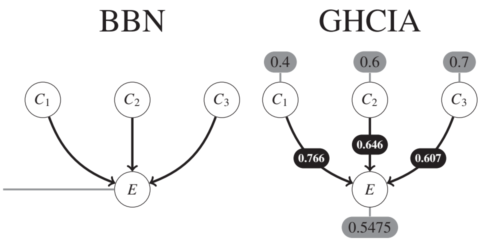


Figure 2: BBN and GHCIA representations of conditional probabilities

The modeling power of GHCIA, in terms of interactions, is also limited compared to a BBN. In a BBN, the conditional probabilities for a fact are specified for all combinations of the facts it is causally dependent on. In GHCIA, the conditional probabilities are specified for all causes independently, not for all possible combinations of causes. This property could be called *structural haziness* of causality. However, from the point of view of the feasibility of expert elicitation of model inputs, this difference means that there are less conditional probabilities to be elicited. The exact number of elicited probabilities for a model with n nodes is n^2. Fig. 2 illustrates the difference between a BBN and GHCIA in description of probabilistic dependencies.

In the BBN model of Fig. 2, a probability for each possible configuration of the causes C_1, C_2 and C_3 is obtained as the product of the probabilities of the causes (or their complements in case the cause does not occur). The probability of the effect E is defined by the modeler for each configuration. The probability of E is simply the sum of $p(E)$ in each configuration multiplied by the probability of the configuration in question. The GHCIA model, presented alongside on the right in Fig. 2, represents the precise information of the BBN to the precision limits of its modeling language. The 'independent initial probability' the effect E in the GHCIA model has can be obtained directly from the BBN model as the probability of E in a case where no information or evidence is available. This probability (0.548) is visible in the $p(E = T)$ column, bottom row. The probabilities conditional to individual causes could be obtained by changing the probability of each cause, one at a time, to 1, and recomputing the probability for E. Populating the BBN model requires 11 values, whereas for the GHCIA model, 7 values suffice. Some information from the BBN representation is lost, but less input values need to be elicited: GHCIA represents the causalities in an approximate fashion, with fewer inputs. In a case of structurally complex causation, where an effect node has a high number of cause nodes, this difference becomes important. For a GHCIA model, the number of conditional probabilities to be elicited grows in a quadratic fashion, whereas for a BBN the growth is exponential: if one more binary cause would be added, the number of conditional probabilities in a BBN description of the dependency would be doubled. Table 5 illustrates this.

As initial and conditional probabilities in GHCIA and SMIC models are expected to meet the conditions specified above, the elicitation of these values may require redefinition of values already elicited, resulting in considerable amount of iteration in the valuation process. The approaches also requires definition of conditional probabilities for all directed variable pairs in the model. While the number of elicited inputs in the case of a structurally complex model may be significantly lower than in a BBN, the number of descriptors has to remain relatively low to keep the elicitation process feasible. Godet et al.[64] actually recommend that the number of descriptors in a SMIC model should not exceed 6. Most actual modeling cases require the use of a much greater number of descriptors to produce actionable information for decision support. Attempting to model any real system or decision-making context with a very limited number of descriptors means that the model turns out highly abstracted, and its analytical outputs are of high abstraction level as well, and its decision support use limited. For a GHCIA model, a feasible number of descriptors may be significantly higher compared to SMIC, as the requirements for valid conditional probability valuations are less stringent. The modeling power is still limited by the binary descriptors and the lack of temporal structure.

3.3. BASICS

The BASICS approach[69] has been proposed after the GHCIA approach for application of probabilistic reasoning in foresight applications and futures thinking. BASICS is a probabilistic logic aiming at identifying scenarios, or combinations of facts, that are mutually consistent in the sense of being probable to occur together. The BASICS nodes are multi-state descriptors, with a probability distribution for the states, similar to a BBN. The edges describe causal influences on the head node, conditional to the tail node being in a certain state: When the state of the tail node is resolved during model evaluation, the probabilities of states of the head node are updated.

BASICS does not employ sampling in its model evaluation, as the GHCIA approach, and doesn't produce posterior probability distributions for the nodes. Instead, the model evaluation is a deterministic process: the model is evaluated twice for each possible state of its nodes, first assuming the state in question to 'be true' or occur, and second the state to 'be false' or not occur. The other nodes are evaluated in sequence, so that the most probable state is selected for it and the probability updates for that state on other states are performed. Each model evaluation produces a set of node states occurring in that evaluation, and this set can be interpreted as a scenario. This process yields $s \times 2$ scenarios for a model with s states in total for its nodes. The motivation is to find scenarios that are "probable and consistent"[67], in the light of the supplied prior probabilities and interactions. The scenarios that emerge from multiple different evaluations are interpreted to be probable and consistent, warranting further study with other analytical techniques. JL-algorithm[67] is derived from BASICS, and proposes changes to the model evaluation procedure to eliminate effects of the ordering of the descriptors in the user input, as they are significant in some BASICS implementations.

BASICS has a more limited inference aim than BBN or GHCIA: the aim is simply to generate a small set of scenarios and to identify whether or not same scenarios are produced with different starting assumptions about individual node states. The intended use coincides with the SMIC approach discussed in Section 3.2, as well as the approaches discussed in Section 3.6. The process does not aim at computing or estimating posterior probabilities as BBN or GHCIA models. BBN and GHCIA models, on the other hand, can be used for identifying consistent model configurations, covering the analysis aim of BASICS.

The modeling language of the BASICS approach further simplifies the description of the probabilistic influences, compared to the GHCIA approach. The probability-changing interactions that the model components have on each other are expressed as *references* to probability-updating functions[67,68,69], which alter the descriptors' probabilities 'contextually'. This means that adjustment by the same function will result in a different amount of probability change in the influenced descriptor, depending on the value of the adjusted probability at the time of the adjustment. Figure 3 illustrates how current probabilities are mapped to updated probabilities with the updating function set available in BASICS.

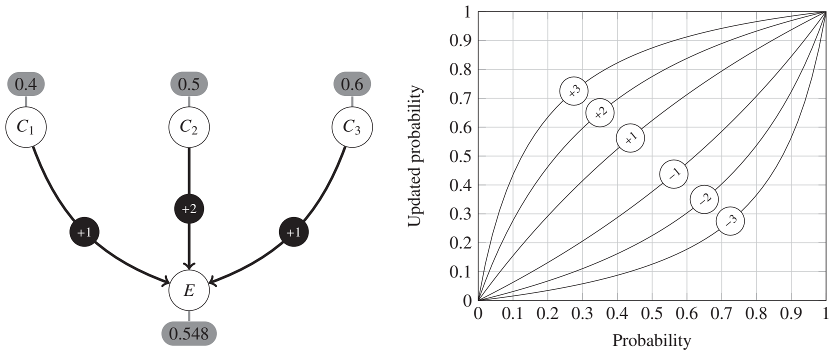


Figure 3: Probability updating in BASICS.

The GHCIA probability updating is based on an updating function as well: a *single* updating function maps current probabilities to updated probabilities, taking the current probability P, initial probability P_i and the conditional probability P_c defined for the edge as arguments. In BASICS, there is a set of six updating functions, each of which simply takes the current probability as an argument and maps it to an updated probability. The description of probabilistic influences, for the modeler, is now simply to reference the appropriate updating function, depending on the perceived magnitude of the influence: +1 to model a small probability-increasing influence of the cause on the effect, −3 to model a strong probability-decreasing influence.

The approach taken in BASICS is, in comparison to GHCIA, another step towards more intuitive valuation of the model. GHCIA bargains on the *structural* precision of the causality, by only holding information on single cause specific conditional probabilities, instead of a conditional probability table describing probabilities of the effect in all possible state configurations of all of its causes. BASICS bargains on both structural and *valuational precision*, modeling both the structure and the magnitude of the causalities in a hazier, more approximate way compared to a BBN. As the probability updating is fully contextual, there is no need to specify a set of initial and conditional probabilities compliant to a set of probability axioms as in GHCIA. Impacts do not need to be specified for all model state pairs, as in GHCIA, where a conditional probability is needed for all node pairs. Multi-state nodes can model what a basic BBN can model, with a structurally and valuationally hazy precision. What is gained by losing the precision is an easier, faster model valuation process in expert elicitation.

BASICS and JL-algorithm make it possible to identify consistent scenarios, but the inference and analytical outputs are limited to that, and probabilistic inference is not possible with the computational process of BASICS. The decision support offered by the approach is thus indirect and limited. Like GHCIA and SMIC, the descriptors have no temporal structure or ordering. This fact also limits the modeling power. The modeling language, however, lends quite well to expert elicitation, reducing the number of inputs required for structurally complex models and perhaps being more suitable for the hazy expert valuation than the conditional probability orientation of

GHCIA.

3.4. AXIOM

The AXIOM approach[70,71] combines features from BBN, GHCIA and BASICS. While technically different, functionally it could be seen as a special case of a BBN, where

1. graph cycles are allowed,
2. posterior probabilities are estimated by sampling, as in GHCIA, and
3. probabilistic influences are described in a cross-impact language, i.e. by delegating the updates to updating functions, instead of populating effect node specific conditional probability tables.

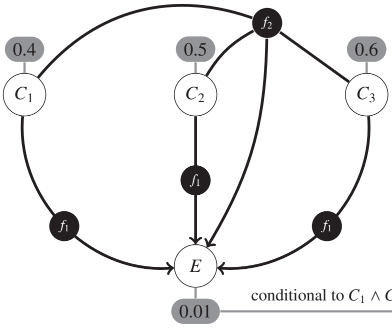
AXIOM uses updating functions to perform the updates, but the idea is extended from GHCIA and BASICS approaches. An AXIOM model can have an arbitrary number of updating functions, as opposed to BASICS, which has a fixed set of six updaters. The updating functions close over the model, and can use any information in the model to determine the magnitude of probability update. This could mean making the updates conditional to any number of causes instead of just one, as is the case in BASICS. In this sense, the AXIOM edges are hyperedges, connecting a set of causes to an effect, and carrying a reference to an updating function.

AXIOM nodes have a *timestep* property, which determines the evaluation logic during the model evaluation. The timestep property values indicate the temporal position of the node in relation to other nodes in the model. Nodes with a lower timestep value are evaluated before nodes with higher values; Nodes with an equal timestep value are evaluated in random order. This way, the temporal structure of the model can be specified: the lower timestep nodes are guaranteed to be resolved and exert their influence over higher timestep nodes in the model evaluation, unlike in GHCIA or BASICS. Nodes with equal timestep values occur 'simultaneously', in an analytical sense, or at the level of a single model evaluation in the Monte Carlo process, in random order.

The AXIOM updating approach partially eliminates the structural haziness of the updating in GHCIA and BASICS. Fig. 4 illustrates a case of probabilistic dependence this feature is useful. The BBN conditional probability table on the right side of Fig. 4 shows how the probabilistic impact of the three causes C_1, C_2 and C_3 is *synergic*: all causes somewhat elevate the probability of effect E, but the probability increase is modest when just one or two of the causes are present. The occurrence of *all* three causes raises the probability to 0.98.

Such synergic probabilistic influences, that can precisely be modeled in a BBN model, cannot be modeled with the individual-cause approach taken in GHCIA and BASICS, but can be approximated with AXIOM-style hyperedges. Valuationally the description is hazy, although perhaps not as hazy as in BASICS, as the AXIOM model can, if needed, have a greater number of updating functions. Structurally the description is hazier than a BBN description, but less hazy than in GHCIA or BASICS. This modeling power comes at no cost in the sense that modeling the additional structural accuracy to the probabilistic influence is not forced on the modeler; The dependence could be modeled with single-cause influences as well, discarding the structural precision if desired.

The results of AXIOM model evaluations, that is, the generated 'scenarios' where each model node has a state, are saved to AXIOM *iteration* objects. The probabilistic inference is based on treating this collection of generated 'possible worlds' as a sample. The approach is capable of



0.4 **C1**	*0.5* **C2**	*0.6* **C3**	*0.1865* **E**
T	T	T	0.99
T	T	F	0.125
T	F	T	0.125
T	F	F	0.05
F	T	T	0.125
F	T	F	0.05
F	F	T	0.05
F	F	F	0.01

$$f_1(p) = (((0.32 + 1)^2) \times p)/(4 \times 0.32 \times p + ((0.32 - 1)^2))$$
$$f_2(p) = (((0.86 + 1)^2) \times p)/(4 \times 0.86 \times p + ((0.86 - 1)^2))$$

Figure 4: Probability updating functions in AXIOM.

providing analytical outputs of similar nature as a BBN, such as predictive, diagnostic and mixed probabilistic inference.

With reservation to the haziness of the inputs and the inevitable haziness of the outputs, the decision support capabilities of AXIOM are very much congruent with BBNs and influence diagrams: any AXIOM node can act as a decision node or an utility node, and the software implementation directly supports setting nodes as decision nodes through the intervention statement mechanism. The reliance on sampling based estimation means that these outputs are extracted in a computationally rather expensive way, but they are available and can be extracted as batch processing. BBN implementations using exact computational methods are able to provide the results in real time after changes to the model, whereas the AXIOM implementation requires a recomputation of the iterations after changes to display the posterior probabilities.

The cyclic graphical nature of an AXIOM model allows for extraction of similar outputs as the structural and morphological approaches discussed in the next subsections. These could be said to be available in a BBN as well, but the acyclicity causes the use of BBNs to be somewhat limited for structural and morphological analysis. As consecutive AXIOM evaluations can be used to output a list of full system configurations, the output could be used for estimating conditional probability tables for a BBN. This means that AXIOM can be used in modeling the parts of the system where expert informants are the main source of inputs, and other parts of the model, for which there might be empirical data available, could be algorithmically learned into a BBN model and the two models combined as a single BBN model.

3.5. Structural analysis

Michel Godet has used the term 'structural analysis' (64) to refer to an analytical process that studies "systems consisting of interrelated elements", and aims to reveal, through a computational transformation, a more 'real' picture of the structure of the relationships between the system components. MICMAC method is the computational transformation associated with Godet's structural analysis. The later ADVIAN (72) approach is derived from MICMAC, and proposes improvements to it.

MICMAC and ADVIAN models can be represented as directed cyclic graphs, where the nodes represent variable concepts: they only have a description and no other properties, such as an associated probability, a set of states with probabilities, or a node type. The description is in a form of a proposition, hypothesis or postulate about the state of the system. The edges represent *direct* causal influence tail node variables have on head node variables. The strength or magnitude of each edge is expressed with a positive number. Also negative numbers can be used, but this of no consequence to the analysis results, as only impact magnitudes are considered in MICMAC and ADVIAN. The magnitudes of the causal influence are not specified in terms of probability change, but only as relative magnitudes, relating the influences to other influences in the same model.

The model is normally presented as an impact matrix, where the row variable is the impactor and the column variable is the impacted variable: the impact matrix presents the direct influences the nodes have on each other. The row sum of the impact values reflects the overall direct systemic influence of the row variable; the column sum, in turn, reflects the overall direct systemic dependence of the column variable. The variables can be ordered according to this direct influence or dependence, and this ordering based on direct impacts is the initial ordering in the MICMAC approach[(63,64)].

MICMAC aims to reveal the 'hidden' structure of the impacts by accounting for the indirect influences extant in the system. These indirect influences are inferred from the model of the direct impacts. MICMAC and ADVIAN approaches are both based on the matrix multiplication approach, where the impact matrix is iteratively squared. Squaring the direct impact matrix once reveals the indirect impacts of 2^{nd} order, or the indirect impacts between variables with one intermediary variable. Repeating the matrix exponentiation operation reveals the higher-order indirect impacts. For each iteration, a new ordering of the variables can be produced. In MICMAC, the terminating condition for the iteration is when the ordering no longer changes. This MICMAC ordering is thought to reflect the higher-order interactions and the differences between the direct initial ordering and the MICMAC ordering are the analytical interest in using MICMAC approach. In ADVIAN, the row and column sums for each iteration of squaring the impact matrix are saved and the process yields a total sum reflecting the influence or dependence of each variable. This enables a degree of quantification of the magnitude of the direct and indirect impacts, but does not consider the direction of the impacts.

The EXIT approach[(13,73)] is a more recent proposal for structural modeling and analysis. In EXIT, the impacts are specified to be probability-changing direct causal interactions, and the direction of the probability change is accounted for: the impacts can also be negative, and this causal antagonism is considered in the computation. The computation of the total directed pairwise impacts is based on computing a relative impact for each impact chain, or a sequence of direct impacts, extant in the cross-impact system, and summing them. The search space for large models with 15 or more descriptors becomes unfeasibly great for full computation, so a strategy of stratified sampling over the search space is used to estimate the total impact[(13)].

The approaches explicitly identifying as methods for structural analysis are conceptually and functionally related to cognitive maps[(74,75,76)] and their fuzzified versions, fuzzy cognitive maps (FCMs). Axelrod's non-fuzzy formal cognitive maps are signed directed graphs, where nodes represent variable concepts. Edges represent causal connections. Positive edges are interpreted to causally increase the effect, negative edges causally decrease the effect. Causal propagation of variables on each other is inferred by means of reachability matrices. The aim is to infer what the total impact of a cause on an effect is. This is done by investigating the indirect effects of the cause on the effect, or all possible causal paths connecting the cause and effect. A single indirect effect is negative if the number of negative causal edges in the path is odd, positive if the number is even. The total effect is interpreted to be positive if all indirect effects are positive, negative if all indirect effects are negative, and indeterminate otherwise. In practical modeling cases, this often leads to indeterminacy dominating in the total effects(77).

Kosko's fuzzy causal algebra extends the causal propagation scheme of cognitive maps(77). The possible applications and challenges of fuzzy cognitive maps in foresight have been assessed by Jetter and Kok(78). In fuzzy cognitive maps, the concept nodes have an activation level in the range $[0, 1]$. This activation level reflects their fuzzy truth value: a value close to 1 indicates a strong fuzzy membership of the concept in the category 'true', and conversely a value close to 0 indicates the concepts strong fuzzy membership in the category 'false', or weak membership in the category 'true'(77,79). The magnitudes of the causal impacts can be valuated in expert elicitation with an ordinal scheme with a limited set of fuzzy values, such as {none $\lesssim$ some $\lesssim$ much $\lesssim$ a lot}, but on a computational level these fuzzy valuations are expressed as reals in range $[-1, +1]$, and are the edge weights in the graphical representation.

FCM models are resolved in an iterative process where the concept values change during computation steps, which are repeated until the system reaches equilibrium, or does not change anymore. A new concept value activation vector is computed by multiplying the current activation vector by the impact matrix and mapping the entry values of this vector to range [0,1] by applying a 'squashing function' such as $f = \frac{1}{1+e^{-\lambda x}}$, where selection of λ determines the degree of squashing behaviour, and repeating this computation iteratively until the activation vector no longer changes. This equilibrium state of the system reflects a posterior understanding of the concept relationships(80,81), informing which concepts end up active with the modeled assumptions about interactions.

Functionally, Kosko's fuzzy algebra based causal propagation overlaps to some degree with the structural cross-impact analysis in general. Technically the approaches taken to formulate an understanding of the node relationships posterior to the consideration of the influence of the impact network differ significantly. The MICMAC, ADVIAN and EXIT approaches seek to order or quantify the indirect impacts, while the FCM approach is to observe the effect of the impact over a dynamic process, and the equilibrium activation state of the concepts is the basis of inference concerning higher-order relationships in the system.

The structural analysis approaches offer a very simple set of primitives for modeling causalities in a system with a relatively high level of abstraction. The modeling process is fast, in comparison to other discussed modeling approaches. In all structural approaches presented, a single impact value is provided for all edges in the graphical model, and the nodes carry no information about their possible states: a 20-variable structural model requires supplying a maximum of 380 impact values. The high abstraction level implies that the structural modeling approach is useful in efforts to formulate understanding and theory about the complex causal interlinkages in the modeled system, but the analytical output is often not highly actionable in strategic decision support use. They can, however, deliver a more informed picture of the interactions of the system components, based on a systematic expert process.

3.6. Morphological analysis

Morphological analysis aims at using system models or modeled decision problems for identifying logical, consistent or probable system states, or reducing the total 'problem space' into a smaller, internally consistent 'solution space'(14). The models used for morphological analysis are required to contain information about the 'agreement' of the system descriptors, so that system configurations where the states of the descriptors are 'in agreement' or 'harmonic' may be identified. Graphically, morphological models can be directed or undirected. The nodes are binary or multi-state. The edges should, at a minimum level, contain boolean information of 'agreement' or consistency between nodes in specific states. The degree of agreement (or disagreement) can also be expressed with a numeric indicator.

The general morphological analysis (GMA) approach to modeling [82,83] is to define the most important dimensions of the system or the problem complex to be investigated; For each of these dimensions, a set of possible values, or states, is defined. A 'field configuration' or 'morphotype' in the GMA terminology is designated by selecting a single value for each dimension: this combination represents a 'solution' within the problem complex, or more generally a system in a particular state. Each enumerated possible state in the model is assessed in terms of logical consistency against the states of other dimensions. How the consistency evaluation is expressed at the model level is dependent on the implementation of the approach, but generally the pairwise incompatibility or inconsistency is simply expressed by a boolean flag [82,83]. Such morphological models can be expressed as simple graphs.

Mapping the pairwise inconsistencies enables weeding out algorithmically the system configurations, which are inconsistent given some assumption of the states of other dimensions in the model. The viable 'solution space', the possible combinations of the system states that have not been bound in the initial assumptions, can now be presented to the analyst: the model can be asked questions in the format "assuming these states for these dimensions, what is the option space for the rest of the dimensions".

Cross-Impact Balances approach (CIB) also aims at "identification of plausible configurations of qualitatively defined impact networks" [84,85,86]. The degree of promoting or restricting influence the possible states of system descriptors have on other descriptors is expressed with more granularity than in the GMA approach, using a qualitative judgement scale(positive or negative numbers, normally integers). The CIB algorithm explores the configuration space and identifies a set of configurations which exhibit a balanced combination according to the CIB criteria.

The morphological analysis approach can be useful in identification of internally consistent system configurations or scenarios. The modeling process is, in relation to models explicitly computing probabilities, easier and the model evaluation process is relatively simple. Morphological modeling can also be a realistic approach in cases where the expert informants are not expected to be able to assess interactions between the system descriptors in terms of probability changes at all, but only on a more intuitive-heuristic level.

The morphological models can be understood to be probabilistic as well, even when the concept of probability is somewhat masked in them. The 'morphological agreement' of two facts can be understood as them being 'probable' or perhaps 'not improbable' to occur together. Even the binary scale used in GMA can be thought to map into probabilities, so that non-agreement means a joint probability of the two nodes being zero or close to zero, and agreement the probability of their joint occurrence to be above zero. This in mind, BBN, GHCIA, and AXIOM can be used for morphologically oriented analysis: all of them can be used to compute probabilities for full configurations of all model facts, and the most probable ones could be understood to be the consistent configurations.

The backwards inference and mixed inference (see Section 3.1), a typical reasoning facility provided by BBNs, can also be seen as a form of morphological reasoning. Given an assumption about the state of some nodes of a BBN model, the backwards inference simply tells what is the probable state of other nodes of the modeled system. This type of reasoning in the case of BBNs is not generally thought to be morphological, but the aim is similar.

4. Inference aims of probabilistic logics in foresight

The analytical aims of probabilistic reasoning techniques in foresight fall into three classes that are not mutually exclusive: structural, morphological and probabilistic. *Structural* analysis focuses on the structure of the causal network: Structural information is inferred from the structure of the network of causal influences. It can provide the analyst an improved understanding of the relationships of the model variables or descriptors, and their role in the modeled domain overall. The inference is based on the discovery of the indirect impacts. *Morphological* analysis deals with the compatibility, consistency or congruence of facts or configurations of facts. It is used to identify viable, harmonious or logical *morphological configurations* of the modeled domain. By doing that, the likely alternative scenarios for the system or consistent solutions to a problem can be explored. Explicitly *probabilistic* analysis provides the greatest degree of direct decision support, as it makes it possible to analytically *simulate* the functioning of the modeled domain, test it under different conditions, and observe how interventions influence the probabilities. The probability information can be used in conjunction with utility functions, making the identification of an intervention set that is optimal according to some criteria straightforward, resulting in easy decision support use.

Explicitly probabilistic models hold greater amounts of information than structural or morphological models, so the cost or difficulty of creating them is higher. They can, on the other hand, be used for structural and morphological analysis as well. Some discussed modeling techniques, namely SMIC[(64)] and BASICS[(69)] could be used for probabilistic inference as well, if their computational transformations were redefined, but as they are documented, their analytical use is restricted to delivering morphological information. Structural-natured information can be extracted from BBN, GHCIA or AXIOM by simply observing the change in probabilities as each singular model state is assumed to be true or false. A structural impact matrix can be populated by collecting the probabilities of other states into the matrix under the assumption that the ‘row variable’ or the currently manipulated variable is true. The difference between the prior probability and the posterior probability reflects the influence the ‘row variable’ has on the other variables or states. Morphological information can be extracted as the probabilities of full or partial model configurations, i.e. the joint probabilities of combinations of facts. The most probable combinations can be thought to be consistent and logical.

Probabilistic causal models need to have a way to describe the probabilistic dependencies the modeled facts have on the other facts, specifying quantified probability changes conditional to the dependencies. This can be done by defining conditional probability tables as in Bayesian networks, defining initial and single-cause conditional probabilities and using the odds ratio technique[(62)], or defining probability updating functions which change the initial probabilities conditional to the system being in a specific state as used by the BASICS approach[(69)], JL-algorithm[(67)], and AXIOM[(70)]. These different ways of specifying the probabilistic impacts have their strengths and weaknesses, but no matter which one of them is used, from the perspective of an expert elicited model the probabilistic data is an additional layer of information to be elicited.

Structural and morphological information can be inferred *without* a quantitatively specific probabilistic description of the impacts the model components have on each other. The causal impacts need to be described by their magnitude only in relation to other impacts in the model, and these impacts do not need to map to specific quantified changes in probability values: the structural or morphological information can be extracted from such *relative* impact valuations. For this reason, structural and morphological modeling is clearly easier for eliciting experts, as they need to supply a smaller amount of information to create a fully valuated model, but also as the additional layer of conceptual complexity in the form of quantified probability is not involved in the modeling. While the modeling process is easier, the models are of higher abstraction level compared to probabilistic models, and their direct decision support use is more difficult.

5. Approaches compared

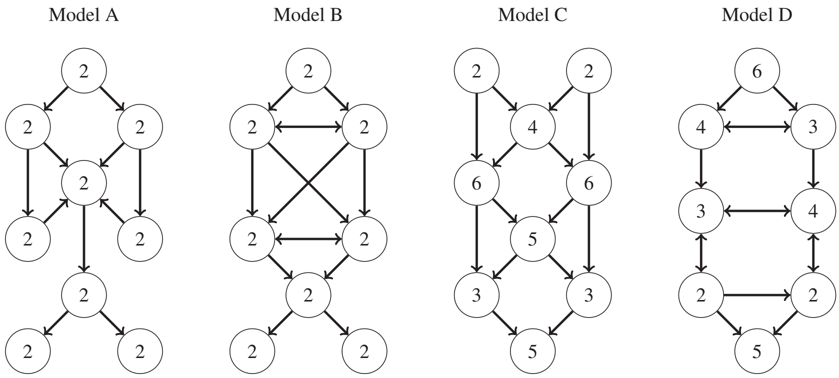


Figure 5: Graph representations of 4 models. Edges represent dependencies; node numbers indicate the number of states the node has.

Fig. 5 displays the dependency structures of four models, that are used to illustrate the differences in amount of input information required by the discussed modeling approaches. The node numbers denote the number of possible states the node in question has. The edges indicate a dependency, with the interpretation that the descriptor of the head node is dependent on the descriptor of the tail node, or conversely, the descriptor of the tail node exerts influence on the descriptor of the head node. Models A and B only have binary descriptors, so they can be modeled with binary or variable concept nodes. Models A and C are acyclic, so they can be modeled as a BBN, unlike models B and D, which have structural loops.

Table 5 shows the number of inputs required in different modeling approaches generally, and in the specific cases of the four models presented in Fig. 5. This comparison illustrates the differences in the amount of required input information for building formal models with the approach, given a conceptual model of specific complexity in number of states and dependency structure. It must be noted that the simple count of input values does not directly reflect the difficulty or cognitive and time cost of model valuation, as the input values are conceptually different in different approaches. BBN, GHCIA and SMIC operate on conditional probabilities. Naked conditional probabilities could be said to be at least slightly more costly to elicit in an expert process than updating function references or relative magnitude indicators. Similarly, the updating function references are likely cognitively more demanding than the relative magnitude indicators, as the elicited experts need to be familiar with the set of updating functions used, and keep the semantics of the updating functions in mind during model valuation.

For BASICS, CIB and AXIOM, a range of values is given instead of an exact number. In the case of BASICS, the high end of the range is the maximum count of input values. As all possible

Table 1: Number of inputs using different approaches in modeling cases of Figure 5

	Generally	Model A	Model B	Model C	Model D
BBN	$\sum_{i=1}^{N} p(n_i) \times s(n_i)$	62	-	521	-
GHCIA	N^2	81	64	-	-
SMIC	$2 \times N^2 - N$	153	120	-	-
BASICS	$\leq S^2 - S, \sim \frac{1}{2}(S^2 - S)$	24-53	33-72	114-253	79-174
AXIOM	$\sim \frac{1}{2}(S^2 - S)$	24-53+	33-72+	114-253+	79-174+
MICMAC/ADVIAN	$\leq N^2 - N$	11	14	-	-
EXIT	$\leq N^2 - N$	11	14	-	-
FCM	$\leq N^2 - N$	11	14	-	-
GMA	$\leq S^2 - S$	44	64	244	166
CIB	$\leq S^2 - S$	20-44	29-64	110-244	75-166

Note: N is the number of nodes in the model, S is the total number of states in all the model nodes, $s(n_i)$ is the number of states node n_i has, and $p(n_i)$ is the number of state combinations parents of node n_i have, or 1 if n_i has no parents.

causal influences are normally never modeled, the realistic count for input values would be the low end of the range, assumed[1]to be 45% of the maximum input count. The same assumption has been made in the case of the CIB approach. Even this is slightly pessimistic and a lower count of inputs might suffice in many modeling cases. For AXIOM, identical ranges are tabulated, but the theoretical upper bound of inputs is much higher if multi-cause influences are allowed. The theoretical upper bound, however, does not reflect the realistic count of input values in AXIOM modeling.

In the cases of BBN, GHCIA and SMIC, a single input value count is tabulated. In these approaches, all input values need to be supplied. Auxiliary techniques could be defined and used to reduce the number of values to be elicited in all approaches, and in the case of BBN models, such techniques are explored and used(26,27,54). Use of auxiliary techniques for input elicitation may significantly lower the input count in the case of a BBN, but their applicability depends a lot on the context, and the most straightforward approaches for reducing the input count are applicable only for continuous variables, discretized continuous variables or logically ordered sets of possible node states, whose distribution can be thought as a singular object. In an expert elicitation process using GHCIA and SMIC, the conditional probability values of all nodes can initially be equal to the initial probabilities of the nodes in question, and only changed from these assumed valuations if the elicited experts wish to model a causal dependency. This approach considerably reduces the number of conditional probability values to be elicited. However, this may possibly violate the probability constraints discussed in Section 3.2, so technically all possible graph edges need to be valuated.

Table 5 illustrates the exponential growth of required input information in the case of a BBN, and gives an idea on how the required information increases in the case of the other modeling approaches. The presented models are still quite small in terms of node count and structural complexity, and populating the conditional probability tables of a BBN in very complex models quickly becomes unfeasible by means of expert elicitation, unless some auxiliary approaches

[1]The initial experiments with modeling using the AXIOM approach suggest that not much more than 45% of the possible single-cause impacts are normally modeled by elicited expert groups.

are used. Use of such auxiliary approaches will likely, however, bring the same structural and valuational haziness and approximateness to the BBN model which is characteristic to models using a more approximate mode of modeling in the first place, such as BASICS and AXIOM.

Table 2: Approaches compared in regard to modeling languages, nature of computational transformation and inference possibilities.

	Structural precision	Valuational precision	Incorporating statistical data	Modeling temporal dimension	Sampling based computation	Probabilistic inference	Structural inference	Morphological inference
BBN	High	High	✓	With model structure	✓	✓	Limited	Limited
GHCIA	Low	Medium-high	Limited		✓	✓	Limited	Limited
SMIC	Low	Medium-high	Limited		✓	Limited	Limited	✓
BASICS	Low	Low-medium				Limited	Limited	✓
AXIOM	Medium-high	Medium		Timestep approach	✓	✓	✓	✓
MICMAC, AD-VIAN	Low	Low					✓	
EXIT	Low	Low			✓		✓	Limited
FCM	Low	Low					✓	
GMA	Low	Low						✓
CIB	Low	Medium						✓

Table 2 tabulates the primary dimensions of the discussed approaches for a potential user. As discussed in Sections 3.2, 3.3 and 3.4, structural precision of modeling means the ability to model causal dependencies contingent to several causes, instead of dividing the joint influence a set of causes may have together to each individual cause in the set. Valuational precision refers to the ability to model the magnitudes of probabilistic influences in a precise way. These two modes of precision are at their highest level in Bayesian belief networks. Compared to BBN, the other tabulated approaches hand over some degree of structural precision, valuational precision, or both. This makes the expert elicitation process easier, and makes valuation of structurally complex models with a high number of nodes and dependencies feasible.

Well-defined processes exist for Bayesian networks [33,87] for incorporating statistical data in the modeling, such as learning algorithms capable of extracting the model parameters or structure from datasets. In the case of nodes with only binary models, similar approaches could in principle be used with GHCIA or SMIC as well, although this has not been done to the knowledge of the authors. The binary nature of the descriptors in GHCIA and SMIC makes the use of data in their parameterization quite limited, however. Using statistical data to valuate a BASICS or an AXIOM model is not unthinkable, but ways to do it have not been presented. A much more sensible workflow for using AXIOM in conjunction with statistical data would be to perform the expert informant based part of the modeling with it, use the output to algorithmically learn a BBN model, and augment the BBN model with statistical data.

The ability to incorporate a time dimension in the models could be said to be of high importance especially in foresight applications. BBN is able to conceptually represent time in the model structure, but the acyclic graphical form of the model imposes some limitations: descriptors with an uncertain temporal ordering cannot be modeled, as the causal structure in a BBN is unambiguous. The timestep approach taken in AXIOM gives more leeway in modeling in this regard. The other discussed approaches do not offer ways to represent time at the model level.

Computation in GHCIA, SMIC, AXIOM and EXIT is technically based on sampling. This causes the need to perform the sampling again when model valuations are changed, and the modeler-analyst needs to wait for the results for some period of time. While this time may not be long, this property means that no real-time updates are available and interactive use of the models by changing values and immediately seeing the results is not available. This must be seen as a negative characteristic for some use purposes of the discussed models. The BBN implementations are able, at least when the model is not very complex, to display the results immediately, supporting interactive analytical use. Generally, for approaches not relying on sampling for results, a fast implementation can be developed and interactive use is possible.

BBN, GHCIA and AXIOM approaches support probabilistic inference, meaning the computation of posterior probability distributions for the descriptors given some assumptions about the model facts. For all approaches, the outputs must be understood to be as approximate as the inputs. BBN makes it possible to describe the probabilistic dependencies in an exact way, but in a case where the inputs are acquired in an expert elicitation process, their precision is likely of clearly lower precision than what the approach permits. In GHCIA and AXIOM, the inputs are more approximate by virtue of the modeling languages. The binary nature of the GHCIA nodes somewhat limits the probabilistic inference possibilities of the approach, and not all possibilities of a BBN model can be approximated with it. Save the approximateness and haziness of the outputs, an AXIOM model can be used for most of the analysis that can be performed with a BBN model. SMIC and BASICS approaches *could* be used for probabilistic inference as well, considering the information content of their models, but the computational transformations associated with these techniques only support the extraction of morphological outputs.

Structural inference is the primary use of MICMAC, ADVIAN, EXIT and FCMs. Given that structural inference aims at forming an understanding of the relationships of the descriptors with consideration to the influence network, the information content of the models of all discussed approaches could deliver structural outputs to a degree. Only the structural approaches(MICMAC, ADVIAN, EXIT and FCMs) and BBNs, AXIOM and GHCIA support such outputs directly. In the case of BBN, the structural inference is somewhat limited due to the acyclic graphical form and the preclusion of loops. The CIB approach could be used for a similar end, if a computational process for structural inference was defined.

Morphological analysis aims at identification of consistent, logical and non-conflicting configurations of facts. The task of identifying such configurations can be well approached through probabilistic reasoning: the *not improbable* configurations can be seen as consistent. The CIB approach[(84)] defines the model valuations as promoting or restricting causal influences, so in this sense the approach taken in it for identifying logically consistent sets of facts is probabilistic in nature. The GMA language, which only has two relations available, namely consistent and non-consistent, can be mapped into a probabilistic language easily: non-consistent means impossible and consistent possible. This way, outputs of morphological nature can be delivered by the approaches modeling probability. Technically, the structural analysis approaches could deliver morphological outputs as well, again with the condition that a suitable computational transformation would be defined. These possibilities have not been explored in the cases of MICMAC, ADVIAN, EXIT or FCMs.

The choice between the discussed approaches for a modeling task depends on the capacity of the expert informants to provide valuations for the model and the analytical aims. If the informants are not expected to be able to assess probabilities in modeling, the structural and morphological approaches may be a better fit, as the modeling is likely to be easier with a conceptually simpler modeling approach. However, including explicit probability information in the model will enable covering more ground analytically.

6. Conclusions and discussion

There exists a set of strategic and decision-making problems for which there is no truly descriptive statistical data which captures the essential parts of what is to be modeled but for which an expert knowledge base exists to base modeling on[84,85]. This is often the case in strategic considerations, foresight and futures thinking. For modeling and decision support in this niche, methodological solutions to formalize expert understanding and knowledge bases of various 'soft disciplines' and make them more actionable in decision-making are needed[77]. These methodological solutions should have modeling languages suitable for the expert processes used in the collection of inputs and formal definition of the models, and inference mechanisms to extract as much analytical information as possible from the models to justify the costly modeling effort.

A much discussed application domain for such solutions are so-called wicked problems and complex systems, which consist of complicatedly entangled components and subsystems[88,89]. For these domains, it is important to be able to harness the knowledge base and soft systems understanding of several experts, whose joint expertise may adequately cover the complex domain being modeled. As the systems are complex and often conceptually hazy, the modeling approaches should support iterative work and re-definition of the concept set used in modeling, often leading to re-definition of the model structure as well. In this regard, approaches with a lower information requirement may sometimes fare better than approaches with a higher information requirement, such as Bayesian belief networks. Bayesian belief networks are a widely used and mature approach for probabilistic reasoning, with well defined processes and tooling for augmenting empirical data with expert knowledge. They can at this point be seen as a standard tool for general probabilistic reasoning. Bayesian networks can also be utilized to similar analytical ends as several other reviewed modeling approaches, as discussed in Section 4 and Section 5. Use of probabilistic reasoning approaches with a lower information requirement in modeling and a less rigid modeling language, in conjunction with Bayesian approaches, is one possibility for modeling and analysis of expert knowledge bases on domains that are difficult to model otherwise.

The discussed approaches are, in their original sources, described with quite different terminology and concepts. These incongruent concepts are not trivially mapped to the concepts used by other approaches. This makes comparison of different approaches difficult. The positioning of the various alternatives for describing knowledge bases of expert elicited information against each other is challenging. A full scrutiny of each approach is required before their analytical possibilities can be outlined. The conceptual and functional overlap of the discussed methods are not necessarily well understood by the potential users. It is possible that even the authors of several methods are not well aware of the existence of techniques bearing functional similarity to the ones they have presented. This is indicated by the lack of broader discussion about related approaches in the papers presenting the methodological contributions.

This review brings several modeling approaches under the same methodological discourse by describing them using basic graph theory concepts. This has not been done before, and is valuable as a better-fitting approach to a specific research case or modeling problem might be available, but is difficult to find, as the methodological discussion on expert informant oriented modeling is so factionalized and divided. The factional and disintegrated nature of the discussion also stifles further methodological development. Solutions developed in one family of techniques are not explored in other families and effective learning between methodologies is missing. Further development of some reviewed approaches might lead to convergence of different methods. Comparative review of the various approaches of different methodological clusters might spark new progress in the methodology of modeling based on expert elicitation and mainstream its utilization in research.

Biographies

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References

[1] H. A. Linstone, M. Turoff, The Delphi Method: Techniques and Applications, Addison-Wesley, 1977. URL `http://is.njit.edu/pubs/delphibook/`

[2] A. Rogut, B. Piasecki, Foresight methodology as a tool for elaboration of plans for sustainable management of water, energy, the environment and society, Ecohydrology & Hydrobiology 11 (3-4) (2011) 261–272.

[3] R. Rohrbeck, Exploring value creation from corporate-foresight activities, Futures 44 (5) (2012) 440–452.

[4] S. E. Seker, Computerized argument Delphi technique, IEEE Access 3 (2015) 368–380. `doi:10.1109/ACCESS.2015.2424703`.

[5] R. Alizadeh, P. D. Lund, A. Beynaghi, M. Abolghasemi, R. Maknoon, An integrated scenario-based robust planning approach for foresight and strategic management with application to energy industry, Technological Forecasting and Social Change 104 (2016) 162–171. `doi:http://dx.doi.org/10.1016/j.techfore.2015.11.030`.

[6] S. H. Jore, I.-L. F. Utland, V. H. Vatnamo, The contribution of foresight to improve long-term security planning, Foresight 20 (1) (2018) 68–83.

[7] A. Lehikoinen, Bayesian network applications for environmental risk assessment, Ph.D. thesis, University of Helsinki (2014).

[8] U. B. Kjærulff, A. L. Madsen, Bayesian Networks and Influence Diagrams: A Guide to Construction and Analysis, Springer, 2011.

[9] P. Aguilera, A. Fernndez, R. Fernndez, R. Rum, A. Salmern, Bayesian networks in environmental modelling, Environmental Modelling & Software 26 (12) (2011) 1376–1388. doi:https://doi.org/10.1016/j.envsoft.2011.06.004.
URL http://www.sciencedirect.com/science/article/pii/S1364815211001472
[10] W. M. Bolstad, Introduction to Bayesian Statistics, John Wiley, 2007.
[11] S. Alter, The evaluation of generic cross-impact models, Futures 11 (2) (1979) 132–150. doi:https://doi.org/10.1016/0016-3287(79)90034-X.
URL http://www.sciencedirect.com/science/article/pii/001632877990034X
[12] J. J. Heckman, R. Robb, Alternative methods for evaluating the impact of interventions, Journal of Econometrics 30 (1) (1985) 239–267. doi:http://dx.doi.org/10.1016/0304-4076(85)90139-3.
[13] J. Panula-Ontto, K. A. Piirainen, EXIT: An alternative approach for structural cross-impact modeling and analysis, Technological Forecasting and Social Changedoi:10.1016/J.TECHFORE.2018.06.046.
URL https://www.sciencedirect.com/science/article/pii/S004016251731644X
[14] I. Johansen, Scenario modelling with morphological analysis, Technological Forecasting and Social Change 126 (2018) 116–125. doi:https://doi.org/10.1016/j.techfore.2017.05.016.
URL http://www.sciencedirect.com/science/article/pii/S004016251730656X
[15] R. A. Kelly, A. J. Jakeman, O. Barreteau, M. E. Borsuk, S. ElSawah, S. H. Hamilton, H. J. Henriksen, S. Kuikka, H. R. Maier, A. E. Rizzoli, H. van Delden, A. A. Voinov, Selecting among five common modelling approaches for integrated environmental assessment and management, Environmental Modelling & Software 47 (2013) 159–181. doi:https://doi.org/10.1016/j.envsoft.2013.05.005.
URL http://www.sciencedirect.com/science/article/pii/S1364815213001151
[16] S. L. Choy, R. O'Leary, K. Mengersen, Elicitation by design in ecology: Using expert opinion to inform priors for Bayesian statistical models, Ecology 90 (1) (2009) 265–277.
[17] M. Leonelli, J. Q. Smith, Bayesian decision support for complex systems with many distributed experts, Annals of Operations Research 235 (1) (2015) 517–542. doi:10.1007/s10479-015-1957-7.
URL http://link.springer.com/10.1007/s10479-015-1957-7
[18] S. J. Russell, P. Norvig, Artificial Intelligence: A Modern Approach, Pearson Education Limited, 2016.
[19] K. S. Van Horn, From propositional logic to plausible reasoning: A uniqueness theorem, International Journal of Approximate Reasoning 88 (2017) 309–332. doi:10.1016/J.IJAR.2017.06.003.
URL https://www.sciencedirect.com/science/article/pii/S0888613X16302249
[20] J. Pearl, Causality: Models, Reasoning and Inference, 2nd Edition, Cambridge University Press, New York, NY, USA, 2009.
[21] J. A. Sokolowski, C. M. Banks, Principles of Modeling and Simulation: A Multidisciplinary Approach, Wiley, 2009.
URL https://books.google.fi/books?id=wOOikQEACAAJ
[22] H. J. Adèr, Advising on Research Methods: A Consultant's Companion, Johannes van Kessel Publishing., 2008.
[23] D. E. Schindler, R. Hilborn, Prediction, precaution, and policy under global change, Science 347 (6225) (2015) 953–954. doi:10.1126/science.1261824.
URL http://www.ncbi.nlm.nih.gov/pubmed/25722401http://www.sciencemag.org/lookup/doi/10.1126/science.1261824
[24] C. A. Pollino, O. Woodberry, A. Nicholson, K. Korb, B. T. Hart, Parameterisation and evaluation of a Bayesian network for use in an ecological risk assessment, Environmental Modelling & Software 22 (8) (2007) 1140–1152.
[25] P. M. Kuhnert, T. G. Martin, S. P. Griffiths, A guide to eliciting and using expert knowledge in Bayesian ecological models, Ecology letters 13 (7) (2010) 900–914.
[26] A. O'Hagan, C. E. Buck, A. Daneshkhah, J. R. Eiser, P. H. Garthwaite, D. J. Jenkinson, J. E. Oakley, T. Rakow, Uncertain Judgements: Eliciting Experts' Probabilities, John Wiley & Sons, Chichester, UK, 2006. doi:10.1002/0470033312.
URL http://doi.wiley.com/10.1002/0470033312
[27] A. James, S. L. Choy, K. Mengersen, Elicitator: An expert elicitation tool for regression in ecology, Environmental Modelling & Software 25 (1) (2010) 129–145. doi:10.1016/J.ENVSOFT.2009.07.003.
URL https://www.sciencedirect.com/science/article/pii/S1364815209001704
[28] P. Boets, D. Landuyt, G. Everaert, S. Broekx, P. L. M. Goethals, Evaluation and comparison of data-driven and knowledge-supported Bayesian belief networks to assess the habitat suitability for alien macroinvertebrates, Environmental Modelling & Software 74 (2015) 92–103. doi:10.1016/J.ENVSOFT.2015.09.005.
URL https://www.sciencedirect.com/science/article/pii/S1364815215300487
[29] F. V. Jensen, T. D. Nielsen, Bayesian Networks and Decision Graphs, Springer, 2007.
[30] J. Pearl, Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference, Elsevier, 2014.
[31] S. Dorner, J. Shi, D. Swayne, Multi-objective modelling and decision support using a Bayesian network approximation to a non-point source pollution model, Environmental Modelling & Software 22 (2) (2007) 211–222.

doi:10.1016/J.ENVSOFT.2005.07.020.
URL https://www.sciencedirect.com/science/article/pii/S1364815205001817

[32] M. Rahikainen, I. Helle, P. Haapasaari, S. Oinonen, S. Kuikka, J. Vanhatalo, S. Mäntyniemi, K.-M. Hoviniemi, Toward integrative management advice of water quality, oil spills, and fishery in the Gulf of Finland: A Bayesian approach, AMBIO 43 (1) (2014) 115–123. doi:10.1007/s13280-013-0482-7.
URL http://link.springer.com/10.1007/s13280-013-0482-7

[33] C. Riggelsen, Learning parameters of Bayesian networks from incomplete data via importance sampling, International Journal of Approximate Reasoning 42 (1-2) (2006) 69–83. doi:10.1016/J.IJAR.2005.10.005.
URL https://www.sciencedirect.com/science/article/pii/S0888613X05000654

[34] L. Uusitalo, S. Kuikka, P. Kauppila, P. Söderkultalahti, S. Bäck, Assessing the roles of environmental factors in coastal fish production in the Northern Baltic sea: A Bayesian network application, Integrated Environmental Assessment and Management 8 (3) (2012) 445–455. doi:10.1002/ieam.180.
URL http://www.ncbi.nlm.nih.gov/pubmed/21309077http://doi.wiley.com/10.1002/ieam.180

[35] R. G. Cowell, P. Dawid, S. L. Lauritzen, D. J. Spiegelhalter, Probabilistic Networks and Expert Systems: Exact Computational Methods for Bayesian Networks, Springer Science & Business Media, 2006.

[36] S. Mäntyniemi, P. Haapasaari, S. Kuikka, R. Parmanne, M. Lehtiniemi, J. Kaitaranta, Incorporating stakeholders' knowledge to stock assessment: Central Baltic herring, Canadian Journal of Fisheries and Aquatic Sciences 70 (4) (2013) 591–599. doi:10.1139/cjfas-2012-0316.
URL http://www.nrcresearchpress.com/doi/10.1139/cjfas-2012-0316

[37] L. Uusitalo, S. Kuikka, A. Romakkaniemi, Estimation of Atlantic salmon smolt carrying capacity of rivers using expert knowledge, ICES Journal of Marine Science 62 (4) (2005) 708–722. doi:10.1016/j.icesjms.2005.02.005.
URL https://academic.oup.com/icesjms/article-lookup/doi/10.1016/j.icesjms.2005.02.005

[38] S. Kuikka, O. Varis, Uncertainties of climatic change impacts in Finnish watersheds: A Bayesian network analysis of expert knowledge, Boreal Environment Research 2 (1) (1997) 109–128.

[39] A. Lehikoinen, E. Luoma, S. Mäntyniemi, S. Kuikka, Optimizing the recovery efficiency of finnish oil combating vessels in the gulf of finland using Bayesian networks, Environmental Science & Technology 47 (4) (2013) 1792–1799. doi:10.1021/es303634f.
URL http://pubs.acs.org/doi/10.1021/es303634f

[40] G. Carmona García, C. Varela Ortega, J. Bromley, The use of participatory object-oriented Bayesian networks and agro-economic models for groundwater management in Spain (2011).
URL http://agris.fao.org/agris-search/search.do?recordID=AV2012056200

[41] S. Johnson, K. Mengersen, Integrated Bayesian network framework for modeling complex ecological issues, Integrated Environmental Assessment and Management 8 (3) (2012) 480–490. doi:10.1002/ieam.274.
URL http://www.ncbi.nlm.nih.gov/pubmed/21853523http://doi.wiley.com/10.1002/ieam.274

[42] P. Weber, L. Jouffe, Complex system reliability modelling with dynamic object oriented Bayesian networks (DOOBN), Reliability Engineering & System Safety 91 (2) (2006) 149–162. doi:10.1016/J.RESS.2005.03.006.
URL https://www.sciencedirect.com/science/article/pii/S0951832005000967

[43] S. E. Fienberg, When did Bayesian inference become "Bayesian"?, Bayesian Analysis 1 (1) (2006) 1–40. doi:10.1214/06-BA101.
URL http://projecteuclid.org/euclid.ba/1340371071

[44] S. B. McGrayne, The Theory that would not die : how Bayes' Rule cracked the Enigma Code, hunted down Russian Submarines, & emerged triumphant from two Centuries of Controversy, Yale University Press, 2011.

[45] J. F. Carriger, M. G. Barron, M. C. Newman, Bayesian networks improve causal environmental assessments for evidence-based policy, Environmental Science & Technology 50 (24) (2016) 13195–13205. doi:10.1021/acs.est.6b03220.
URL http://www.ncbi.nlm.nih.gov/pubmed/27993076http://pubs.acs.org/doi/10.1021/acs.est.6b03220

[46] K. B. Korb, A. E. Nicholson, Bayesian Artificial Intelligence, CRC Press, 2011.

[47] O. Pourret, P. Naïm, B. Marcot, Bayesian Networks: A Practical Guide to Applications, Vol. 73, John Wiley & Sons, 2008.

[48] D. Heckerman, A. Mamdani, M. P. Wellman, Real-world applications of Bayesian networks, Communications of the ACM 38 (3) (1995) 24–26.

[49] R. K. McCann, B. G. Marcot, R. Ellis, Bayesian belief networks: Applications in ecology and natural resource management, Canadian Journal of Forest Research 36 (12) (2006) 3053–3062.

[50] O. Varis, J. Kettunen, H. Sirviö, Bayesian influence diagram approach to complex environmental management including observational design, Computational Statistics & Data Analysis 9 (1) (1990) 77–91.

[51] D. Cinar, G. Kayakutlu, Scenario analysis using Bayesian networks: A case study in energy sector, Knowledge-

Based Systems 23 (3) (2010) 267–276. doi:https://doi.org/10.1016/j.knosys.2010.01.009.
URL http://www.sciencedirect.com/science/article/pii/S0950705110000110

[52] U. B. Kjærulff, A. L. Madsen, Bayesian Networks and Influence Diagrams: A Guide to Construction and Analysis, Springer New York, 2013.

[53] Norsys Software Corporation, Netica 4.08 (2008).

[54] B. Das, Generating conditional probabilities for Bayesian networks: Easing the knowledge acquisition problem, arXiv preprint cs/0411034.

[55] M. J. Druzdel, L. C. Van Der Gaag, Building probabilistic networks: "Where do the numbers come from?", IEEE Transactions on knowledge and data engineering 12 (4) (2000) 481–486.

[56] M. J. Druzdzel, L. C. Van Der Gaag, Elicitation of probabilities for belief networks: Combining qualitative and quantitative information, in: Proceedings of the Eleventh conference on Uncertainty in Artificial Intelligence, Morgan Kaufmann Publishers, 1995, pp. 141–148.

[57] L. C. van der Gaag, S. Renooij, C. L. Witteman, B. M. Aleman, B. G. Taal, How to elicit many probabilities, in: Proceedings of the Fifteenth Conference on Uncertainty in Artificial Intelligence, Morgan Kaufmann Publishers, 1999, pp. 647–654.

[58] O. Varis, A belief network approach to modeling of environmental change: The methodology and prospects for application, Tech. rep., International Institute of Applied Systems Analysis (1994).
URL http://pure.iiasa.ac.at/id/eprint/4169/

[59] O. Varis, A belief network approach to optimization and parameter estimation: Application to resource and environmental management, Artificial Intelligence 101 (1998) 135–163.

[60] T. Gordon, H. Hayward, Initial experiments with the cross impact matrix method of forecasting, Futures 1 (2) (1968) 100–116. doi:http://dx.doi.org/10.1016/S0016-3287(68)80003-5.

[61] T. J. Gordon, Cross-impact matrices: An illustration of their use for policy analysis, Futures 1 (6) (1969) 527–531.

[62] T. J. Gordon, Cross impact method, Tech. rep., United Nations University Millennium Project (1994).

[63] M. Godet, F. Bourse, P. Chapuy, I. Menant, Futures Studies: A Tool-box for Problem Solving, Futuribles, GERPA Prospective, 1991.

[64] M. Godet, J. F. Coates, Unesco, From Anticipation to Action: A Handbook of Strategic Prospective, Future-oriented studies, Unesco Publishing, 1994.

[65] J. C. Duperrin, M. Godet, SMIC 74–A method for constructing and ranking scenarios, Futures 7 (4) (1975) 302–312. doi:https://doi.org/10.1016/0016-3287(75)90048-8.
URL http://www.sciencedirect.com/science/article/pii/0016328775900488

[66] A. Doucet, N. Freitas, N. Gordon, An introduction to sequential Monte Carlo methods, in: Sequential Monte Carlo Methods in Practice, Springer New York, New York, NY, 2001, pp. 3–14. doi:10.1007/978-1-4757-3437-9_1.
URL http://link.springer.com/10.1007/978-1-4757-3437-9{_}1

[67] J. Luukkanen, Role of planning philosophy in energy policy formulation, Ph.D. thesis, Tampere University of Technology (1994).

[68] S. Enzer, Cross-impact techniques in technology assessment, Futures 4 (1) (1972) 30–51. doi:http://dx.doi.org/10.1016/0016-3287(72)90023-7.

[69] E. J. Honton, G. S. Stacey, S. M. Millett, Future Scenarios: The BASICS Computational Method, Economics and policy analysis occasional paper, Battelle Columbus Division, 1984.

[70] J. Panula-Ontto, AXIOM approach for modeling and analysis of complex systems, in: R. Saarimaa, M. Wilenius (Eds.), Futures of A Complex World, University of Turku, Finland Futures Research Centre, 2018, pp. 72–90.

[71] J. Panula-Ontto, The AXIOM approach for probabilistic and causal modeling with expert elicited inputs, Technological Forecasting and Social ChangeIn press, accepted for publication 11.10.2018.
URL https://doi.org/10.1016/j.techfore.2018.10.006

[72] V. Linss, A. Fried, The ADVIAN classification–A new classification approach for the rating of impact factors, Technological Forecasting and Social Change 77 (1) (2010) 110–119.

[73] J. Panula-Ontto, J. Luukkanen, J. Kaivo-oja, T. O'Mahony, J. Vehmas, S. Valkealahti, T. Björkqvist, T. Korpela, P. Järventausta, Y. Majanne, M. Kojo, P. Aalto, P. Harsia, K. Kallioharju, H. Holttinen, S. Repo, Cross-Impact Analysis of Finnish Electricity System with Increased Renewables: Long-run Energy Policy Challenges in Balancing Supply and Consumption, Energy Policy 118 (2018) 504–513. doi:10.1016/J.ENPOL.2018.04.009.
URL https://www.sciencedirect.com/science/article/pii/S0301421518302246

[74] R. M. Axelrod, Structure of Decision: The Cognitive Maps of Political Elites, Princeton University Press, 1976.
URL http://www.jstor.org/stable/j.ctt13x0vw3

[75] E. C. Tolman, Cognitive maps in rats and men, Psychological Review 55 (4) (1948) 189–208.
URL http://www.ncbi.nlm.nih.gov/pubmed/18870876

[76] C. Eden, On the nature of cognitive maps, Journal of Management Studies 29 (3) (2007) 261–265. doi:10.1111/j.1467-6486.1992.tb00664.x.

URL http://doi.wiley.com/10.1111/j.1467-6486.1992.tb00664.x
[77] B. Kosko, Fuzzy cognitive maps, International Journal of Man-Machine Studies 24 (1) (1986) 65–75. doi:10.1016/S0020-7373(86)80040-2.
URL https://www.sciencedirect.com/science/article/pii/S0020737386800402
[78] A. J. Jetter, K. Kok, Fuzzy cognitive maps for futures studies–A methodological assessment of concepts and methods, Futures 61 (2014) 45–57. doi:https://doi.org/10.1016/j.futures.2014.05.002.
URL http://www.sciencedirect.com/science/article/pii/S0016328714000809
[79] H.-J. Zimmermann, Fuzzy set theory, Wiley Interdisciplinary Reviews: Computational Statistics 2 (3) (2010) 317–332.
[80] O. A. Osoba, B. Kosko, Fuzzy cognitive maps of public support for insurgency and terrorism, The Journal of Defense Modeling and Simulation 14 (1) (2017) 17–32.
[81] P. P. Groumpos, Fuzzy cognitive maps: Basic theories and their application to complex systems, in: Fuzzy Cognitive Maps, Springer, 2010, pp. 1–22.
[82] T. Ritchey, Problem structuring using computer-aided morphological analysis, Journal of the Operational Research Society 57 (7) (2006) 792–801. doi:10.1057/palgrave.jors.2602177.
URL http://dx.doi.org/10.1057/palgrave.jors.2602177
[83] T. Ritchey, Principles of Cross-Consistency Assessment in General Morphological Modelling, Acta Morphologica Generalis 4 (2).
[84] W. Weimer-Jehle, Cross-impact balances: A system-theoretical approach to cross-impact analysis, Technological Forecasting and Social Change 73 (4) (2006) 334–361. doi:10.1016/j.techfore.2005.06.005.
URL https://doi.org/10.1016/j.techfore.2005.06.005
[85] W. Weimer-Jehle, Cross-impact balances: Applying pair interaction systems and multi-value Kauffman nets to multidisciplinary systems analysis, Physica A: Statistical Mechanics and its Applications 387 (14) (2008) 3689–3700. doi:https://doi.org/10.1016/j.physa.2008.02.006.
URL http://www.sciencedirect.com/science/article/pii/S0378437108001659
[86] W. Weimer-Jehle, J. Buchgeister, W. Hauser, H. Kosow, T. Naegler, W.-R. Poganietz, T. Pregger, S. Prehofer, A. von Recklinghausen, J. Schippl, S. Vogele, Context scenarios and their usage for the construction of socio-technical energy scenarios, Energy 111 (2016) 956–970. doi:http://dx.doi.org/10.1016/j.energy.2016.05.073.
[87] S. Acid, L. M. de Campos, J. M. Fernandez-Luna, S. Rodriguez, J. M. Rodriguez, J. L. Salcedo, A comparison of learning algorithms for Bayesian networks: A case study based on data from an emergency medical service, Artificial Intelligence in Medicine 30 (3) (2004) 215–232, bayesian Networks in Biomedicine and Health-Care. doi:https://doi.org/10.1016/j.artmed.2003.11.002.
URL http://www.sciencedirect.com/science/article/pii/S0933365703001325
[88] V. A. Brown, J. A. Harris, J. Y. Russell, Tackling Wicked Problems Through the Transdisciplinary Imagination, Earthscan, 2010.
[89] B. W. Head, J. Alford, Wicked problems: Implications for public policy and management, Administration & Society 47 (6) (2015) 711–739. arXiv:https://doi.org/10.1177/0095399713481601, doi:10.1177/0095399713481601.
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PUBLICATION

II

AXIOM Approach for Modeling and Analysis of Complex Systems

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AXIOM Approach for Modeling and Analysis of Complex Systems

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Abstract

AXIOM is an approach for modeling and analysis of complex systems based on expert-sourced data. It proposes a systems modeling language and a computational process to extract information of higher analytical value from a model built using the language. AXIOM can be placed in the family of cross-impact analysis techniques, and it proposes solutions for several practical problems associated with systems modeling using the established cross-impact techniques. This paper presents the AXIOM modeling language primitives, outlines the computational process and shows how the evaluated AXIOM model can be used for analysis of the modeled system.

1. Introduction

This paper describes the AXIOM approach for complex systems modeling and analysis. Modeling is generally defined as creating an approximation of the real world or a portion of reality [41, 3]. Such approximations or *models* can then be used in simulation of the real system they represent. Simulation is done to improve understanding of the real system, test how the system behaves under different conditions, and study the effects of changes, thus supporting planning and decision-making. International Council on Systems Engineering (INCOSE) [24] defines a *system* as a "collection of elements that together produce results not obtainable by the elements alone". Systems thinking entails understanding the parts of reality under analysis as a set of components, that are logically connected abstractions of some real world objects or phenomena [11, 99].

Systems modeling is therefore a process of representing reality using a *modeling language* which defines the available types components, and the logical connections and relationships between them for building the representation. The process of trying to capture the essential aspects of a system or a problem domain can as such be a useful learning experience [11]. However, as the components and their relationships and connections are modeling inputs, the *analysis* part of system modeling and analysis must derive its added value from a process of performing some kind of evaluation or simulation on the model. This process aims at revealing the emergent properties of the system itself, which can be difficult to observe by just looking at the system components at the lowest

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level of aggregation [11, 99-103]. The emergent properties are *systemic*, reflecting how the components and their connections function as a system.

Modeling a system involves abstracting the real system components and aspects into the model components and drafting the structure of their relationships, using the constructs available in the modeling language. The modeling process relies on a theory of the system, which guides the framing of the system, the inclusion or exclusion of components, and the aggregation level. Systems modeling does not necessarily go beyond this conceptual level representation of the system. In order to be able to perform evaluation of the model or use it for simulation, the relationships between the components should be *valuated* in some more formal logical or mathematical form. If such a form is not developed, the analysis that can be done on the basis of the system model remains more or less intuitive and heuristic: there is no transformation that can be done on the model to reveal the systemic "emergent properties".

The typical way of defining the relationships or connections between the components of the system model is to acquire a sufficient amount of quantitative data [41] from statistics or empirical measurements on the modeled domain, and to derive a mathematical expression for the relationship on the basis of this available data. This data-driven approach obviously requires that the modeled components and relationships *a*) are quantifiable, and *b*) data about them is or can be made available for the modeling. The requirements of highly data-driven modeling can lead to omission of many important and interesting aspects of the system in modeling, or systems for which empirical data is not readily available not being subject to analysis with a systems modeling approach. For some systems, empirical data can be an impossibility: especially modeling employed in foresight and futures can deal with phenomena that do not yet exist and therefore can have no hard data available about them.

In lieu of empirical or statistical data, the system knowledge and understanding of knowledgeable people or *experts* of the modeled domain can be used in the process of formal valuation of the relationships between the model components. *Cross-impact analysis approaches* are a family of techniques to model systems based on expert-sourced information. The cross-impact approach goes beyond a conceptual-level model of a system, enabling, depending on the technique, some form of model evaluation or system simulation, aimed at extracting information about the emergent properties of the system. Tapping into expert-sourced data enables systems modeling in a theory-driven way, grounded in expert judgment and understanding: Cross-impact methods as modeling and analysis approaches fall in between empirical data-driven computational models and argumentative systems analysis, and they exhibit a high degree of disciplinary heterogeneity While a number of cross-impact techniques exist, there are barriers for adoption of the cross-impact approach, due to impracticalities in the modeling languages, intransparent documentation and lacking software implementations. AXIOM is a novel cross-impact approach, which proposes solutions for practical problems in existing cross-impact modeling techniques, with the aim of creating a clearly more feasible approach for systems modeling based on expert-sourced data. It also aims at providing output of more analytical value from the cross-impact modeling effort. AXIOM is transparently documented and implemented as free software, and is a ready-to-use tool for theory-driven systems modeling and simulation.

2. Cross-impact approaches

Cross-impact analysis has a long history in systems analysis and various foresight applications [19; 20; 43; 13; 28; 5; 26; 34; 15; 7; 33; 35; 29; 9; 25; 8; 16; 17; 21; 27; 44; 12; 36; 42; 1; 3; 4]. The original motivation for the development of the approach was to complement the Delphi method by introducing analysis of interaction between elements of a given system [19; 20; 21; 17]. Recent research has focused mainly on application of the approach [10; 2; 6; 12; 18] and there has not been much methodological development. In spite of the methodological discussion, barriers exist for utilization of the cross-impact approach in modeling and research: many cross-impact techniques are not very transparent in their documentation and lack software tools and implementations.

Cross-impact analysis could be described as an analytical technique for studying a system, and particularly interaction within it. A system is seen to consist of several components, states, events and forces that are partially dependent on each other and therefore have influence on each other. The objects are modeled as system descriptors. System descriptors are referred to by different terms by authors of different cross-impact techniques. Gordon [21] uses the term *event*, Godet et al. [17] speak of *hypotheses*, and Honton et al. [23] use the term *descriptor*. The influence the objects of the modeled system have on each other are given a model representation as impacts. Impacts can be represented as conditional probabilities [21; 17], references to probability-adjusting functions [23; 32; 37], impact indices [28; 17; 38], or simply a boolean indicator of interaction of some kind [17, 83].

The aim of cross-impact analysis is to extract information about the indirect and systemic interactions between the system components on the basis of the information on direct interactions. In a system with more than a few components, the indirect interactions can effectuate over a complex web of mediating components. Accounting for the effect of these interaction webs can reveal surprising and counter-intuitive relationships between the system components: seemingly unrelated components can be important for each other in a systemic way, and conversely an important direct impact of a component on another may be cancelled out or reversed by the systemic effects.

The inputs for cross-impact analysis include the system descriptors, their direct interactions and the valuations of properties for the descriptors and interactions. Typically this input data is provided by people with expertise considered relevant for the modeled system or topic. Technically one expert who supplies all the input data is enough to perform the analysis. Normally, however, there are several experts, and the facilitation of the expert process to supply the input data is of central importance for the cross-impact modeling exercise. The expert inputs can be collected in a Delphi-like expert panel, via a questionnaire, or some combination of these. This paper presents a cross-impact modeling language and a computational technique for processing the built cross-impact model and extracting information from it; it does not propose a particular solution for the use of experts in the cross-impact modeling. However, the questions of expert selection, model building, facilitating expert group work in model valuation and other processual details are very important for the modeling undertaking. For discussion of these aspects of cross-impact modeling see e.g. [31; 14; 17; 16; 40; 2; 6].

The existing cross-impact techniques vary greatly in terms of their inputs, computational process and outputs, but they can be grouped into three categories based on the analytical output they produce. The categories and the specific techniques in these categories are

1. Structural orientation
   - MICMAC [16; 17]
   - ADVIAN [30]
   - EXIT [38]
   - KSIM [28]
2. Morphological orientation
   - Cross-impact balances approach [44]
   - BASICS [23]
   - JL-algorithm [32]
3. Probability orientation
   - Gordon's technique [22; 21]
   - SMIC [16; 17]
   - AXIOM

The **structurally oriented approaches** focus on the impact network structure, and derive their analytical added value from revealing the indirect impacts between system descriptors and relating them to the direct impacts in some way. The most used technique in this category appears to be the MICMAC [17] approach, which is a computational approach based on matrix multiplication, and a part of a larger analytical approach Godet calls "structural analysis". A derivative of MICMAC has been also proposed [30]. The KSIM approach [28] is quite different from the other cross-impact approaches listed, but can, with reservation, be placed in the structurally oriented group of approaches. The structurally oriented techniques require fewer inputs than the other approaches, and provide a faster and easier modeling process, but the analytical output is more abstract and less actionable.

The **morphological orientation** of cross-impact analysis enables identifying logical, probable or consistent states for the system. A system state can be understood to be the combination of particular states for the system components. It can also be thought of as a scenario. This utility of cross-impact analysis overlaps morphological analysis [see 39]. Some morphologically oriented cross-impact techniques deal with probabilities explicitly and some do not. Documented approaches in this category are the cross-impact balances approach [44], BASICS [23], and JL-algorithm [32]. BASICS and JL-algorithm could also be seen as probability-oriented techniques, but their implementations output only probabilities for system states, their added value being of the morphological type.

The **probability-oriented approaches** explicitly deal with probabilities and therefore require that the system descriptors or their possible states are assigned initial or *a priori* probabilities. Additionally, they require some expression of how the probabilities of the system descriptors are adjusted during the evaluation of the cross-impact model. This can mean defining a conditional probability matrix [21; 17] or referencing probability adjustment functions [23; 32; 37]. The basic output of the model evaluation is a new set of probabilities for the system descriptors, the *a posteriori probabilities*, which are the probabilities when the emergent, systemic effects have been factored in. The modeling phase of the probability-oriented approach to cross-impact analysis is more difficult and time-consuming than in the other orientations, but this approach offers the greatest analytical possibilities. This approach is the most suited for simulation-type analysis with a cross-impact model, and can be used for testing effects of changes in or interventions to the system. The probability-oriented approaches can be also used for delivering similar analytical outputs as the structural approach and the morphological approach. The best-known techniques in this group are Gordon's method [22; 20; 21] and SMIC [15; 16; 17]. AXIOM is also in this category.

3. Advantages of the AXIOM approach

As stated in Section 2, AXIOM is a probability-oriented cross-impact approach, and the probability-oriented approaches in general have the greatest analytical possibilities among the different varieties of cross-impact methods. What are the advantages of AXIOM in comparison to other probability-oriented approaches? AXIOM combines the strengths of several documented cross-impact techniques in order to create a general systems modeling tool, that is feasible, flexible and makes analytically powerful. The combination of the best features of various approaches makes AXIOM a recommendable method for use in cross-impact modeling. The advantages of AXIOM, in comparison to other probability-oriented cross-impact approaches, are the following:

1. **Model valuation in AXIOM is relatively easy.** For the probability-oriented cross-impact approaches, valuation refers to the task of assigning initial (a priori) probabilities for the system descriptors and defining conditional probabilities for them or expressing the interactions between the descriptors in some other way. The impact valuation phase in AXIOM is decisively easier when compared to cross-impact methods which represent interactions as conditional probabilities (such as Gordon's method or SMIC). The cognitive cost of providing a large number of conditional probabilities is very high for the expert valuators. The conditional probability valuations are needed for all ordered pairs of hypotheses in the model, even when the model valuators would conclude that there is no direct interaction between the hypotheses. For example, the conditional probability valuation $P(A|B) = P(A)$ might violate the probability axioms, so no "default" conditional probability value exists: all interactions have to be valuated. The valuations have to comply with the probability axioms, and as the number of hypotheses grows, simply finding a compliant valuation solution might become difficult (at least without a help of a computer program specifically designed for this purpose). In this difficult valuation process, the qualitative-nature understanding of the experts about the interactions in the modeled system might get distorted in the attempt to find an acceptable valuation solution, changing the focus from modeling the system in the best way possible on the basis of expert knowledge into a sudoku-like number-placement exercise.

2. **AXIOM is suited for cross-impact models with a large number of components.** Cross-impact techniques which represent the interactions as conditional

probabilities are not well suited for constructing system models with a large number of components. The cognitively expensive valuation phase heavily limits the practical number of components in the model. Godet et al. [17, 149] actually recommend that the number of hypotheses should not exceed 6.

Modeling systems with such a small number of hypotheses is very limiting. In a system model with a handful of components represented by hypotheses, if those hypotheses are detailed and concrete, many relevant factors and driving forces are left outside the cross-impact model. Conversely, if the hypotheses are loaded with a lot of content so that each hypothesis represents many factors and driving forces simultaneously, the abstraction level of the hypotheses gets very high. This high abstraction level will make the model valuation difficult and ambiguous. The interpretation of results is likely to suffer from the high abstraction level and drawing concrete policy recommendations on the basis of the model might turn out difficult. Either way, practical and useful cross-impact modeling is very difficult if the nature of the cross-impact technique per se limits the number of model components.

As the object of interest in cross-impact modeling is the impact network of the modeled system, the limitations on the number of components in cross-impact models also limit the interestingness of the analysis. In a system model of few components, the impact chains cannot be very long. If the ability to investigate higher-order interactions, long impact chains and complex systemic effects is an important motivation to do cross-impact analysis, the cross-impact modeling technique should definitely support this aspiration.

3. **AXIOM primitives have comparatively high modeling power.** AXIOM statements have multiple possible values (called *options*), unlike Gordon's method or SMIC. It is easy to make the case that the multi-valued AXIOM statements are a better solution than separate boolean hypotheses for constructing useful and relevant cross-impact models. Boolean hypotheses can, to some degree, be used to model mutually exclusive system states akin to AXIOM options, but they are much less convenient and error-prone in modeling as they require the exclusiveness to be explicitly defined through conditional probabilities. Additionally, boolean hypotheses cannot model the exhaustiveness of AXIOM options: there is no mechanism to ensure that the probability distribution of a supposedly exclusive and exhaustive set of boolean hypotheses will remain valid during the model evaluation.

   AXIOM also has a statement property called *timestep.* The timestep property makes it easy to model passage of time in the cross-impact model. Incorporating temporal aspect to cross-impact modeling is a feature of AXIOM that greatly increases its power to model real systems compared to methods that do not offer a mechanism to model time. Providing a way to model time makes it easier to construct models from the perspective of modeling interventions: today's decisions can be modeled to take their effect on the future states of the system in a very convenient and natural way instead of providing means to only model a system with a single temporal space where events happen and system states take place without any temporal structure.

4. **AXIOM provides more analytical possibilities.** In Gordon's method and Godet's SMIC method, especially the process of studying the effect of interventions

and policy actions on the modeled system is, compared to AXIOM, cumbersome (although this might be more dependent on the implementation than the method). Modeling interventions requires changes to the cross-impact model and possibly redefinition of the conditional probabilities. The AXIOM method offers tools to design the simulation of interventions cleanly in the model building phase, and the focus of the analytical outputs is from the start in the effects of the different intervention sets, which makes it easy to extract practical policy recommendations. In addition to this, a number of further analytical outputs can be easily extracted on the basis of the AXIOM computation.

Above-stated strengths of the AXIOM approach, the freely available implementation, and the transparent documentation of the computation details make AXIOM a strong candidate for a general cross-impact modeling approach.

4. AXIOM modeling language, concepts and model evaluation

Any modeling approach has a modeling language associated with it, meaning a set of *modeling primitives* or building blocks to describe the characteristics of the real-world system that is being modeled. The building blocks for an AXIOM model are *statements* and their possible values called *options*, and *impacts* between the options. There are, however, a number of other important concepts that are also discussed in this section. Fig. 1 presents an entity-relationship model of the important concepts of the AXIOM approach.

Statements represent system aspects or components that can have a state. They roughly correspond to what Gordon [21] calls *events*, Godet et al. [16] call hypotheses and [23] call *descriptors*. AXIOM statements can have two to unlimited possible states (called *options*) whereas events or hypotheses in Gordon's or Godet et al.'s approaches only have a binary state (true or false) when evaluated or a state of being undetermined before evaluation. A statement should have *a*) a unique, identfying label *b*) a description detailing what they represent in the model *c*) a set of options *d*) a timestep value (explained in **timestep** definition), and *e*) a flag for whether the statement is to be treated as an intervention (explained in **intervention** definition). The options under a statement should be exclusive and exhaustive. Exclusiveness means that only one option can be evaluated to be the state of the statement (instead of more than one option being 'true'). Exhaustiveness means that the options should cover the possible states of the component or aspect of the real system that corresponds to the AXIOM statement. This is rarely possible in practice. Selecting the most relevant possible states for an AXIOM statement is a part of framing of the model. Models in general can never cover all parts and details of the modeled system. They should focus on covering the pertinent and essential parts, aspects and features of the modeled system, in order to be useful (if the model is as complex as the reality, its usefulness is questionable).

Options represent the different possible states a system component modeled as an AXIOM statement can have. Every option in an AXIOM model has *a*) one statement the fall under, *b*) identifying label, *c*) a description of what they represent, *d*) an

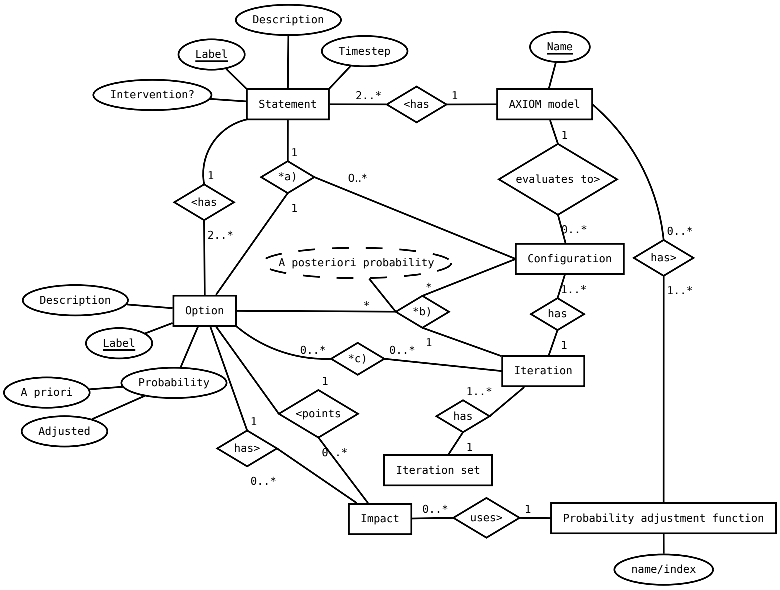

Figure 1: ER model of the AXIOM concepts.
***a)** *Statement* is evaluated to an *option* in a single *configuration*
***b)** A *configuration* in an *iteration* has a single *option* for each *statement* in the model; the *a posteriori probability* of each option is the rate of occurrence of the option in configurations in the iteration.
***c)** An *iteration* can have *options* as active interventions.

immutable a priori probability e) a mutable, adjusted probability valuation, and f) a (possibly empty) set of impacts directed to other options in the model. The immutable a priori probability is the initial, expert-sourced probability valuation of an option. The a priori probability is interpreted as the probability of the option to become true, as estimated when no other information about the system or its state is available; the a priori probability valuation is given in a context where the states of the other statements are unknown. The mutable probability valuation might change during model evaluation, as impacts in the model are realized or take place. The set of a priori probabilities and the set of mutable probabilities under a statement both form a probability distribution, meaning that the sum of values in both sets of probabilities must equal 1 at all times. The AXIOM options are flexible and can model the possibilities of the modeled system in various ways. It is possible that the different options under a statement embody a very clear and atomic value or fact about the system, such as a number or a percentage, or a single boolean fact. It is also possible that the options represent a big group of connected details, or a mini-scenario. These different uses can be combined in the same model unproblematically.

Impacts are probability-changing influences between options. Impacts have an owning option and a target option. Impacts are realized when their owning option is evaluated to be the state of the statement it falls under; when an option is known to be *true*, its impacts ensue.

Impacts, when realized, change the probability of their target option in some way. In AXIOM, the exact amount of probability adjustment is determined with probability adjustment functions (defined later). Any option o in an AXIOM model can have zero to $n_m - n_o$ impacts, where n_m is the number of options in the model and n_o is the number of options under the statement the option o falls under. This is because there can be no need to adjust the probability of options that are under the same statement as the owning option of the impacts; the owning option of an impact is already evaluated to be the state of its statement upon the time of realization of any impact.

An impact points to a probability adjustment function, that map the mutable, adjusted probability of the target option to a new adjusted probability value. The new probability value of the target option now reflects the valuation of the target option's probability when new information has become available (as the owning option is now known to be true). The probability adjustment functions have names, which can be indices: a set of names of probability adjustment functions could be {'−3', '−2', '−1', '+1', '+2', '+3'}. Probability adjustment function '−3' could refer to a significant negative change in probability, while '−1' could refer to a slight negative change in probability. '+3' could refer to a significant positive change in probability. What is a significant positive change in probability means different things in different contexts. A very improbable event or descriptor state might see its probability going from 0.00001 to 0.00100, making it a hundred times more probable but still having a very low probability. On the other hand, a probable event or descriptor state might have a probability of 0.8; Its probability cannot see a hundredfold increase. A strong positive change in its probability means a reduction in its uncertainty, and the adjustment must be no bigger than a part of the remaining 0.2 probability, that the probable descriptor will not be true. This kind of contextual probability adjustment is achieved by using probability adjustment functions: In AXIOM, the impact an option (when true) will have on the probability of some other option is expressed as a reference to (or as a name of) a probability adjustment function. This approach avoids the need to define a conditional probability matrix. The difficulties of using a conditional probability matrix in expressing the interactions in the cross-impact model has been discussed in Section 3. The probability adjustment function approach is an easier and more flexible way to express the cross-impact interactions.

Probability adjustment functions map probability values into new, adjusted probability values. In AXIOM, the named probability adjustment functions are used to contextually change the probabilities of options. They can be freely defined by

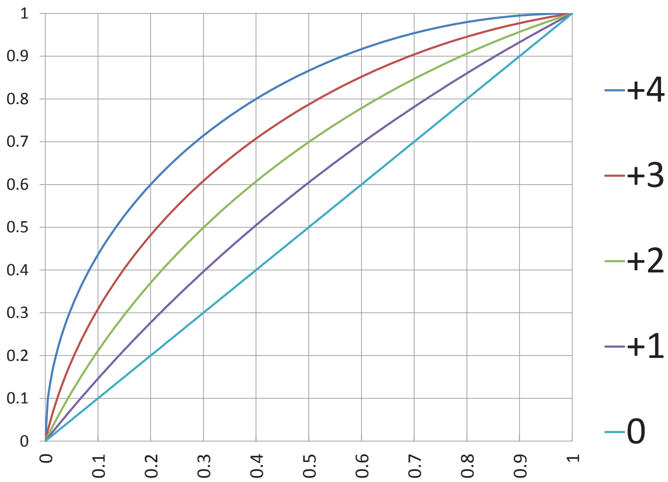

Figure 2: Examples of AXIOM probability adjustment functions

the analyst. The adjustment functions need to have a domain and range of $[0, 1]$. Fig. 2 presents the graphs of four probability adjustment functions.

However, the probability adjustment functions should adjust probabilities in a way that is easy to understand and coherent from the perspective of the model valuators. For this reason, there are recommended properties the functions should have, in order for them to provide a clear and understandable way for the expert valuators to express interactions within the AXIOM model.

- They should be symmetric about the line $y = -x + 1$
- Should have the property $y(x_0) < y(x_1)$ when $x_0 < x_1$
- Should have the property $y(x) > x$ if the name of the function implies positive (probability-increasing) impact, and the property $y(x) < x$ if the name of the function implies negative (probability-decreasing) impact.

The probability adjustment functions in Fig. 2 have this property. These recommendations can be disregarded by the modeler(s) if some functions not conforming to these requirements is seen as useful in the model valuation.

When the adjusted probability of an option of an AXIOM statement is changed according to the used probability-adjusting function, the probabilities of the other options under the impacted statement must be adjusted too. We can call the probability adjustment of the option that is the target of the impact *primary probability adjustment* and the probability adjustment of all the other options under the impacted statement *secondary probability adjustment*. The secondary probability adjustment is necessary because the probabilities of the options of a statement form a probability distribution and the sum of the probabilities of the options must always be equal to 1.

The primary and secondary probability adjustment are performed so that the probability of the impacted option is changed according to the probability adjustment function pointed by the impact, *(primary adjustment)* and the probabilities of the other options change so that their summed probability is equal to the complement of the new adjusted probability of the impacted option and the probability share each of these other options gets out of that summed probability is equal to their share of their summed probability before the probability adjustment *(secondary adjustment)*. When the other options under the same statement as the impacted option is have their probabilities adjusted in this way, the total sum of the probabilities of all the statement's options remains equal to 1.

Timestep is a property of an AXIOM statement. It defines the temporal position of a statement in relation to other statements in the model. In model evaluation, the statements with the lowest timestep are evaluated before statements with a higher timestep value. Statements that have the same timestep value are evaluated in random order. In other words, in AXIOM model evaluation, statements are evaluated in groups of statements that share a timestep value. This makes it possible to simulate a system with temporal depth: events or descriptor states to take place in the near future can influence the descriptors that lie further in the future. A policy implemented in the next four years might have an impact of a particular economic scenario being true in the next four year period. Timesteps can be years, but they can also simply be ordinal numbers of the time categories (however they are defined in the actual model building), only their ordering as numbers is significant from the point of view of model evaluation.

Statement evaluation means assigning a state for an AXIOM statement, or setting one of the statement's options as its value. This is done probabilistically, with each option of the statement having a probability equal to its current adjusted (mutable) probability of being selected as the state of the statement. When a statement is evaluated to a state (one of its options) all the impacts of the state option ensue or "take place". The probabilities of the target options of the ensuing impacts are adjusted according to the probability adjustment functions associated with the ensuing impacts. After this, the statement is evaluated and has a known state.

Model evaluation means evaluating all of its statements. As explained in the *timestep* definition, the statements are evaluated in time categories, from lowest(earliest) to highest(latest), and statements in the same time category are evaluated in random order. During the model evaluation process, as more information about the state of the system becomes available, the probabilities of options in yet unevaluated statements are adjusted to reflect the effect of the newly available information. After evaluation of every statement, the model now has a state, as it now has a value for each of its statements. This combination of values is called a configuration: Model evaluation produces a configuration. For full details on the model evaluation, AXIOM algorithms pseudocode and a full example of an AXIOM model evaluation are presented in [37].

Configuration is the result of the model evaluation. The information content of a configuration is a set of options, one option for each statement in the model. The options in the configuration are the options evaluated to be the states of each of the statements in a single model evaluation. A configuration can be understood as a scenario for the modeled system. As the model is evaluated multiple times, the resulting sets of configurations or *iterations* are used to derive a posteriori probabilities for the model options and other higher-order information. This is discussed in Section 5.

Intervention statements are treated in a special way in the model evaluation. Any statement can be flagged as an intervention statement in AXIOM model construction. They are not evaluated in the normal probabilistic way as non-intervention statements. In a single model evaluation, an intervention statement will have a predefined state; their state is determined when the model evaluation commences. Other details of the model evaluation are the same: the impacts of the predetermined options of the intervention statements take place when the intervention statement is taken up for evaluation. The states of the intervention statements change only between different iterations.

The function of intervention statements is that they can model policy actions, strategic options available to actors in the system or some other intervention-type aspect of the system. They provide an easy way to study the impacts and systemic effects of the different options available for the real-world component or aspect that the intervention statement represents.

Iteration is a list of configurations. A single model evaluation produces a configuration and several consecutive model evaluations produce an iteration. The utility of iterations is to be able to calculate the frequencies of different model options from a set of configurations with identical characteristics. Identical characteristics means same interventions, same model valuations and same model components. The frequence of occurrence of each option in an iteration is the *a posteriori* probability of that option.

The number of configurations in an iteration is not defined in the AXIOM method. The more model evaluations (and resulting configurations) the less the randomness of the Monte Carlo process effects the option frequencies. This is why a high number of configurations is recommended. For iterations that will be used for extracting final results to be analysed, at least 10^6 configurations is recommended. This recommendation is for calculating the a posteriori probabilities of individual options. If the idea is to compute a probability for a morphology or "partial scenario", i.e. the frequency of configurations that contain a specific set of options, the number of configurations should be even higher.

Iteration set is simply a set of iterations. The utility of an iteration set is to enable comparisons between the outputs of different model setups. The different model setups most commonly mean a different intervention combination (see **intervention**

statements) but can also mean different a priori probability and impact valuations and inclusion and exclusion of different statements and options. When the model has flagged intervention statements, the AXIOM software implementation will automatically create an iteration set containing an iteration for each intervention combination derivable from the flagged intervention statements. This facility makes it straightforward to investigate how alternative policy actions modeled by the options of intervention statements affect the a posteriori probabilities of other model options.

The definitions of the concepts of the AXIOM approach outline the AXIOM modeling language and the computation process of AXIOM. The full description of the process is detailed in [37], with pseudocode for the algorithms and a step-by-step computation example provided.

5. Output and analysis

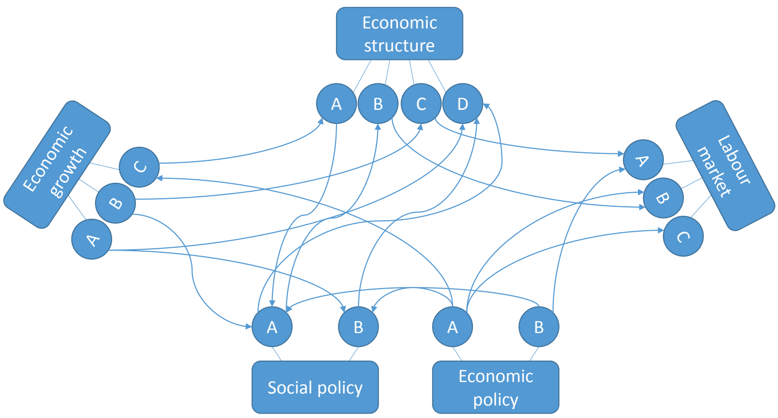

Figure 3: A conceptual system model

Fig. 3 presents a conceptual model of an economic system and a strategic decision-making problem framework. The (hypothetical) real system is modeled using AXIOM primitives: Statements, representing social policy, economic policy, economic growth, economic structure, and labour market aspects in the system; Options, describing possible states for the modeled system aspects, or *subscenarios* for the system aspects; and impacts, representing the influences that different subscenarios (AXIOM options), if realized, have on the likelihood of other subscenarios being realized. In the conceptual system model of Fig. 3, economic policy subscenario A influences the probability of labour market subscenarios B and C, while economic policy subscenario B influences the probability of labour market subscenario A. The model valuations (a priori probabilities and impact valuations) are not presented in the conceptual model. For purposes of the example, let's assume an expert group has performed the model valuation and the model can be evaluated with the AXIOM computation process.

Statements "Social policy" and "Economic policy" represent policy interventions to the system. Both statements have two options. Assuming these two statements are flagged as intervention statements, there are four possible combinations of interventions to investigate. Table 1 presents an example of the basic output of AXIOM. The table presents the a posteriori probabilities for the different model options of the conceptual system model presented in Fig. 3. The second column displays the a priori probabilities. The third column presents the a posteriori probabilities in a case where no statement is treated as an intervention statement. These probabilities have the systemic interactions and higher-order impacts factored into them.

Table 1: AXIOM iteration set consisting of five iterations, one without active interventions and four iterations with different intervention combinations

	a priori	no policy	SP_A + EP_A	SP_A + EP_B	SP_B + EP_A	SP_B + EP_B
Social policy A ($\mathbf{SP}_A$)	0.825	0.860	1	1	0	0
Social policy B ($\mathbf{SP}_B$)	0.175	0.140	0	0	1	1
Economic policy A ($\mathbf{EP}_A$)	0.258	0.260	1	0	1	0
Economic policy B ($\mathbf{EP}_B$)	0.742	0.740	0	1	0	1
Economic growth A ($\mathbf{G}_A$)	0.028	0.045	0.137	0.480	0.331	0.613
Economic growth B ($\mathbf{G}_B$)	0.715	0.717	0.425	0.041	0.581	0.192
Economic growth C ($\mathbf{G}_C$)	0.258	0.237	0.438	0.479	0.088	0.195
Economic structure A ($\mathbf{S}_A$)	0.144	0.176	0.357	0.438	0.027	0.469
Economic structure B ($\mathbf{S}_B$)	0.242	0.289	0.028	0.157	0.314	0.204
Economic structure C ($\mathbf{S}_C$)	0.152	0.185	0.118	0.046	0.413	0.232
Economic structure D ($\mathbf{S}_D$)	0.461	0.350	0.497	0.359	0.246	0.094
Labour market A ($\mathbf{L}_A$)	0.439	0.485	0.322	0.235	0.457	0.643
Labour market B ($\mathbf{L}_B$)	0.328	0.361	0.230	0.526	0.008	0.329
Labour market C ($\mathbf{L}_C$)	0.233	0.154	0.448	0.239	0.536	0.027

Columns 4–7 in Table 1 present the a posteriori probabilities of the model options under different intervention combinations. Column 4 presents the a posteriori probabilities assuming a combination of social policy A and economic policy A; column 6 the a posteriori probabilities under a combination of social policy B and economic policy A. If the subscenario A for economic growth would be desirable, its probability would be maximized under a policy combination of social policy B and economic policy B (column 7). Similarly, if labour market subscenario B would be particularly undesirable, its probability would be minimized under social policy B combined with economic policy A (column 6).

A posteriori probabilities for individual options under different assumptions and policy combinations are easy to read from this output. The analyst may however be interested in more complex questions, such as what kind of policy mix would maximize (or minimize) the likelihood of a particular system morphology. Such morphologies in the case of the example model could be "Economic growth A" and "Labour market B" ($G_A \wedge L_B$) or "Economic growth B" and not "Labour market C" ($G_B \wedge \neg L_C$), or perhaps something more complicated such as $(G_B \vee G_C) \wedge (S_A \vee (S_B \wedge L_C))$. The AXIOM iteration object is suited for calculating probabilities of such morphologies and performing various frequent itemset mining operations that might be of use for the analyst.

Table 2: Using AXIOM iteration object to compute probabilities of system states as frequencies of morphologies

Morphology	p	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}	c_{15}	c_{16}	c_{17}	c_{18}	c_{19}	c_{20}
SP_A	0.80	1	0	1	1	0	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1
SP_B	0.20	0	1	0	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0
EP_A	0.35	0	0	1	0	0	1	1	0	1	0	1	0	0	0	0	0	0	1	1	0
EP_B	0.65	1	1	0	1	1	0	0	1	0	1	0	1	1	1	1	1	1	0	0	1
G_A	0.25	1	0	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1
G_B	0.50	0	0	0	1	1	0	1	1	0	0	1	1	0	0	1	1	1	0	1	0
G_C	0.25	0	1	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	1	0	0
S_A	0.25	1	0	0	0	1	0	1	0	0	0	1	0	0	0	1	0	0	0	0	0
S_B	0.25	0	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	1	1	0	0
S_C	0.30	0	1	1	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	1	0
S_D	0.20	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	1
L_A	0.55	1	1	1	1	0	0	1	0	1	0	0	1	0	1	0	0	1	0	1	1
L_B	0.35	0	0	0	0	1	1	0	1	0	1	0	0	1	0	1	1	0	0	0	0
L_C	0.10	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0
$G_A \wedge L_B$	0.05	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
$G_B \wedge \neg L_C$	0.45	0	0	0	1	1	0	1	1	0	0	0	1	0	0	1	1	1	0	1	0
$(G_B \vee G_C) \wedge (S_A \vee (S_B \wedge L_C))$	0.25	0	0	0	0	1	0	1	0	0	0	1	0	0	0	1	0	0	1	0	0

Table 2 displays an iteration of 20 configurations, frequencies of different individual options within these 20 configurations, and frequencies of three example morphologies. 20 configurations is obviously insufficient to derive the a posteriori probabilities from the occurrence frequencies, but the principle is the same in an iteration of any number of configurations.

6. Software implementation

AXIOM is implemented as a Java program, and it can be downloaded from `https://github.com/jmpaon/AXIOM`. The GitHub page provides basic instructions for use and links to more resources on AXIOM.

7. Discussion

The AXIOM approach proposes a new modeling language and a computational process to extract information of higher added value from a system model built with that language. The rationale for a new probability-oriented or simulation-oriented cross-impact approach is illustrated in Section 3 by pointing out practical difficulties of modeling systems with the primitives available in Gordon's cross-impact approach and SMIC and proposing improvements, that have been incorporated into AXIOM approach. Section 4 discussed the AXIOM modeling language primitives, the computational process and how the evaluated AXIOM model can be used for analysis of the modeled system.

As a general systems modeling approach, the best fitness of AXIOM lies in high-level systems modeling where expert understanding of the system could be seen as the best source of information. For some modeling domains, the approach of using expert-sourced data is obviously not the best approach. For instance, technical systems with well-known limits and clearly measurable relationships and characteristics, the AXIOM modeling language, while a possible approach, is not a natural fit. Approaches like AXIOM can, however, offer tools to model systems from a very different perspective and attempt to incorporate aspects of the system that would be difficult or impossible to model using a more traditional data-driven approach. Combining theory-driven modeling and data-driven modeling in the same modeling framework provides interesting possibilities and warrants further experimentation, study and methodological development.

References

[1] Agami, N., Saleh, M., El-Shishiny, H., 2010. A fuzzy logic based trend impact analysis method. Technological Forecasting and Social Change 77 (7), 1051–1060.
URL https://doi.org/10.1016/j.techfore.2010.04.009

[2] Alizadeh, R., Lund, P. D., Beynaghi, A., Abolghasemi, M., Maknoon, R., 2016. An integrated scenario-based robust planning approach for foresight and strategic management with application to energy industry. Technological Forecasting and Social Change 104, 162 – 171.

[3] Bañuls, V. A., Turoff, M., 2011. Scenario construction via delphi and cross-impact analysis. Technological Forecasting and Social Change 78 (9), 1579–1602.
URL https://doi.org/10.1016/j.techfore.2011.03.014

[4] Bañuls, V. A., Turoff, M., Hiltz, S. R., 2013. Collaborative scenario modeling in emergency management through cross-impact. Technological Forecasting and Social Change 80 (9), 1756–1774.
URL https://doi.org/10.1016/j.techfore.2012.11.007

[5] Blackman, A., 1973. A cross-impact model applicable to forecasts for long-range planning. Technological Forecasting and Social Change 5 (3), 233–242.
URL https://doi.org/10.1016/0040-1625(73)90002-4

[6] Blanning, R. W., Reinig, B. A., 1999. Cross-impact analysis using group decision support systems: an application to the future of Hong Kong. Futures 31 (1), 39–56.

[7] Bloom, M. F., 1977. Time-dependent event cross-impact analysis: Results from a new model. Technological Forecasting and Social Change 10 (2), 181–201.
URL https://doi.org/10.1016/0040-1625(77)90044-0

[8] Brauers, J., Weber, M., 1988. A new method of scenario analysis for strategic planning. Journal of Forecasting 7 (1), 31–47.
URL https://doi.org/10.1002/for.3980070104

[9] Burns, J. R., Marcy, W. M., 1979. Causality: Its characterization in system dynamics and KSIM models of socioeconomic systems. Technological Forecasting and Social Change 14 (4), 387–398.
URL https://doi.org/10.1016/0040-1625(79)90036-2

[10] Chander, M., Jain, S. K., Shankar, R., 2013. Modeling of information security management parameters in indian organizations using ism and micmac approach. Journal of Modelling in Management 8 (2), 171–189.

[11] Checkland, P., 1999. Systems Thinking, Systems Practice. Wiley.

[12] Choi, C., Kim, S., Park, Y., 2007. A patent-based cross impact analysis for quantitative estimation of technological impact: The case of information and communication technology. Technological Forecasting and Social Change 74 (8), 1296–1314.
URL https://doi.org/10.1016/j.techfore.2006.10.008

[13] Dalkey, N. C., 1971. An elementary cross-impact model. Technological Forecasting and Social Change 3, 341–351.
URL https://doi.org/10.1016/s0040-1625(71)80022-7

[14] Enzer, 1971. Delphi and cross-impact techniques. Futures 3 (1), 48 – 61.

[15] Godet, M., 1976. Scenarios of air transport development to 1990 by SMIC 74—a new cross-impact method. Technological Forecasting and Social Change 9 (3), 279–288.
URL https://doi.org/10.1016/0040-1625(76)90012-3

[16] Godet, M., Bourse, F., Chapuy, P., Menant, I., 1991. Futures Studies: A Tool-box for Problem Solving. Futuribles (series). GERPA Prospective.

[17] Godet, M., Coates, J., Unesco, 1994. From Anticipation to Action: A Handbook of Strategic Prospective. Future-oriented studies. Unesco Publishing.

[18] Gorane, S., Kant, R., 2013. Supply chain management: modelling the enablers using ISM and fuzzy MICMAC approach. International Journal of Logistics Systems and Management 16 (2), 147–166, pMID: 56158.

[19] Gordon, T., Hayward, H., 1968. Initial experiments with the cross impact matrix method of forecasting. Futures 1 (2), 100 – 116.

[20] Gordon, T. J., 1969. Cross-impact matrices: An illustration of their use for policy analysis. Futures 1 (6), 527–531.

[21] Gordon, T. J., 1994. Cross impact method. Tech. rep., United Nations University Millennium Project.

[22] Gordon, T. J., Hayward, H., 1968. Initial experiments with the cross impact matrix method of forecasting. Futures 1 (2), 100–116.

[23] Honton, E., Stacey, G., Millett, S., 1984. Future Scenarios: The BASICS Computational Method. Economics and policy analysis occasional paper. Battelle Columbus Division.
[24] International Council on Systems Engineering (INCOSE), 2017. What is systems engineering? URL http://www.incose.org/AboutSE/WhatIsSE
[25] Ishikawa, M., Toda, M., Mori, S., Kaya, Y., 1980. An application of the extended cross impact method to generating scenarios of social change in japan. Technological Forecasting and Social Change 18 (3), 217–233.
URL https://doi.org/10.1016/0040-1625(80)90024-4
[26] Jackson, J. E., Lawton, W. H., 1976. Some probability problems associated with cross-impact analysis. Technological Forecasting and Social Change 8 (3), 263–273.
URL https://doi.org/10.1016/0040-1625(76)90004-4
[27] Jeong, G. H., Kim, S. H., 1997. A qualitative cross-impact approach to find the key technology. Technological Forecasting and Social Change 55 (3), 203–214.
URL https://doi.org/10.1016/s0040-1625(96)00209-0
[28] Kane, J., 1972. A primer for a new cross-impact language – KSIM. Technological Forecasting and Social Change 4 (2), 129 – 142.
[29] Kaya, Y., Ishikawa, M., Mori, S., 1979. A revised cross-impact method and its applications to the forecast of urban transportation technology. Technological Forecasting and Social Change 14 (3), 243–257.
URL https://doi.org/10.1016/0040-1625(79)90080-5
[30] Linss, V., Fried, A., 2010. The ADVIAN classification–a new classification approach for the rating of impact factors. Technological Forecasting and Social Change 77 (1), 110–119.
[31] Linstone, H., Turoff, M., 1977. The Delphi Method: Techniques and Applications. Addison-Wesley, available online at http://is.njit.edu/pubs/delphibook/.
[32] Luukkanen, J., 1994. Role of planning philosophy in energy policy formulation. Ph.D. thesis, Tampere University of Technology, tampere University of Technology publications # 129.
[33] Martino, J. P., Chen, K.-L., 1978. Cluster analysis of cross impact model scenarios. Technological Forecasting and Social Change 12 (1), 61–71.
URL https://doi.org/10.1016/0040-1625(78)90035-5
[34] Mitroff, I. I., Turoff, M., 1976. On the distance between cross-impact models: A set of metric measures for cross-impact analysis. Technological Forecasting and Social Change 8 (3), 275–283.
URL https://doi.org/10.1016/0040-1625(76)90005-6
[35] Nováky, E., Lóránt, K., 1978. A method for the analysis of interrelationships between mutually connected events: A cross-impact method. Technological Forecasting and Social Change 12 (2-3), 201–212.
URL https://doi.org/10.1016/0040-1625(78)90056-2
[36] Pagani, M., 2009. Roadmapping 3g mobile TV: Strategic thinking and scenario planning through repeated cross-impact handling. Technological Forecasting and Social Change 76 (3), 382–395.
URL https://doi.org/10.1016/j.techfore.2008.07.003
[37] Panula-Ontto, J., 2016. AXIOM Method for Cross-Impact Modeling and Analysis. Master's thesis, University of Tampere, available online at http://tampub.uta.fi/handle/10024/100041.
[38] Panula-Ontto, J., Piirainen, K., 2017. EXIT method for cross-impact analysis, unpublished.
[39] Ritchey, T., 2006. Problem structuring using computer-aided morphological analysis. Journal of the Operational Research Society 57 (7), 792–801.
URL http://dx.doi.org/10.1057/palgrave.jors.2602177
[40] Seker, S. E., 2015. Computerized argument delphi technique. IEEE Access 3, 368–380.
[41] Sokolowski, J., Banks, C., 2009. Principles of Modeling and Simulation: A Multidisciplinary Approach. Wiley.
URL https://books.google.fi/books?id=wOOikQEACAAJ
[42] Thorleuchter, D., den Poel, D. V., Prinzie, A., 2010. A compared r&d-based and patent-based cross impact analysis for identifying relationships between technologies. Technological Forecasting and Social Change 77 (7), 1037–1050.
URL https://doi.org/10.1016/j.techfore.2010.03.002
[43] Turoff, M., 1971. An alternative approach to cross impact analysis. Technological Forecasting and Social Change 3, 309–339.
URL https://doi.org/10.1016/s0040-1625(71)80021-5
[44] Weimer-Jehle, W., 2006. Cross-impact balances: A system-theoretical approach to cross-impact analysis. Technological Forecasting and Social Change 73 (4), 334–361.

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III

The AXIOM Approach for Probabilistic and Causal Modeling with Expert Elicited Inputs

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The AXIOM Approach for Probabilistic and Causal Modeling with Expert Elicited Inputs

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Abstract

Expert informants can be used as the principal information source in the modeling of socio-techno-economic systems or problems to support planning, foresight and decision-making. Such modeling is theory-driven, grounded in expert judgment and understanding, and can be contrasted with data-driven modeling approaches. Several families of approaches exist to enable expert elicited systems modeling with varying input information requirements and analytical ambitions.

This paper proposes a novel modeling language and computational process, which combines aspects from various other approaches in an attempt to create a flexible and practical systems modeling approach based on expert elicitation. It is intended to have high fitness in modeling of systems that lack statistical data and exhibit low quantifiability of important system characteristics. AXIOM is positioned against bayesian networks, cross-impact analysis, structural analysis, and morphological analysis. The modeling language and computational process are illustrated with a small example model. A software implementation is also presented.

Keywords: Systems modeling, Modeling techniques, Decision support, Cross-impact analysis, Belief networks, Expert elicitation
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1. Introduction

This paper proposes a novel modeling language and computational process, which combines aspects and analysis elements from various other approaches in an attempt to create a flexible and practical systems modeling approach based on expert elicitation. Modeling systems based on expert elicited inputs has potential in modeling systems that are difficult to model based on statistical data. Traditionally the modeling of systems has been strongly data-driven [1], although a hybrid approach of augmenting data-driven models with expert information [2,3,4] has become more commonplace in modeling and decision support activities. The reliance on statistical data limits the use of models and modeling in research and decision-making, as *a)* only systems and problems with good statistical data availability will be modeled, *b)* only elements, aspects and properties of systems that are easily quantified and have good data availability will be included in the models, and *c)* generally, modeling will be considered as a possible approach only in domains where data availability is good. The methodological orientation of modeling towards easily quantifiable aspects of reality may cause models, and the decision support that they offer, become biased or limited in strategic scope and perspective. Involving expert informants in the modeling process as an alternative input source can help to account for critical considerations poorly covered by statistical data [2,3,4,5,6].

A number of modeling and analysis techniques intended to be used in conjunction with expert elicitation have been proposed since the late 1960's, mainly in the futures studies and foresight domain, referred to by the original authors as techniques for cross-impact analysis [7,8,9], structural analysis [10,11], and morphological analysis [12,13]. Bayesian networks and influence diagrams are a widely used decision support tool, and they are often augmented with expert elicited knowledge [5,14]. While they are used in foresight applications [15,16,17], their use is less common, as their characteristics make them somewhat impractical in systems modeling with high abstraction level and high structural complexity.

AXIOM draws design features regarding the modeling language, computational process and inference from several existing modeling approaches with fitness to modeling systems or decision-making problems with expert-elicited model inputs. The design aim of AXIOM has been to identify the most viable design features of existing approaches for the expert elicited modeling niche, combine them in the same analytical framework, and expand on the ideas adopted in them to further elevate the fitness for expert informant processes. The most important of these approaches are bayesian networks and influence diagrams, the cross-impact approach by Gordon and Hayward and its derivatives, and the BASICS approach. The characteristics of these techniques are discussed and appraised in terms of fitness for expert informant oriented modeling. AXIOM builds on and expands on many of the ideas introduced by existing approaches, as discussed in Section 3 with the aim of providing better tooling for modeling based on expert elicited inputs and making the formal modeling a more viable research and analysis approach in domains that are difficult to model using other modeling approaches.

This paper also discusses the main analytical orientations of expert informant based modeling approaches, identifying structural, morphological and probabilistic orientations. In terms of analytical output, AXIOM can produce outputs of all of the mentioned orientations, covering a great deal of the utilization area of other discussed modeling approaches. The use of AXIOM in decision support, probabilistic inference, as well as extraction of morphological and structural insights is illustrated in Section 4.3 with a small example model. A software implementation of the approach is freely available, and its development is ongoing. The further development of the AXIOM framework and its software implementation are discussed in Section 6.

2. Literature review

2.1. Systems Thinking, Modeling and Simulation

System is defined [18] as a "collection of elements that together produce results not obtainable by the elements alone": system parts work together. Systems thinking is geared towards understanding the systemic phenomena: The individual parts of the system are known and understood (they are "inputs" to the systems thinking), but their operation together, as a *system*, and the result of this operation are less understood and are the main object of interest in systems thinking [19].

Systems thinking entails understanding a part of reality as a set of components, which are abstractions of real-world objects and phenomena [19]. The system as a whole can be described with these more atomic abstractions, which are logically connected by relationships of some kind. Practice of such systems thinking might lead to a more formal representation of the system, often called a system model [1]. The amount of information and detail in the system representation, or model, varies greatly. The information content of the model determines what kind of higher-order information can be extracted from the model, and what kind of insights can be made available.

Modeling is therefore creating an approximation or abstraction of the real world or a part of reality [1]. As abstractions, models attempt to capture the essential parts of reality. What is essential is determined dominantly by information needs, the questions the model is supposed to answer. Models representing the system with sufficient detail and formality can be used for simulation. If a model represents the system, simulation represents the *operation* of the system [20,21]. Simulation has a temporal aspect. The representation of the operation can mean a continuous-time representation, if sufficient details are available in the model. On the other hand, the operation can also be represented as a starting point and an end point. In this two-step description of the operation of the system, a starting state is fed to a transformation and a transitioned state is output as the "end" result.

Systems modeling is said to be strongly data-driven, meaning that the formal descriptions or definitions of the relationships connecting the model components are extracted from statistical data. These formal descriptions are normally presented as mathematical equations relating the model variables. Often techniques such as regression analysis are used for parameterization of the relationships [1]. Even when the estimation of details of the relationships is based on data, such model is still considered "a formal representation of a theory" [22]; Data-driven modeling is fundamentally based on theoretical-level understanding of the system rather than 'hard' empirical evidence.

A common problem in systems modeling is data inavailability [1], due to difficulties in quantifying the essential parts of the modeled system at the precision required by data-driven modeling approaches or the costs of data acquisition. Data inavailability limits modeling, both in application area of systems thinking and modeling (as only systems with good data availability will be modeled) and utility and reliability (as only system aspects for which data is available will be included in the models). These limitations might result in incomplete or biased models, which leave possibly crucial aspects of the system unmodeled and unaccounted for. The methodological limitations of modeling are reflected in the decision-making process using the modeling results, as their strategic and policy scope omits important considerations.

In some modeling domains, empirical data is an impossibility. For instance, foresight-oriented modeling of socio-techno-economic systems has to account for changing or emerging system characteristics that are not manifested in existing statistical data, as well as possible occurrence of singular historical events for which no frequentist-type data can exist. Historical data does not necessarily capture or reflect the way the modeled system is changing, even when the change and the dynamics involved might be well understood by experts of the modeled system.

Data-driven modeling is often called mathematical modeling, and thus contrasted with modeling approaches emphasizing an intuitive-logical way of describing the properties of the modeled systems. Underpinning the mathematicity of modeling can lead to a false impression of the model being based on a solid mathematical foundation: in the minds of the model users, the irrefutability of mathematics lends itself to the outputs of the model. However, in data-driven modeling, the fundamental choices about the model structure and logic are made not based on some axiomatic mathematical principles or empirical evidence but theory, expertise, intuition, or even guesswork. The theoretical foundation of models and simulations can sometimes be obscured by their claimed mathematicity. Often this theoretical foundation of the model is laid out in a rather informal and unstructured way, by a small modeling team or just one single person doing the modeling, and the foundation and theoretical choices made are not explicated. Given the high technical expertise requirement of data-driven modeling approaches the model-building team might consist of experts of the *modeling approach*, instead of experts of the modeled domain.

The theory-based structure of causalities and dependencies of models built using the data-driven approach is often nontransparent. Understanding the logical structure of the models might require good understanding of the underlying mathematics. Even with such expertise, understanding the structure might often be laborious. This cognitive cost of examining and understanding the model will often make the models "black boxes" whose output is used without good grasp of the logical structure underlying the model: from a user perspective, the general causal logic of the model might remain unclear.

The expert informant-based approach to modeling, or expert elicitation of model inputs, is an alternative to data-driven modeling[5,23]. Expert insight of the modeled system may cover domains or system aspects for which data in the required format for modeling does not exist, but which are still known at some level of detail, enough to base the modeling on[3,4,6]. While the data-driven approaches can rely on expert inputs as well, expert elicitation is in secondary role, and not the methodological focus. The expert informant oriented modeling approaches typically attempt to provide a *modeling language* more suitable for modeling the system with expert-sourced information, rather than requiring the experts to directly specify mathematical equations which relate the system components to each other. This language should support the heuristic-logical mode of work, and be natural in use of an expert-oriented modeling process. A suitable modeling language relies on a less exact precision in description of the model component relationships than what is typical in a data-driven model, where the relationships can be parameterized on the basis of the available empirical data, using techniques like regression analysis. Several modeling languages aiming at enabling expert description of systems have been proposed alongside various analytical methods. These are discussed in Section 2.2. Specific methods of high relevance to and methodological overlap with AXIOM are detailed in Section 3. The modeling language will determine the level of detail and the nature of information in the expert informant sourced system model. Given a fairly simple modeling language, the system description may be relatively transparent, in comparison to the system description of the data-driven approaches. The nature of the information, in turn, determines what kind of transformations can be done on it to extract some kind of higher-order information from the model.

While modeling approaches with focus on expert informant sourced data do exist, there are important improvements to be made to increase both the fitness of the modeling language for expert elicitation working mode of modeling, and the inference procedures used to extract analytical value from the model. Section 2.2 discusses a number of systems modeling approaches with fitness for expert informant oriented modeling and identifies their analytical aims. Section 2.3 assesses the design options of these approaches, from the angle of fitness for modeling based on expert elicitation. Section 3 gives a description of modeling approaches with significant overlap with the AXIOM approach in some dimension, explains the similarities and differences and presents the argumentation for the design choices made in AXIOM. Several issues identified in the review justify further methodological development in the field. Section 4 presents the AXIOM modeling language and computational process, as well as possible analytical outputs. The contribution of this paper is methodological: it proposes a novel approach for a specific systems modeling and simulation niche, with an above-state-of-the-art fitness for the intended purpose. The language and the analysis process is illustrated with an example model previously [(9,13)] used to illustrate two other modeling approaches. A free software implementation of the approach is also presented.

2.2. Established Expert Informant Oriented Modeling Approaches

Expert elicited systems modeling is practiced under several different names or labels. These include cross-impact analysis [(7,9,10,24,25,26,27)], structural analysis [(10,11,24,28,29)], morphological analysis [(12,13)], cross-consistency analysis [(30)] and bayesian belief networks and influence diagrams, bayesian decision support systems, or bayesian decision support systems [(14,16,17,31,32,33,34,35)]. There are several documented modeling approaches and associated computational processes within each mentioned branch of modeling. They have a great deal of conceptual and functional overlap, but also important differences. All approaches *(a)* utilize expert elicitation *(b)* in building a model representation of a real-world system or decision-making problem, *(c)* that can be represented as a graph, nodes as the system descriptors and edges describing their relationships, *(d)* to be used in analysis of the system, inference or decision support by means of a computational transformation on the model.

The expert informant driven modeling processes can result in conceptual models of low formality, for which there are no particular computational transformations or inference mechanisms available. Conceptual models, as well as the expert-driven process itself, can be very useful in understanding the system, and can yield processual benefits [(36)] without any specific formal inference. However, when the model representation of the system is at a sufficient level of formality to analyse computationally, these approaches provide some process of computation and inference to facilitate the analysis of the models. The information content of the models determines what kind of further computational transformations are available to extract higher-order analytical information. Three distinct analytical orientations, not mutually exclusive, of expert informant oriented modeling can be identified.

1. In the *structural* orientation, the focus is on the structure of the relationship network. The aim is to form a picture of the *systemic relationships* of the model variables, inferred from the description of the direct relationships. The systemic relationship reflects the indirect or mediated influence between the variables, in addition to the direct influence: the inference mechanism aims at revealing the indirect relationships between the variables in some way. As the indirect relationships are discovered, on the basis of the direct relationships given as input, a new understanding of the relationships emerges.

   Analytical outputs of structural nature can be extracted from a graphical model where nodes represent system components, events, driving forces and trends, without necessarily having any additional information, and edges (directed or undirected) represent *direct* relationships of some kind, possibly having an indicator of magnitude representing the strength of the relationship (relative to other relationships in the model). Methods focusing on this utility are MICMAC(10,24), ADVIAN(28), and EXIT(29,37). Cognitive maps(38) and fuzzy cognitive maps(39) also have similar analysis aims, although they are not typically identified as structural analysis approaches.

2. The *morphological* orientation aims at identifying logical, consistent or probable system states, or reducing the total 'problem space' into a smaller, internally consistent 'solution space'(30). A system state is a specific combination of states of the system descriptors. A requirement for deriving morphological utility is that the model contains information about the 'agreement' of the system descriptors, so that system configurations where the states of system descriptors are 'harmonic' may be identified. Hence, the nodes should have state properties, such as a boolean indicator of them being true or false, or a discrete state (a single state out of a set of possible states). Morphological information can also be inferred from probabilistic information about the relationships of the model components: Nodes may(9,10) or may not(12,13,40) have probability information about their possible states. The edges should, at a minimum level, contain boolean information of "agreement" or consistency between the specific states of the model nodes. Methods oriented morphologically include BASICS(9), JL-algorithm(41), general morphological analysis(12), Field Anomaly Relaxation(40)), SMIC(10,24), and the cross-impact balances approach(13).

3. The *probabilistic* orientation aims at probabilistic inference about the system, deriving the probability distributions for random variables in the model, given a set of variables with an assumed value. Probabilistic modeling orientation requires more input information than structural or morphological orientation, as probabilities are computed explicitly: The probabilistic conditionalities and dependencies need to

be described in a more specific way. The additional model information enables wider analytical possibilities. The obvious disadvantage is that the modeling is more costly in terms of time and effort. This can be a challenge for the modeling if the access to expert informants is limited.

The probabilistic orientation offers the greatest degree of direct decision support, as the effects of interventions can be observed from the probability distributions of random variables capturing some aspects of the system that are relevant for decision-making. The analytical utility comes from using the model for examining the systemic effects of events and developments, or strategic actions and interventions. Probabilistic information can be coupled with *utility functions*, which help identifying the optimal intervention combination maximizing utility or minimizing harm by some criteria. Probabililistically oriented modeling techniques include Gordon-Hayward cross-impact analysis (7,25,26), bayesian networks and influence diagrams (14,31,32,33,35), and AXIOM.

The various alternatives differ in terms of *(a)* the information content of the descriptors, *(b)* the way (and in what detail) interactions are modeled, *(c)* the nature or interpretation of that interaction, *(d)* the possibility to model the temporal dimension, and *(e)* whether cyclical relationships are allowed. These features lead to the approaches being of a certain *(f)* difficulty level for the expert informants used as the information source. and a *(g)* focus on a specific analytical orientation. The next subsection discusses these key design options of the various established approaches, and consideres their preferability and problems in the context of modeling relying strongly on expert elicitation for input data acquisition.

2.3. Motivation for Further Methodological Development

Given the numerous documented approaches for creating graphical system models by means of expert elicitation, what is the motivation for developing new methods? A modeling approach with high fitness for this specific purpose should have a modeling language which is generic, but flexible and expressive, to enable model representation of all kinds of systems and heterogenous system features. This flexibility should be provided by a practical way for expressing the system characteristics, which takes into account the expert informant resources, which are, in practice, always limited. The ideal approach should also produce outputs from which all discussed analytical utilities can be extracted. Against this ideal of a modeling approach with optimal fitness for expert-elicited systems modeling, a number of problems, for which the AXIOM approach proposes solutions to, can be identified in the established approaches.

1. **Modeling power.** The modeling languages of Gordon-Hayward cross-impact analysis (25), SMIC (10), MICMAC (10), and ADVIAN (28) only offer boolean system descriptors, which represent events of or hypotheses about the modeled system. A modeling language with more modeling power allows system descriptors to have an arbitrary number of possible states. This makes it possible to clearly model system states that are mutually exclusive and exhaustive: such system properties cannot be reliably modeled with binary descriptors. System descriptors with an arbitrary number of possible values enables a flexible way of modeling a real system at arbitrary level of detail: Multivalued descriptors, used in bayesian networks and

influence diagrams, BASICS, and AXIOM, can model, in principle, any kind of system feature or property, from low-level and atomic detail such as a number or a share, to a high-level descriptor of the system, such as a subscenario describing a possible state of a subsystem, packaging a great deal of information.

In most expert informant based systems modeling techniques discussed in Section 2.2, the modeling languages do not provide a way to represent the temporal dimension of the model, meaning that the system descriptors do not have a temporal position in relation to each other. All system descriptors are thought to exist in the same temporal space and are resolved "simultaneously" at the level of the computational transformation performed on the model, details varying by the specific technique. For several systems, the ability to model passage of time and the temporal relationship between the descriptors is highly desirable to create meaningful models. The bayesian network representation of systems(4,6,23,42) enables modeling a temporal aspect, but in a structurally deterministic way and with limited flexibility: the temporal logic of the model could be said to be coupled with the model structure. AXIOM descriptors have a *timestep* property that enables positioning the descriptors in the temporal dimension in relation to each other with arbitrary precision. A representation of time of relatively low precision is probably the best fit for expert informant oriented modeling, but any level of precision is made possible in a simple way with the timestep property.

Bayesian networks as graphical system models impose structural limitations on the modeling of relationships, as bayesian networks are directed acyclic graphs: cyclic interaction is not allowed in bayesian network models. As the AXIOM transformation is based on a monte carlo process and bidirectional interaction is therefore non-problematic, this limitation to modeling power is eliminated.

2. **Expression of interactions.** For all models of the approaches discussed in this paper, the description of interaction between the system descriptors is the most information-laden part of the model. In terms of valuating the models, the expert informants used as data source will spend most of their time describing the interactions. If the experts are understood to be the primary source of input information for the model, the amount of detail they need to give as input is a trade-off against the complexity of the model structure and the time the experts have available for contemplating the valuation of the interaction. The more information is needed to express the details of the relationships between the system descriptors, the smaller number of descriptors can be considered and the less time there is to consider the relationships carefully, assuming that the expert informant time is limited. In the approaches not dealing with probabilities explicitly, the interactions are expressed in a simple way, with boolean indicators or magnitude indicators; this simplicity makes for easy model valuation, but analytically such models can provide only structural and morphological utility.

   Many approaches dealing with probabilities(7,10,23,42) require definition of a system conditional probabilities as a way to express their interdependencies. Conditional probabilities allow for expressing the descriptor interactions in a very detailed and exact way, but they require much more time and effort from the expert informants. In Gordon-Hayward cross-impact analysis(7) and SMIC(10), the model valuators define a conditional probability matrix which is in agreement with the probability axioms. This is often a considerable effort, and in the case of SMIC, Godet actually recommends[10] that the number of descriptors does not exceed six. This heavily limits the practical modeling power of cross-impact models of Gordon-Hayward cross-impact analysis and SMIC: the system model must, to remain feasible from valuation perspective, be very high-level and abstract, limiting its value as a decision support tool. In models based on bayesian networks, conditional probabilities are expected for a descriptor for the cartesian product of the possible states of its dependencies. If the probability distribution of the possible states of a system descriptor with four states is dependent on five other descriptors with four possible states, 4096 conditional probabilities should be defined for the dependent descriptor; in a complex system with possibly hundreds of descriptors, a case of a descriptor being dependent on ten other descriptors with four possible states each, 4194344 conditional probabilities would be required to fully define the dependence. In this sense, defining the model interactions as conditional probabilities is not a minor nuisance that places a requirement of more time being used in the modeling effort, but a hard practical limit to the complexity of the model of interactions of a system.

In the case of relying solely on expert informant valuation in modeling, one must ask what is the realistic upper limit of precision for expert informants when defining interactions of system descriptors as conditional probabilities. If the valuations of expert informants are assumed to be hazy, approximate quantifications, a compromise between the precision of definition of interactions and speedy and cognitively less expensive valuation process appears justified. An alternative approach to the use of conditional probability tables in description of probability-updating interactions between system descriptors is to use references to *probability updating functions*. They update the probabilities contextually, doing away with the need to define full conditional probability tables. This approach is discussed by Enzer[43] and first adopted in the BASICS approach[9]. Later it has been used in the JL-algorithm[41]. AXIOM also uses this basic idea of simplifying the description of probability updates, but expands on the idea. While describing the interactions in a complex system model with a large number of descriptors is still challenging, with the probability updating function reference approach the task becomes much more feasible: the most complex describable relationship in a case of a four-state descriptor dependent on ten other four-state descriptors, would require *at most* 204 valuations (normally less), contrasted to the 4194344 valuations required for description of the relationship using conditional probabilities. Often a smaller number of valuations would suffice in the updating function approach.

Providing a simplified way for expert informants to define the model interactions increases the modeling power of the modeling language in a very important way: it makes larger system models possible. If the modeling approach heavily limits the size and complexity of the model and the number of the descriptors, the model remains very high-level and abstract. Analysis of such models remains abstract as well. Modeling approach should support larger models as much as possible, to enable modeling that can produce the most policy-relevant outputs. Emphasizing the fitness of the modeling language to build large system models is also beneficial since systems modeling is often the most interesting and useful when models are more extensive: surprising, counter-intuitive and interesting systemic, emergent and higher-order interactions and long causal chains that would be difficult to analyze intuitively can only exist in models that have a relatively large number of system components represented.

3. **Inference and analytical output.** While the information available in the models of approaches discussed in this paper might enable, with changes to the computational process, the use of the model information to answer several different questions about the modeled system, many approaches do not discuss these ways of higher-order information extraction in their documentation or make them available in their software implementations. The versatility and usefulness of the analytical outputs of the expert informant based modeling approaches can thus be improved as well. The inference capabilities of most approaches are oriented either structurally, morphologically or probabilistically. As building system models is an extensive and work-intensive effort, it would be desirable that the approach could deliver outputs of all orientations, as is the case with AXIOM.

3. Methodological Influences and the Methodological Contribution

As stated in the introduction, AXIOM builds upon the design choices introduced in existing modeling approaches. The most important influences of AXIOM approach are, in order of importance, *a)* bayesian networks and influence diagrams[42,44,45], *b)* the Gordon-Hayward cross-impact analysis[7,26], and its later derivative SMIC[10,24] and *c)* the BASICS approach[9,27]. These techniques are discussed here in more detail to adequately position AXIOM against them, explain what are their problematic aspects in expert informant oriented modeling, and what is proposed in AXIOM to solve the identified issues.

From bayesian networks and influence diagrams, AXIOM takes the basic inference principles and the model of decision support use. In comparison to bayesian networks, the AXIOM modeling language provides more freedom to the modeler, allowing cyclic interaction in the modeling of causalities and a way to define the temporal structure of the model with the timestep property of the statements, decoupling the model temporal dimension from the structure of causal dependencies. AXIOM also proposes analytical processes which are not typically used in the case of bayesian networks, but which can be found in the cross-impact analysis, structural analysis and morphological analysis tradition. From the Gordon-Hayward cross-impact analysis, AXIOM takes the idea of evaluating the model in a monte carlo process, but provides an easier and more feasible way for describing the knowledge base of the expert informants, by means of updating functions. The updating functions approach, in turn, is inspired by the BASICS approach[9,27], and its derivative JL-algorithm[41]. AXIOM significantly expands on the idea of BASICS updating functions. Other important influences are the above-discussed structural and morphological approaches, such as MICMAC[10], ADVIAN[28], general morphological analysis[12], and cross-impact balances approach[13]. These approaches are technically quite far from AXIOM, but AXIOM design enables performing analysis that result in insights of structural and morphological nature, with a relatively low increase in conceptual complexity in the modeling.

The contribution of this paper is the proposal for a new expert informant based systems modeling approach. The design aim of the approach is to combine the best method design aspects of the older cross-impact analysis tradition, also expanding on these ideas, and use the hybrid approach for similar probabilistic inference and decision support as bayesian networks and influence diagrams are used, with an eye on the feasibility of full expert elicitation in model parameterization, and flexible and expressive modeling language. The AXIOM modeling language and computational process are summarized in Section 4 and and the analytical possibilities are illustrated with an example system model in Section 4.3.

3.1. Bayesian Networks and Influence Diagrams

Bayesian belief networks are models for probabilistic causal reasoning [(42)]. They are widely used in scientific, industrial, and decision support applications. The basic use case for them in decision support is inferring the change in the probability distributions of the states of the node descriptors in the network, when other nodes are set to be in a known state, to represent a decision-making context, or a set of assumptions to be tested for their effect on the system. Alternatively changes can be made to the probability distributions of nodes of interest, to capture different assumptions about the distribution and to observe the effects of those assumptions. The probabilistic inference in a bayesian network can be *predictive*, dealing with probability changes of effects given information about their causes, but also *diagnostic*, inferring the likely causes based on the observed effects [(46)].

The graphical representation of a bayesian network is a directed acyclic graph, which describes causal relationships denoted by directed edges between variables or descriptors denoted by graph nodes. The bayesian network nodes are probabilistic random variables and can represent almost any types of system properties. The random nodes can represent mutually exclusive discrete states, but also continuous quantitative system properties, and both types can be used in the same model. For influence diagrams, a special case of bayesian belief network, also *decision nodes* and *utility nodes* are available as modeling primitives [(44)], representing alternative decisions or policies. Decision nodes affect the probability distributions of the random nodes. Utility nodes receive information from random or decision nodes, and model the utility, harm, gain or cost of the states of their dependencies: they represent the decision making criteria, against which alternative decisions are assessed and compared against each other. In a model holds several decision nodes, optimization of policy or interventions can be suggested by search of the combination of decision alternatives maximizing the expected utility or minimizing expected negative utility or harm. [(44,46)].

The graph edges represent causal dependency relationships of the head nodes on tail nodes, or as the bayesian network is a directed acyclic graph, dependency of child nodes on their parent nodes. The relationships are numerically defined by populating the node-specific conditional probability tables with conditional probability distributions. The parent nodes are causes and their child nodes are effects, which can in turn be causes for other effects further down the causal hierarchy. This distribution contains information on the probability of a variable being in a certain state, dependent on the state of its causes. For defining the dependencies numerically, several methods can be applied: deterministic or probabilistic simulations [(47,48)], using learning algorithms on empirical or statistical data directly[49,50], and expert elicitation[2,5,35], or some combination of these. It is common to augment the model information with expert informant elicited knowledge.

Modeling using bayesian networks is well supported by software implementations such as Netica[51] and Hugin[52] that enable versatile analytical outputs, well beyond the basic output of bayesian probability updating in a graph given some assumptions about the node states. Bayesian networks, however, specifically in systems modeling relying chiefly on expert elicited inputs, can be problematic. The number of required inputs, in cases of structurally complex models, easily becomes unmanageably high. As the structural complexity of the dependencies in the model increases, the amount of information required by the conditional probability table representation of the relationships grows exponentially. The number of conditional probabilities to be elicited for an effect e, in a case of n dependencies for e, is $\prod_{i=1}^{n} s(c_i) \times s(e)$, where $s(c_i)$ is the number of possible states a specific cause c_i can have, and $s(e)$ is the number of possible states of the dependent effect. An effect node with three possible states, and three dependencies, each also with three possible states, requires 81 conditional probabilities to have its relationship defined. While this number of values can be elicited from a determined expert group, it is laborious, as the 81 values will only define the relationship of *one* effect on its causes–and the model might have tens or hundreds of such effects. 4-state node with 5 dependencies having 4 possible states each would require elicitation of 4096 conditional probabilities. This is, with certainty, too much to ask even from the most dedicated expert panel. Such dependency structures are, based on the initial experiments of modeling with AXIOM, not uncommon in the way an expert group might want to model a system.

In expert elicitation of probability tables, the dependency structure of the model has to remain relatively simple to keep the number of elicited values manageable. The elicitation can aim at extracting parameters for probability distributions instead of the distributions directly, and this may reduce the work load, but this approach is normally applicable only for continuous variables, or discretized continuous variables. For discrete distributions without a logical ordering, probability updating signals implemented as updating functions as per the BASICS approach[9] or AXIOM approach are a possible, but apparently unutilized solution to reduce the elicitation work load.

Unlike other approaches discussed in this work, a bayesian network graph is acyclic, thus the method does not allow modeling of cyclic interaction. The temporal aspect of the system, in cases where the system is modeled as a bayesian network, is tightly coupled with the graph structure: no ambiguity about the cause-effect relationship between nodes is allowed, and structural inference loops are not normally possible. This imposes limitations on the expressive power of the model in higher abstraction level modeling exercises, such as modeling of societal, political or technological developments, typical in foresight.

AXIOM is, out of the approaches discussed in this chapter, conceptually and functionally, while not technically, closest to bayesian networks. An AXIOM model could be approximated with a bayesian network by *a)* allowing graph cycles in the bayesian model, *b)* replacing the bayesian updating logic with a monte carlo process, and *c)* describing the probabilistic effects of nodes on others by references to updating functions, akin to BASICS or AXIOM, instead of conditional probability tables. In this sense, AXIOM could be seen as a special case of a bayesian network, or to generalize into one. While full implementation of AXIOM is not apparently possible with e.g. the Hugin[52] or Netica[51] software, due to the limitations of the conditional statements that could be used to approximate the AXIOM updating functions, a relatively similar computation could, with great effort, be implemented within Hugin or Netica. To the best of the author's knowledge, such approach has never been used in the context of bayesian networks. AXIOM explicitly aims at providing similar inference capabilities as bayesian networks, making both predictive and diagnostic inference possible by means of the AXIOM iteration objects, discussed and illustrated in Section 4.3.

AXIOM provides direct decision support use, similar to influence diagrams, by use of the intervention statements in lieu of the decision nodes of the influence diagrams, and using any AXIOM statements in the model in a similar way utility nodes are treated in influence diagrams. The main difference is the modeling language, allowing causal loops, the timestep property, and easier description of interactions. Building and expanding on the updating functions approach adopted in BASICS(9,27), AXIOM provides a more feasible way to describe the expert knowledge base on the probabilistic interactions between the states of the descriptors, as the conditional probability table based description is replaced by a hazier and more approximate, but dramatically easier description. Adopting this approach means that the number of inputs to be elicited grows only linearly as the dependency structure becomes more complex, whereas in a bayesian network, the growth is exponential. Extraction of analytical outputs of structural or morphological nature can be performed with bayesian networks to a degree, although the meaningfulness of such analysis is limited due to the acyclic nature of the bayesian network. AXIOM approach supports structural and morphological analysis well, and the use of an AXIOM model for these purposes is illustrated in Section 4.3.

3.2. Gordon-Hayward Cross-Impact Analysis and SMIC

The early experiments with modeling the causal relationships on the basis of expert elicited inputs in the context of futures studies and foresight were performed in the late 1960's(7,26). The motivation for these modeling experiments was to be able to provide an auxiliary technique for forecasting and foresight work done utilizing expert panels, especially the Delphi technique. Gordon and Hayward(7) called the approach augmenting the Delphi technique by incorporating consideration of the interaction between the future events *cross-impact analysis*.

The next two decades saw a lot of discussion(7,8,26,53,54,55,56,57,58,59,60,61,62,63,64,65) on the methodological details of foresight-oriented cross-impact techniques and applications of, incremental amendments to and methodological proposals inspired by the cross-impact technique have been published with lower frequency since(10,13,24,25,34,66,67,68,69,70,71,72,73).

The techniques normally referred to as cross-impact analysis, and relatively widely used, are the Gordon-Hayward cross-impact analysis(7,25,26), henceforth referred to as GHCIA, and the SMIC approach by(10) . GHCIA and SMIC are probabilistic binary descriptor cross-impact models. If they are represented as graphs, their graph nodes are system descriptors, presenting a hypothesis or a postulate about the state of the system in the future, also called an event by Gordon(25). This state is assigned an initial or *a priori* probability of occurrence, which is the expert estimate of the probability of the hypothesis assuming no available information about the system, meaning that the states of the other descriptors is unknown.

Represented graphically, graphs for both approaches are cyclic, unlike a bayesian network. The edges carry information about the occurrence probability of the head node hypothesis, conditional to the occurrence of the tail node hypothesis. In the SMIC approach, the edges additionally carry information about the occurrence probability of the head node hypothesis, conditional to the non-occurrence of the tail node hypothesis [10,74]. In GHCIA, the probability of the head hypothesis conditional to the non-occurrence of tail hypothesis is inferred [25].

The expert-elicited conditional probabilities are, in the case of GHCIA, checked for compliance with the standard probability axioms. The following conditions for probabilities of any two hypotheses i and j should be met:

1. $0 \leq P(i) \leq 1$
2. $0 \leq P(i|j) \leq 1$
3. $\frac{P(i)-1+P(j)}{P(j)} \leq P(i|j) \leq \frac{P(i)}{P(j)}$

If the initial conditional probabilities do not fall within permissible bounds, it is the task of the expert group to resolve the inconsistency by changing either the conditional probabilities or the initial probability valuations. In the case of SMIC, the permissible bounds are reasoned in a different way and are more strict [74]. The SMIC software implementation features a linear optimization function [10], which corrects the initial expert-sourced valuations into permissible bounds, aiming to keep the corrected valuations as close to the original expert valuations as possible. The emphasis is on the discovery of a system of conditional probability valuations that is consistent by the SMIC criteria.

When the conditional probabilities have been defined, model evaluation can be performed. The evaluation process is a monte carlo process, where truth values are assigned to model descriptors in random order, according to the defined probabilities. When a descriptor is assigned a truth value, the probabilities of other descriptors are updated, using the odds ratio technique described by Gordon [25]. When all descriptors have been evaluated, the system of the model has a fully resolved state. This state can be thought of as a scenario. If a binary descriptor *occurs*, or is in the state true, in the scenario, a counter for its occurrences is incremented. The probabilities of the descriptors are reset to the initial values. The evaluation is repeated a large number of times.

The cross-impacted *posterior* probabilities are computed simply as the occurrence frequency of descriptors in the set of generated scenarios. The posterior probabilities reflect the influence of the impact network and aim at capturing the influence of longer impact chains. In GHCIA, the recommended analytical process is to test various assumptions with the model by changing the initial probability valuations, for instance to simulate interventions. Different initial setups are compared in terms of posterior probabilities. In the case of SMIC, the aim is to identify the most probable scenarios for further examination with other futures methods [10]: the inference of SMIC is *morphological* in nature, although it could relatively easily be used for the same purpose as GHCIA. For a system model of n hypotheses, SMIC outputs the probabilities for 2^n scenarios, ordered by their probability. Godet also recommends deriving an elasticity matrix for the variables by means of performing sensitivity analysis on the initial probability valuations of the variables.

As the interactions between the system components are expressed as conditional probabilities, and these conditional probabilities need to meet the above-stated conditions, the complexity of the system, measured by the number of descriptors, is recommended to be kept low: Godet et al.[10] recommend that the number of descriptors should not exceed 6. Any real systems modeling effort struggles to describe the system with such a limited number of descriptors, and the abstraction level in the model easily remains very high. The BASICS-like probability update strategy is a more viable solution for expert elicited modeling. As the descriptors are binary, mutually exclusive states for system components cannot be easily modeled, and an exhaustive state set cannot be modeled at all. GHCIA and SMIC also have no built-in way to express a time dimension in models: all the system descriptors exist in a single "temporal space". These features limit the modeling power practicality, and usability of the approaches in systems modeling.

From the GHCIA and SMIC, AXIOM inherits the idea of performing the model evaluation as a monte carlo process. The monte carlo process of AXIOM is quite different from GHCIA and SMIC, as its logic is influenced by the temporal relationship of the descriptors expressed with the timestep properties, the use of intervention statements, and possibly the non-simple updating functions, discussed under the description of the BASICS approach. In AXIOM, all the model evaluation rounds can be saved in the *iteration* objects and used as the basis of inference when the aim is to enable more complex probabilistic inference similar to bayesian networks and influence diagrams, or morphological outputs. Compared to GHCIA and SMIC, AXIOM also offers a more practical set of modeling primitives, as the AXIOM system descriptors are multivalued, and they have a built-in way of being temporally positioned against other descriptors with the *timestep* property.

3.3. The BASICS approach

An alternative approach to expressing the conditional probability effects in a cross-impact model is modeling them with *probability-updating signals* instead of plainly numerified conditional probabilities. This type of approach has been discussed by[43] and implemented in the BASICS approach[9,27] and later in the JL-algorithm[41] with incremental improvements.

In the BASICS modeling language, descriptors can have an arbitrary number (greater than one) of possible states, which are assigned prior probabilities, whose sum is equal to 1. The probability-changing interactions that the model components have on each other are expressed as references to probability updating functions. BASICS[9,27] updating functions take a probability to be updated as an argument and return an updated probability, altering the descriptors' probabilities *contextually*: update by the same function will result in a different amount of probability change in the influenced descriptor, depending on the value of the adjusted probability at the time of the update. This makes the description of probabilistic influences in the model hazier and approximate, but also dramatically reduces the difficulty and workload of describing the relationships between the system components. This is especially relevant in a system models with a great number of descriptors and complex dependencies. Expressing the relationships of the system components as references to probability updating functions, such as '+3' to indicate a positive probability-changing impact, or '−1' to indicate a smaller negative probability-changing impact, does away with the need to define conditional probabilities, and instead offers a way to express the interactions in an approximate way, but still keeping the quantified probabilities, central for decision support use, in the analysis.

Compared to the approach where full conditional probability tables, or GHCIA- or SMIC-like conditional probabilities satisfying the constraints defined for those approaches, are used to describe the causal dependency of an effect descriptor on a cause descriptor, the probability updating function approach is an approximate and 'hazy' way to quantitatively express the causal dependency. Similar dependency structures can be expressed, but a degree of accuracy is lost. What is gained is the easier way to describe the causal rules in the system, as the experts who are elicited can, instead of specifying conditional probabilities, invoke an appropriate probability update by referencing an updating function by the name of that function.

An example set of BASICS-like updating functions is graphed in Fig. 2. AXIOM also employs such updating functions. Updating functions of AXIOM are intended to be more versatile than the updating functions of BASICS, with the capability of both using other information in the model than the current probability for mapping it to an updated probability, and performing other updates to the model than simply updating probability values, such as immediately compelling a descriptor into a state and firing its updates instead of only updating probability distributions.

BASICS does not employ a Monte Carlo process in its model evaluation, and doesn't aim at producing a *posterior* probability distribution for the states of the system descriptors. In some applications of BASICS [27], posterior probabilities computed from the configurations produced by the model evaluation rounds are displayed, but it must be noted that the number of rounds performed in the BASICS approach is insufficient to compute posterior probabilities in the same sense as is done in bayesian networks, GHCIA, or AXIOM. Instead, BASICS employs a deterministic process, where the model is evaluated twice for each possible state of all of its descriptors, assuming the state in question to "be true" or occur, and in a different iteration to be "false" or not occur. In the evaluation of descriptors, the most probable state is selected, making the model evaluation deterministic. Each model evaluation produces a set of descriptor states occurring in that evaluation, and this set can be interpreted as a scenario. A model with 10 descriptors, with 3 states each, results in $10 \times 3 \times 2 = 60$ scenarios [9,27].

The motivation is to find scenarios that are "probable and consistent" [9], in the light of the supplied prior probabilities and interactions. The scenarios that emerge from multiple different evaluations are interpreted to be probable and consistent, warranting further study with other analytical techniques. In this sense, the output produced by BASICS is analytically serving a similar purpose as morphological analysis, discussed in Section 2.2. The information content of the BASICS model enables a wider range of outputs, but these possibilities are not documented or explored in the descriptions of the BASICS approach. JL-algorithm is derived from BASICS, and proposes changes to the model evaluation procedure to eliminate effects of the ordering of the descriptors in the user input, as they are significant in some of the BASICS approach implementations [41].

BASICS and JL-algorithm make it possible to identify morphologically consistent scenarios. They do not support simulation-style use of the model for testing the effect of interventions or other changes to the system that can be observed from posterior probabilities. Posterior probabilities could be made available for BASICS if the evaluation process would be changed so that a sufficient number of evaluations would be performed and the evaluation process would be changed to probabilistic instead of the deterministic way With these changes, the BASICS approach would be closer to the AXIOM approach. The analytical output, as the method is documented, is limited to the morphological output of identifying full system configurations that are probable with the given description of prior probabilities and interactions, inferred by the BASICS evaluation process.

From BASICS, AXIOM draws the basic idea of reducing the difficulty of the description of probabilistic rules of the system with contextual probability updates. AXIOM expands on the idea of updating functions used in the BASICS approach and JL-algorithm. The BASICS updating functions simply map a probability to an updated probability, and their only input is the old probability. AXIOM updating functions close over the entire model, and can use any information in it to map probabilities to updated probabilities. The probability updates can be made dependent on not only the occurrence of a single state in the model, but any set of states, or even the current probability distributions of a descriptor or a set of descriptors. This enables e.g. modeling of actor behaviour, that can be dependent on how likely some event or outcome appears at a specific moment. This difference makes the AXIOM updating functions much more expressive: they can be used to describe more complicated dependencies than BASICS updating functions. Conditional logic, that is possible to describe using conditional probability tables akin to bayesian networks, can be approximated with AXIOM updating functions. Additionally, the AXIOM updates can do more than simply change the probability distributions of the effect descriptors: The AXIOM updates can fire actions in the model, such as immediately setting a descriptor to a certain state, or some other change in the model, such as removing impacts, changing the updating functions of these impacts, or doing some other structural change in the model.

In terms of analytical outputs, AXIOM significantly widens the possibilities of BASICS. The BASICS output is morphological. AXIOM can deliver similar outputs, but it considerably expands the analysis of BASICS to the direction of probabilistic inference and decision support performed normally with bayesian networks and influence diagrams. AXIOM approach also supports extraction of structural outputs akin to EXIT, MICMAC and ADVIAN, and fuzzy cognitive maps.

4. The AXIOM Approach

AXIOM is a systems modeling approach designed for a specific niche of systems modeling, modeling of chiefly non-technical, non-deterministic systems with a complex interaction structure and with components of heterogenous nature, such as social, technological, economical, political or cultural components or driving forces. Components or system aspects of this nature often have relatively low quantifiability and data availability. Modeling such systems has to rely mostly on expert informants as the data source for definition of the relationships in the system, as there is not much statistical data to estimate the relationship in the form of a mathematical equation, using statistical modeling approaches such as regression analysis. The design of a modeling approach for this niche has to aim for a modeling language with high modeling power and fitness for use in expert elicitation, and a computational process enabling versatile analytical outputs and the use of the model to give as much information as possible of the modeled system, to compensate for the effort of constructing such a model. The modeling approaches discussed in Section 2.2 offer different solutions to the relevant design questions, and these solutions are assessed against the intended modeling use case requirements in Section 2.3 and Section 3. The design choices of AXIOM are based on this argumentation.

4.1. Modeling Language

The modeling language, or the set of model building blocks of AXIOM, used to describe a system and its interactions, consists of three main primitives: statements, options and impacts. Fig. 1 presents an entity-relationship model[(75)] of the AXIOM concepts.

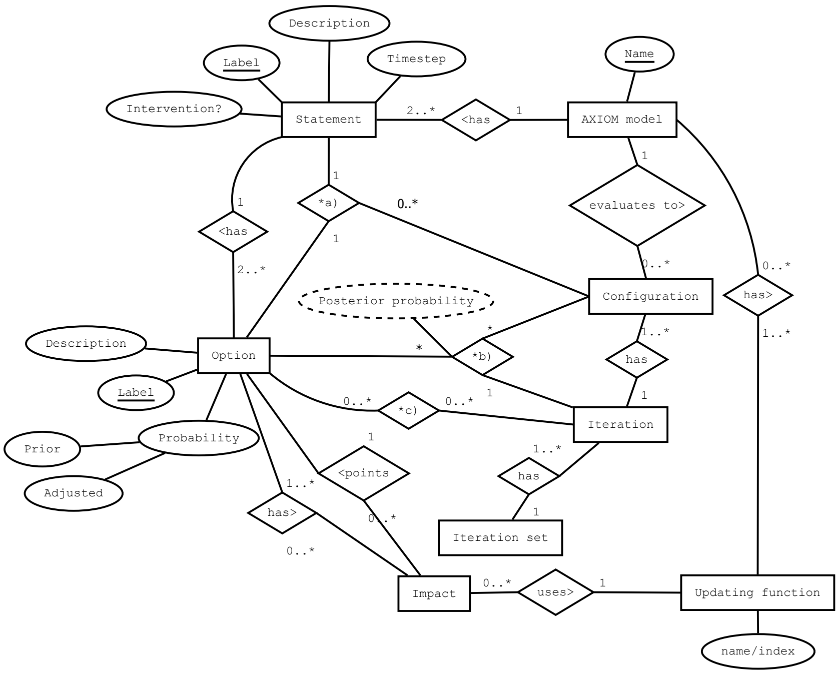

Figure 1: Entity-relationship model of AXIOM concepts.
***a)** *Statement* is evaluated to an *option* in a single *configuration*
***b)** A *configuration* in an *iteration* has a single *option* for each *statement* in the model; the *a posteriori probability* of each option is the rate of occurrence of the option in configurations in the iteration.
***c)** An *iteration* can have *options* as active interventions.

Statements represent components, driving forces and events of the modeled system. They have a temporal position (possibly equal) in relation to other statements in the model, called the *timestep* property. Statements also have a set of *options*, which are the possible values of the statement, or the (modeled) possible states of the system component the statement represents. The options have a probability value, indicating their likelihood to be assigned as the value of their respective statement. The initial probability is called the *prior* or *a priori* probability; the prior probability values of options under the same statement are estimated by the expert informants by assuming no available information about the system outside that particular statement. The options form a probability distribution, and the sum of probability values of all the options of a statement must equal 1: options are mutually exclusive, and thought to fully exhaust the range of possible states of the modeled system component and fully occupy the probability space.

Impacts represent probabilistic causal relationships between the system descriptors. Impacts are normally *simple impacts*, associated with two options in different statements, the cause option and the effect option. When the cause option is evaluated to be true, its effects are fired or 'take place', changing the probability of the effect option, as well as the probabilities of the complement options under the same statement as the effect option. Impacts can also be *non-simple*, modeling more complex dependencies, as discussed in Section 3.3, where several cause options influence the effect option. When the model, during its evaluation, arrives at a state where the causes of an impact are true, a probability update (or some other update, such as a structural update) takes place. At the model level, the action of updating probabilities or doing other updates to the model is performed when the model state changes, meaning that new information about the system is available. This is analogous to "unfolding of the future" in reality: as events take place or system components assume a specific state, the outlook of what might happen next and with what likelihood changes as a result of causalities and new information.

In the initial state of the model, the statements do not have a state, only a probability distribution for their possible values, the options. The *evaluation of a statement* consists of selecting one of the options of the statement (according to the probability distribution), assigning it as the state or value of the statement, and executing the impacts the selected option has, if any. Each option has a likelihood of being selected equal to its current probability value. The selected option is now thought to 'occur' or 'be true'. It has a possibly empty set of impacts targeting other options in other statements in the model. The impacts are now realized and change the probabilities of their target options. The probabilities of other options under the same statement as the target option are also updated in order to preserve a valid probability distribution. If the model has non-simple impacts with several conditions, the occurrence of these conditions is checked when the model state changes, and the updates are performed if conditions are met.

A simple impact is defined by its cause or source option, its effect or target option and an updating function reference, similar to the approach adopted in BASICS [(9)]. An AXIOM model has a set of updating functions, that are referenced by impacts to describe how the impact is meant to update the probability of the effect or target option, or what other updates to perform, in the case of non-simple impacts. Simple functions update the effect option probabilities contextually, mapping the current probability value to an updated value, reflecting the probabilistic influence the impact has on them. The probability updating functions have a domain of $[0, 1]$ and a codomain of $[0, 1]$. Additionally, simple updating functions are recommended to *(a)* be symmetric about the line $y = -x + 1$, *(b)* have the property $y(x_0) < y(x_1)$ when $x_0 < x_1$, and *(c)* have the property $y(x) > x$ if the name of the function implies positive (probability-increasing) impact, and the property $y(x) < x$ if the name of the function implies negative (probability-decreasing) impact. The purpose of describing relationships in the model with updating functions is to circumvent the need to define conditional probability tables (the rationale for this was discussed in Section 2.3). Instead, the effects of knowing that a specific model descriptor is 'true' or that a part of the system is in a certain state are delegated to a specific updating function. Seven simple probability updating functions named '0', '+1', '+2', '+3', '−1', '−2', '−3', are graphed in Fig. 2. Function "0" does not map any change to probability, representing a neutral relationship; "+3" represents the greatest positive change to probability out of the presented functions; "−1" represents a modest negative probability change. This updating function set enables modeling of probability effects as per the BASICS[9] approach. Unlike BASICS, an AXIOM model can have as many updating functions as are seen necessary to describe the relationships in the model.

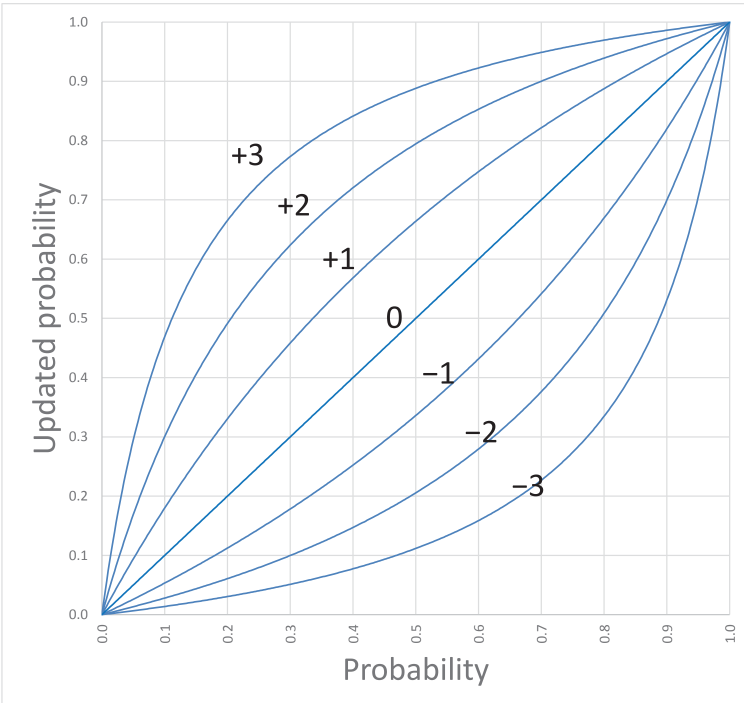

Figure 2: Seven *simple* AXIOM probability updating functions graphed. See also[9] for description of the BASICS updating functions.

Compared to the updating functions in BASICS, an AXIOM updating function can, instead of a probability update, force a statement immediately into a state, consequently firing all the updates linked to that state. Such an update would represent a deterministic relationship of a model state on some other state. AXIOM updating functions also close over the entire model and can use all information in the model, such as current probabilities of any option in it, to determine the amount of probability update. Such updating functions can, for instance, be used to model actor behaviour: The decision or behaviour of an actor would be represented by a statement or a set of statements in the model, and the likelihood of an actor to make a specific decision can be made dependent on the current probabilities of specific model states at the time the decision is made. An important use for the non-simple updating functions is modeling more complex dependencies than what can be modeled by binary updating functions with a cause option and an effect option. A probability update can be made conditional to several facts in the system, such as the occurence of a set of states instead of a single state. In bayesian networks, this type of dependency is expressed with conditional probability tables, and in some cases modelers might want to model such complex probabilistic dependencies. An AXIOM updating function can be made dependent of several facts, making modeling such more complex dependencies possible. Currently the AXIOM implementation supports only simple impacts and simple updating functions directly from input, but non-simple impacts and non-simple updating functions can be implemented by any user by accessing the freely available source code. The user interface will be expanded to support the use of non-simple updates as the development of the implementation proceeds.

4.2. Model Evaluation

Inference in AXIOM is based on a monte carlo process of repeated model evaluations. As illustrated by Fig. 1, a single model evaluation results in a *configuration*, which is saved to an *iteration* object, and several iterations with different initial setups make an *iteration set*. A pseudocode description of the AXIOM model evaluation process, as well as the computation of the *iterations* and *iteration sets* are presented in Appendix A.

A model evaluation means resolving the state of the model, by performing the evaluation of all the statements in the model. The order of evaluation is, firstly dictated by the timestep values of statements, and secondly random: statements with a lower timestep value are always evaluated before statements with a higher timestep value, and statements with equal timestep value are evaluated in random order. After the evaluation of all model statements, every descriptor has a state and therefore the whole model has a state (the combination of descriptor states emerged as a result of the evaluation): all options are either true or false. This result is saved. The probabilities of options are re-initialized to their prior probability values and a new model evaluation process is performed, again saving the result. The evaluation is performed a large number of times: the default number of evaluations in the AXIOM implementation is 10^6, but a higher number may be necessary in complex models to yield accurate estimates of the posterior probabilities. Each evaluation produces a *configuration*, a model state as a combination of descriptor states, which can be thought of as a scenario. The collection of configurations resulting from the monte carlo process is called an *iteration*. It captures the system states that result from a specific set of initial conditions.

From the iteration, it is possible to compute the *a posteriori* or *posterior* probabilities of the options in the model by simply counting the frequency of occurrence for each option. This posterior probability value takes into account the systemic, emergent higher-order interactions in the model. From the information content of the iteration, it is also possible to compute probabilities for *morphologies*, partial system states described by a specific set of options, by counting the frequency of those option sets in the iteration. The iteration is a dataset in the association rule learning sense, so the association rule learning concepts and operations can be used in its analysis. The posterior probabilities of single options, or option combinations (morphologies), are computed as their *support*. Other association rule learning operations like *confidence*, *lift* and *conviction* can also be computed from an iteration.

A major motivation for building system models is to gain the ability to test the behavior of the system under different assumptions, and simulate effects of changes to the system. Such changes can be prior probability valuations, strengths of model impacts, the structure of impacts, or structure of the model in terms of statements and options. Once these changes to the model have been made, the monte carlo process can be performed again, resulting in a new iteration. An *iteration set* is a collection of iterations under different initial setups of the model. The iterations in the iteration set are compared against each other to reveal the effect of the changes made, or the differences of outcomes between the setups.

AXIOM provides an analytical convenience mechanism called *intervention statements* to test the systemic effects of particular interventions. Statements can be flagged as intervention statements, which will then be treated specially in the model evaluation: intervention statements will not be evaluated in the normal probabilistic way, but will rather have a predefined state, already determined when the model evaluation commences. The states of the intervention statements change only between different iterations. Other details of the model evaluation are the same: the impacts of the predetermined options of the intervention statements take place when the intervention statement is taken up for evaluation. When the model has flagged intervention statements, an iteration set will automatically be generated with a single iteration capturing the normal model evaluation results without interventions and the rest of the iterations capturing each possible combination of the options of the flagged intervention statements. The function of intervention statements is that they can model policy actions, strategic options available to actors in the system or some other aspect of the system which the analyst wants to test in different states: intervention statements have the same function as *decision nodes* in influence diagrams.

4.3. Example Model and Analysis of Results

The AXIOM approach is illustrated with a system model presented by Weimer-Jehle for demonstration of the cross-impact balances[(13)] (CIB) approach, which in turn is amended from a BASICS cross-impact model presented by Honton et al[(9)]. The CIB model describes a limited set of drivers for oil price and the interactions between these forces and the oil price. The interactions are of direct causal nature, so the original CIB model is suited to be transformed into an AXIOM model. AXIOM model requires additional information of initial probabilities of options, timestep property values for statements, and probability updating functions, which have been added to the model, based on the judgment of the author. As described by Weimer-Jehle[(13)], the model does not attempt to comprehensively represent the system, but is meant to provide "an illustrative and manageable frame for description of the method". The model consists of five statements, having 3 to 4 options each and 16 altogether, and their directed probability-changing interactions, whose magnitudes are expressed with an integer in the range $[-3, +3]$. The amended AXIOM model with its statements and their timesteps, options and their initial probabilities, and impact valuations in an impact matrix format, is presented in Table 1. The impact magnitude indicators reference to the simple updating

Statement	Timestep	Option	A priori probability	World GDP growth			Borrowing, industrial countries			World tensions			OPEC cohesion			Oil price			
				<2%/yr	2-3%/yr	>3%/yr	high	medium	low	strong	moderate	weak	strong	moderate	weak	<20$	20-35$	35-50$	>50$
World GDP growth	1	<2%/yr	0.40				+2		−2	+2		−2				+2	+1	−1	−2
		2-3%/yr	0.35				−1	+2	−1							−1	+1	+1	−1
		>3%/yr	0.25				−2	+1	+1	−1		+1				−2	−1	+1	+2
Borrowing, industrial countries	1	high	0.25	+1		−1				+1		−1							
		medium	0.50																
		low	0.25	−1		+1				−1		+1							
World tensions	1	strong	0.10	+1		−1	+1		−1				+1		−1	−3	−2	+3	+2
		moderate	0.55																
		weak	0.35	−1		+1	−1		+1				−1		+1	+1	+2	−1	−2
OPEC cohesion	1	strong	0.20													−3	−2	+3	+2
		moderate	0.35													−1	+1	+1	−1
		weak	0.45													+1	+1		−2
Oil price	2	<20$	0.10	−2		+2	−1		+1				−2		+2				
		20-35$	0.30	−1		+1							+2	−1	−1				
		35-50$	0.35																
		>50$	0.25	+1		−1				+1		−1	−1		+1				

Table 1: Example AXIOM model, adapted from Weimer-Jehle[13]

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functions presented in Fig. 2: during the model evaluation, the probabilities of options are adjusted according to the function referenced in the impact matrix. In the table, row descriptors are the impactors and the column descriptors the impacted items: the impact valuation of option “<2%/yr” of statement “World GDP growth” is +2 and can be read from row 1, column 4 of the impact matrix of Table 1.

To illustrate the modeling of temporal dimension, the statement ”Oil price” has been placed in temporal category 2, whereas all the other statements are in category 1, and therefore resolved before the state of the oil price. As a result, the impacts that the ”Oil price” statement is modeled to have never take place in the example model, as all the other statements have already been evaluated before oil price. If additional statements with timestep 2 or higher would be added to the model, oil price could influence them. Similarly, if the timestep property of the oil price statement would be changed to 1, it would be evaluated ”simultaneously” with the other statements and would influence them.

The repeated model evaluation process described in Section 4.2 results in a set of model states, where each statement has a value (one of its options), or *configurations*. This set of configurations is called an *iteration*. Table 2 presents an iteration with 50 configurations, which are displayed in columns, so that the value (option) of the statement in that configuration is represented by a shaded cell. Each statement has been evaluated into one of its options in each configuration. The posterior probability for each of the options is calculated as the frequency of occurrence in the iteration, and presented in the

Table 2: An AXIOM *iteration* consisting of 50 *configurations*.

World GDP growth	<2%/yr	**1a**	■■■□■□■□□■■□□□□□■■□□□□■□□■□□■■□□□■□□■■□□■■□□■□□■■■	0.440
	2-3%/yr	**1b**	□□□□□□□■□□□■□□■□□□□■■■□■■□□■□□□□□□□□□□□■□□■□□■□□□□	0.240
	>3%/yr	**1c**	□□□■□■□□■□□□■■□■□□■□□□□□□□■□□□■■■□■■□□■□□□□■□□■□□□	0.320
Borrowing, industrial countries	high	**2a**	□□■□□□■□□■□□□■□□□□■□□□■□□□□■□□□□□■■□■■□■■□□□■□□■■□	0.320
	medium	**2b**	■□□■■■□□□□■■■□■■■■□■■■□■■■□□■■■■□□□□□□□□□■■□□□■□□■	0.500
	low	**2c**	□■□□□□□■■□□□□□□□□□□□□□□□□□■□□□□□■□□■□□■□□□■□■□□□□	0.180
World tensions	strong	**3a**	□□□□■□■□□■■□□□□□■□□□□□■□■□□□□□□□□□□□□□□□□□□□□□□□□□	0.140
	moderate	**3b**	■■■□□□□■□□□□■■■□□■■■□■□□□■■■■■■□■■□■□■■■□■■□■■■□□□	0.560
	weak	**3c**	□□□■□■□□■□□■□□□■□□□□■□□■□□□□□□□■□□■□■□□□■□□■□□□■■■	0.300
OPEC cohesion	strong	**4a**	□□□□■■□□□□□□□□■□□□□□■■■□□■■□□□□□□□□■□■□□□□■□□■□■□■	0.280
	moderate	**4b**	□□□□□□□■□□■□■■□□□□■■□□□■■□□□■□■□■□■□■□□□□■□□□□■□□□	0.300
	weak	**4c**	■■■■□□■□■■□■□□□■■■□□□□□□□□□■□■□■□■□□□□■■■□□■■□□□■□	0.420
Oil price	<20$	**5a**	□■□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□■□□□□□□■□□□□□□□□□	0.060
	20-35$	**5b**	■□■□□□□■□□□■□□□■□■□■□□□■□□□■□□□■□□□□■□■□□■□□■□□■■□	0.320
	35-50$	**5c**	□□□■■■■□■■■□■■■□■□□□■■■□■■■□■■■□□□■■□■□■□□■■□■■□□■	0.580
	>50$	**5d**	□□□□□□□□□□□□□□□□□□■□□□□□□□□□□□□□■□□□□□□□□□□□□□□□□□	0.040
		1a∧3a	□□□□■□■□□■■□□□□□■□□□□□■□□□□□□□□□□□□□□□□□□□□□□□□□□□	0.120
		5c∨5d	□□□■■■■□■■■□■■■□■□■□■■■□■■■□■■■□■□■■□■□■□□■■□■■□□■	0.620
		¬1c∧¬2a	■■□□■□□■□□■■□□■□■■□■■■□■■■□□■■□□□□□□□□□□□■■□□■□□□■	0.420
		(¬1c∧¬2a)∧(5c∨5d)	□□□□■□□■□□■□□□■□■□□□■■□□■■□□■■□□□□□□□□□□□□■□□■□□□■	0.280

last column. The four last rows of the table display the computation of probabilities of *morphologies*, combinations of options.

By computing occurrence frequencies of options and morphologies, possibly conditional to occurrence of other options and morphologies, various questions related to morphological, structural and probabilistic information needs can be posed to the model. These include

- What is the probability of atomic subscenarios (options) after the systemic effects have been accounted for?
- What are the probabilities of morphologies (specific combinations of system states)?
- Which system states are logical, compatible and consistent, judged by their frequent co-occurrence?
- What are, on the basis of the modeled direct relationships, the indirect, systemic relationships of the system descriptors?
- How will the system behave under a specific intervention or other change? (predictive probabilistic inference)
- What are the likely causes of an effect? (diagnostic probabilistic inference)
- What are the effects of combinations of interventions or changes?
- What are the strongest antecedents to specific system states?
- What are the outcomes of policies or strategies?
- What is the most preferable system state against some criteria?
- What are the most effective interventions to perform on the system to reach that preferable state?

The morphology $1a \wedge 3a$, meaning the combination of low world GDP growth and strong world tensions, has a probability of 0.12. The probability for morphology $5c \vee 5d$, where oil price is higher than 35$, has a probability of 0.62. The third presented morphology $(\neg 1c \wedge \neg 2a)$, a scenario where GDP growth is at most 3% annually and borrowing policy of industrial countries is not high, has a probability of 0.42, and the probability of that morphology occurring together with $5c \vee 5d$ is 0.28. Used in this way, AXIOM delivers analytical outputs of the *morpohological* nature, comparable to the cross-impact balances approach[13], SMIC approach[10], and BASICS and JL-algorithm approaches[9,41]. The 50 configurations presented Table 2 are obviously insufficient to compute posterior probabilities accurately, and the table is presented for illustration of how analytical outputs are derived from AXIOM iteration objects. From a sufficiently large set of configurations, the emergent, systemic characteristics of the model captured by the posterior probabilities can be estimated accurately (or to the degree of accuracy of the elicited inputs).

As the information content of an AXIOM iteration is like an association rule learning dataset, the association rule learning operations can be utilized in its analysis[76,77]. Computing the a posteriori probability of a single option or a more complex morphology is identical to computing the support of an itemset. *Confidence* can be used to compute the conditional probabilities of morphologies, given antecedent morphologies[77]. For instance, The confidence $(\neg 1c \wedge \neg 2a \Rightarrow 5c \vee 5d)$ is the conditional probablity of high oil prices given non-high GDP growth and non-high borrowing scenario. It is calculated as $\frac{\text{SUPPORT}((\neg 1c \wedge \neg 2a)\wedge(5c \vee 5d))}{\text{SUPPORT}(\neg 1c \wedge \neg 2a)} = \frac{0.28}{0.42} = 0.67$. Other association rule learning operations, such as *lift* and *conviction*[77] can be used to discover interesting and important relationships from the iteration objects' data content.

By examining the subset of configurations where a specific option of interest is "true", or the evaluated state of its statement, it is possible to compute the posterior probabilities of other model options, conditional to the presence of the system descriptor option of interest. By comparing these probabilities to the posterior probabilities computed from the total set of configurations, the magnitude of systemic impacts of the option of interest can be estimated as the difference. In a complex system model with complicated interdependencies and extant long causal impact chains, this systemic relationship might turn out to be very different to the modeled direct relationship, as it also accounts for all the indirect, mediated interaction of a system descriptor on another. Table 3 shows an impact matrix, reporting the systemic effect of row options on column options as the change in posterior probability conditional to the guaranteed realization of the row option. The changes that are within a margin of ± 0.015 are highlighted in grey, as these small differences result from the random component of the monte carlo process.

The posterior probability of option "Oil price: 35\$–50\$" is 0.434 overall, looking at the total set of configurations, but conditional to the presence or actualization of option "OPEC cohesion: strong", the probability is elevated to 0.772, and the difference +0.34 is presented in the impact matrix of Table 3 as the amount of probability change the systemic relationship of the impactor (row) descriptor has on the impacted (column) descriptor. This systemic relationship might not be directly observable from the model input data describing the direct interactions. Obviously this tabulation could also be multidimensional, showing the model options' posterior probabilities conditional to several antecedent options simultaneously. Used in this way, AXIOM can deliver analytical value of *structural* nature, comparable to MICMAC[10], ADVIAN[28] and EXIT[29,37] approaches.

Table 4 illustrates the use of AXIOM intervention statements and presents the posterior probabilities of the model options in ten different iterations, representing different

Table 3: Structural analysis using the AXIOM approach: Probability changes of options conditional to other model options.

Effects of	Effects on	World GDP growth			Borrowing, industrial countries			World tensions			OPEC cohesion			Oil price			
		<2%/yr	2-3%/yr	>3%/yr	high	medium	low	strong	moderate	weak	strong	moderate	weak	<20$	20-35$	35-50$	>50$
World GDP growth	<2%/yr				+0.18	−0.13	−0.05	+0.10	0	−0.11	0	0	0	+0.08	+0.02	−0.07	−0.03
	2-3%/yr				−0.11	+0.15	−0.04	−0.06	+0.03	+0.03	0	0	0	−0.05	+0.08	0	−0.04
	>3%/yr				−0.12	0	+0.11	−0.09	−0.04	+0.13	0	0	+0.02	−0.04	−0.10	+0.05	+0.10
Borrowing, industrial countries	high	+0.11	−0.02	−0.10				+0.07	+0.02	−0.08	0	0	0	0	−0.03	+0.02	0
	medium	0	0	0				0	+0.02	0	0	0	0	0	0	0	0
	low	−0.10	0	+0.10				−0.06	−0.04	+0.10	0	0	0	0	+0.03	−0.03	0
World tensions	strong	+0.14	−0.03	−0.11	+0.10	−0.03	−0.07				+0.11	+0.02	−0.13	−0.06	−0.38	+0.43	0
	moderate	+0.03	0	−0.03	0	0	−0.02				0	0	−0.02	+0.03	−0.05	0	+0.02
	weak	−0.08	0	+0.08	−0.06	0	+0.05				−0.06	−0.03	+0.09	0	+0.26	−0.23	−0.03
OPEC cohesion	strong	0	0	0	0	0	0	0	0	0				−0.06	−0.36	+0.34	+0.09
	moderate	0	0	0	0	0	0	0	0	0				−0.04	+0.06	0	0
	weak	0	0	0	0	0	0	0	0	0				+0.05	+0.09	−0.12	−0.02
Oil price	<20$	0	0	0	0	0	0	0	0	0	0	0	0				
	20-35$	0	0	0	0	0	0	0	0	0	0	0	0				
	35-50$	0	0	0	0	0	0	0	0	0	0	0	0				
	>50$	0	0	0	0	0	0	0	0	0	0	0	0				

assumptions about the system. The intervention statements are functionally similar to *decision nodes* of influence diagrams. Statements 'borrowing' and 'OPEC cohesion' have been flagged as intervention statements, so iterations in columns 6–14 display the posterior probabilities of model options under specific combinations of options of the intervention statements. The initial *prior* probabilities are presented in the fourth column ('A priori'). The fifth column ('No intervention') presents the cross-impacted *a posteriori* or *posterior* probabilities in an iteration without active interventions.

The remaining columns present the posterior probabilities under different combinations of options of the flagged intervention statements: each of them captures the systemic effects of a specific combination of a borrowing subscenario and a OPEC cohesion subscenario. Column 6 ("Borrowing:high+OPEC:strong") presents the posterior probabilities assuming a high borrowing policy and a strong OPEC cohesion; the last column presents the same information assuming a low borrowing policy and a weakly cohesive OPEC. The modeling results would seem to suggest, for instance, that the likelihood of high global GDP growth is maximized by observing a policy of low borrowing, and OPEC cohesion is insignificant for GDP growth (this might be considered obvious already by looking at the input data of the miniaturish example model, but observations of this nature are much less obvious in a more complex model). In this way, AXIOM can be used for predictive probabilistic inference, comparable to bayesian networks and influence diagrams[31,42], or Gordon-Hayward cross-impact analysis[7,26], testing the system under different conditions and policies, and comparing the results to other sets of conditions.

A utility function can be defined to help identify preferable combinations of interven-

Table 4: Probabilities of model options under different preconditions

		Utility valuation	A priori	No intervention	Borrowing: high + OPEC: strong	Borrowing: medium + OPEC: strong	Borrowing: low + OPEC: strong	Borrowing: high + OPEC: moderate	Borrowing: medium + OPEC: moderate	Borrowing: low + OPEC: moderate	Borrowing: high + OPEC: weak	Borrowing: medium + OPEC: weak	Borrowing: low + OPEC: weak
World GDP growth	<2%/yr	−2	0.40	0.378	0.492	0.375	0.275	0.492	0.375	0.276	0.491	0.377	0.276
	2-3%/yr	+1	0.35	0.330	0.313	0.344	0.328	0.313	0.344	0.328	0.314	0.342	0.327
	>3%/yr	+3	0.25	0.293	0.195	0.281	0.397	0.195	0.281	0.396	0.195	0.282	0.397
Borrowing, industrial countries	high	−1	0.25	0.258	1	0	0	1	0	0	1	0	0
	medium	+0	0.50	0.537	0	1	0	0	1	0	0	1	0
	low	+1	0.25	0.205	0	0	1	0	0	1	0	0	1
World tensions	strong	−4	0.10	0.162	0.226	0.147	0.099	0.225	0.148	0.099	0.225	0.148	0.1
	moderate	−2	0.55	0.513	0.531	0.531	0.482	0.532	0.53	0.481	0.531	0.532	0.481
	weak	+2	0.35	0.325	0.243	0.322	0.419	0.244	0.322	0.42	0.244	0.321	0.419
OPEC cohesion	strong	+0	0.20	0.194	1	1	1	0	0	0	0	0	0
	moderate	+1	0.35	0.336	0	0	0	1	1	1	0	0	0
	weak	+0	0.45	0.470	0	0	0	0	0	0	1	1	1
Oil price	<20$	+3	0.10	0.070	0.011	0.01	0.009	0.039	0.035	0.029	0.138	0.124	0.107
	20-35$	+1	0.30	0.430	0.07	0.071	0.07	0.469	0.494	0.507	0.49	0.527	0.554
	35-50$	+0	0.35	0.435	0.786	0.77	0.751	0.446	0.419	0.403	0.338	0.308	0.291
	>50$	−4	0.25	0.065	0.134	0.149	0.17	0.046	0.052	0.061	0.034	0.04	0.047
		Utility score	−0.6	+0.1	−3.0	−1.1	+0.9	−1.2	+0.8	+2.8	−1.8	+0.2	+2.1

tions or preferable scenarios overall. In this capacity, AXIOM can deliver similar outputs as an influence diagram. Any AXIOM node can function akin to a *utility node* in an influence diagram, with an appropriate utility function. A simple utility function can be defined by assigning an utility valuation for all model options, as is done in column 3 ("Utility valuation") of Table 4. The unpreferability of an option is expressed with negative utility valuation and preferability with positive valuation. The utility score (in the last row of Table 4) is then computed by multiplying the probability of an option with its index and summing the values. The utility function could also be based on probabilities of more complicated morphologies. Based on this simple utility function, and the very subjective utility valuation of subscenarios represented by the model options, the intervention combination of low borrowing and moderate OPEC cohesion appears the most optimal scenario.

The same information could be derived with association rule learning operations, by only examining configurations where the intervention statements have the desired option as their state, and computing the posterior probabilities for other options from that subset of configurations. The intervention statement functionality, however, limits the number of required evaluations and enables easy comparison of model outputs under different assumptions about the system, this assumed, by the author, to be the typical use case for higher-order information extraction from an AXIOM model.

The *inverse logic* or *diagnostic inference*, or inferring the likely causes given some observed effects, typical in bayesian networks, can be performed with AXIOM as well. The process is simply to generate a sufficient number of configurations, select from those configurations the ones where the observed effects under investigation occur, and compute the posterior probabilities of causes from that set of configurations. Computationally this is inefficient in comparison to the diagnostic inference of bayesian networks, but still completely feasible.

As the AXIOM iteration objects are itemsets, they can be used as input for algorithms that learn bayesian networks from such inputs: a bayesian network can be derived from AXIOM output. The resulting bayesian network can then be augmented with other bayesian network model components based on empirical or statistical data. This enables combining expert-elicited modeling results and data-based modeling results in the same analytical framework.

4.4. Software Implementation

The software capable of performing the AXIOM transformation described in Section 4.2 is freely available[(78)]. The current implementation does not feature advanced association rule learning functionalities, but can output data that can easily be analysed with, for example, free tools available for R environment, such as the `arules` package[(79)]. The main analysis functionalities, iteration sets and intervention statements, are available in the AXIOM implementation. As mentioned in Section 4.1, the implementation does not yet support addition of non-simple updating functions directly from input, but this functionality will be added in the future.

5. Discussion

This paper gave a review of the various modeling approaches based on expert inputs, used in high abstraction level modeling of systems with modeling challenges related to lack of statistical data and exhibiting low quantifiability of important system characteristics. Against the background of this review, the design choices of these approaches were assessed with their fitness to expert informant elicited modeling process in mind. The identified design features with relatively high fitness for this purpose have been the outset for the design of AXIOM as a systems modeling approach. AXIOM proposes a combination of inference practices familiar from bayesian networks and influence diagrams, and the best aspects of several techniques in the cross impact analysis tradition. The aim is to provide a flexible and expressive modeling language suitable for use in modeling using expert informants as the primary data source and versatile analysis facilities covering probabilistic, structural and morphological analytical outputs and insights.

Providing tools and techniques suitable for expert informant oriented systems modeling is important as it brings systems thinking and enables modeling based research in study of systems that would be difficult to model otherwise, using more traditional data driven techniques. Having approaches for modeling of such systems and system aspects adds important tools to modelers' toolbox and to decision support and planning activities. Expert informants as a data source enable adding important considerations to models, possibly improving decision-making by expanding the scope of foresight, strategy and policy-making. With suitable tools, systems modeling based on expert elicited inputs is, from the technical expertise requirement standpoint, easier than data-driven modeling. This may lower the threshold of using modeling as a research approach in fields where modeling is less used. Probabilistic models are also often more accessible and understandable from a model user standpoint: The logical and causal structure and the theoretical foundation of the model is very transparent compared to many data-driven models.

Composing formal representations of real systems is challenging regardless of what the used tools and approaches are, but the process is useful at multiple levels when dealing with dealing with complex systems and 'diabolical' decision-making contexts. The modeling itself, without any computational techniques aimed at discovery of higher-order information from the system model, partitions the expert-laden understanding of the system and the theory of its internal dynamics into an abstracted representation, useful in understanding the system and discussing its features. The formality of the model enables generic computational transformations that can reveal systemic and emergent properties of the model which are difficult to observe intuitively, without inference procedures.

6. Conclusions and Future Work

The development of the AXIOM approach and the software implementation is ongoing. A high priority update to the implementation is to add support for defining non-simple updating functions directly in the user input. Currently the implementation has several sets of updating functions, but defining new updating functions requires changes to the source code.

The modeling language can be expanded in a number of ways. The introduction of system descriptors representing continuous values is a possibility: such modeling primitives are available in software implementations of bayesian networks and influence diagrams. While continuous value descriptors would increase the modeling power marginally, they are not strictly needed, as the same information can be represented with discrete state descriptors, and they are easier for expert valuators of the model, as the probability changes, modeled 'hazily' using the updating function approach, could be argued to be more predictable in their case.

Introducing ways to parameterize parts of an AXIOM model on the basis of statistical data instead of expert elicitation is an interesting idea and might widen the use sphere of the approach considerably, but such parameterization might prove challenging to do in a justified way. A more feasible approach to combine expert elicited modeling and data-driven approaches in the same framework is to perform the heavily expert informant based parts of a systems modeling process with the AXIOM approach, and use the AXIOM output in parameterization of a bayesian network, which can then be augmented with statistical data.

The development of the software implementation from an ease-of-use perspective is probably more important for the adoption of the method than incremental modeling language expansions. Currently the implementation has no graphical user interface: the model is fed to the computer program in a text file. While the current implementation is completely sufficient to perform the analyses presented in this paper, creating a graphical user interface would lower the adoption barrier considerably.

Biographies

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References

[1] J. A. Sokolowski, C. M. Banks, Principles of Modeling and Simulation: A Multidisciplinary Approach, Wiley, 2009.
URL `https://books.google.fi/books?id=wOOikQEACAAJ`

[2] A. O'Hagan, C. E. Buck, A. Daneshkhah, J. R. Eiser, P. H. Garthwaite, D. J. Jenkinson, J. E. Oakley, T. Rakow, Uncertain Judgements: Eliciting Experts' Probabilities, John Wiley & Sons, Chichester, UK, 2006. `doi:10.1002/0470033312`.
URL `http://doi.wiley.com/10.1002/0470033312`

[3] D. N. Ford, J. D. Sterman, Expert knowledge elicitation to improve formal and mental models, System Dynamics Review 14 (4) (1997) 309–340. `doi:10.1002/(SICI)1099-1727(199824)14:4<309::AID-SDR154>3.0.CO;2-5`.

[4] S. L. Choy, R. O'Leary, K. Mengersen, Elicitation by design in ecology: Using expert opinion to inform priors for Bayesian statistical models, Ecology 90 (1) (2009) 265–277.

[5] A. James, S. L. Choy, K. Mengersen, Elicitator: An expert elicitation tool for regression in ecology, Environmental Modelling & Software 25 (1) (2010) 129–145. `doi:10.1016/J.ENVSOFT.2009.07.003`.
URL `https://www.sciencedirect.com/science/article/pii/S1364815209001704`

[6] P. M. Kuhnert, T. G. Martin, S. P. Griffiths, A guide to eliciting and using expert knowledge in Bayesian ecological models, Ecology letters 13 (7) (2010) 900–914.

[7] T. Gordon, H. Hayward, Initial experiments with the cross impact matrix method of forecasting, Futures 1 (2) (1968) 100–116. `doi:http://dx.doi.org/10.1016/S0016-3287(68)80003-5`.

[8] M. Godet, Scenarios of air transport development to 1990 by SMIC 74–A new cross-impact method, Technological Forecasting and Social Change 9 (3) (1976) 279–288. `doi:10.1016/0040-1625(76)90012-3`.
URL `https://doi.org/10.1016/0040-1625(76)90012-3`

[9] E. J. Honton, G. S. Stacey, S. M. Millett, Future Scenarios: The BASICS Computational Method, Economics and policy analysis occasional paper, Battelle Columbus Division, 1984.

[10] M. Godet, J. F. Coates, Unesco, From Anticipation to Action: A Handbook of Strategic Prospective, Future-oriented studies, Unesco Publishing, 1994.

[11] V. Linss, A. Fried, Advanced Impact Analysis: The ADVIAN method–an enhanced approach for the analysis of impact strengths with the consideration of indirect relations, Tech. rep., Chemnitz University of Technology (2009).

[12] T. Ritchey, Problem structuring using computer-aided morphological analysis, Journal of the Operational Research Society 57 (7) (2006) 792–801. `doi:10.1057/palgrave.jors.2602177`.
URL `http://dx.doi.org/10.1057/palgrave.jors.2602177`

[13] W. Weimer-Jehle, Cross-impact balances: A system-theoretical approach to cross-impact analysis, Technological Forecasting and Social Change 73 (4) (2006) 334–361. `doi:10.1016/j.techfore.2005.06.005`.
URL `https://doi.org/10.1016/j.techfore.2005.06.005`

[14] M. Leonelli, J. Q. Smith, Bayesian decision support for complex systems with many distributed experts, Annals of Operations Research 235 (1) (2015) 517–542. `doi:10.1007/s10479-015-1957-7`.
URL `http://link.springer.com/10.1007/s10479-015-1957-7`

[15] M. Culka, Uncertainty analysis using Bayesian model averaging: A case study of input variables to energy models and inference to associated uncertainties of energy scenarios, Energy, Sustainability and Society 6 (1). `doi:10.1186/s13705-016-0073-0`.
URL `https://doi.org/10.1186/s13705-016-0073-0`

[16] J. Bromley, N. A. Jackson, O. J. Clymer, A. M. Giacomello, F. V. Jensen, The use of Hugin® to develop Bayesian networks as an aid to integrated water resource planning, Environmental Modelling & Software 20 (2) (2005) 231–242.

[17] D. Cinar, G. Kayakutlu, Scenario analysis using Bayesian networks: A case study in energy sector, Knowledge-Based Systems 23 (3) (2010) 267–276. `doi:https://doi.org/10.1016/j.knosys.2010.01.009`.
URL `http://www.sciencedirect.com/science/article/pii/S0950705110000110`

[18] International Council on Systems Engineering (INCOSE), What is systems engineering? (nov 2017). URL http://www.incose.org/AboutSE/WhatIsSE
[19] P. Checkland, Systems Thinking, Systems Practice, Wiley, 1999.
[20] J. Banks, J. Carson, B. Nelson, D. Nicol, Discrete-Event System Simulation, Pearson, 2005.
[21] B. P. Zeigler, H. Praehofer, T. G. Kim, Theory of Modeling and Simulation: Integrating Discrete Event and Continuous Complex Dynamic Systems, Academic press, 2000.
[22] H. J. Adèr, Advising on Research Methods: A Consultant's Companion, Johannes van Kessel Publishing., 2008.
[23] C. A. Pollino, O. Woodberry, A. Nicholson, K. Korb, B. T. Hart, Parameterisation and evaluation of a Bayesian network for use in an ecological risk assessment, Environmental Modelling & Software 22 (8) (2007) 1140–1152.
[24] M. Godet, F. Bourse, P. Chapuy, I. Menant, Futures Studies: A Tool-box for Problem Solving, Futuribles, GERPA Prospective, 1991.
[25] T. J. Gordon, Cross impact method, Tech. rep., United Nations University Millennium Project (1994).
[26] T. J. Gordon, Cross-impact matrices: An illustration of their use for policy analysis, Futures 1 (6) (1969) 527–531.
[27] W. R. Huss, E. J. Honton, Scenario planning–What style should you use?, Long Range Planning 20 (4) (1987) 21–29. doi:http://dx.doi.org/10.1016/0024-6301(87)90152-X.
[28] V. Linss, A. Fried, The ADVIAN classification–A new classification approach for the rating of impact factors, Technological Forecasting and Social Change 77 (1) (2010) 110–119.
[29] J. Panula-Ontto, K. A. Piirainen, EXIT: An alternative approach for structural cross-impact modeling and analysis, Technological Forecasting and Social Changedoi:10.1016/J.TECHFORE.2018.06.046.
URL https://www.sciencedirect.com/science/article/pii/S004016251731644X
[30] I. Johansen, Scenario modelling with morphological analysis, Technological Forecasting and Social Change 126 (2018) 116–125. doi:https://doi.org/10.1016/j.techfore.2017.05.016.
URL http://www.sciencedirect.com/science/article/pii/S004016251730656X
[31] E. J. M. Lauría, P. J. Duchessi, A Bayesian belief network for IT implementation decision support, Decision Support Systems 42 (3) (2006) 1573–1588.
[32] K. Kristensen, I. A. Rasmussen, The use of a Bayesian network in the design of a decision support system for growing malting barley without use of pesticides, Computers and Electronics in Agriculture 33 (3) (2002) 197–217.
[33] E. Baran, T. Jantunen, Stakeholder consultation for Bayesian decision support systems in environmental management, Forest 27 (35.6) (2004) 37–1.
[34] A. Ceric, Analysis of interactions between IT and organisational resources in a manufacturing organisation using cross-impact analysis, Journal of Enterprise Information Management 29 (4) (2016) 589–611. arXiv:https://doi.org/10.1108/JEIM-04-2015-0027, doi:10.1108/JEIM-04-2015-0027.
URL https://doi.org/10.1108/JEIM-04-2015-0027
[35] S. Kuikka, O. Varis, Uncertainties of climatic change impacts in Finnish watersheds: A Bayesian network analysis of expert knowledge, Boreal Environment Research 2 (1) (1997) 109–128.
[36] R. A. Kelly, A. J. Jakeman, O. Barreteau, M. E. Borsuk, S. ElSawah, S. H. Hamilton, H. J. Henriksen, S. Kuikka, H. R. Maier, A. E. Rizzoli, H. van Delden, A. A. Voinov, Selecting among five common modelling approaches for integrated environmental assessment and management, Environmental Modelling & Software 47 (2013) 159–181. doi:https://doi.org/10.1016/j.envsoft.2013.05.005.
URL http://www.sciencedirect.com/science/article/pii/S1364815213001151
[37] J. Panula-Ontto, J. Luukkanen, J. Kaivo-oja, T. O'Mahony, J. Vehmas, S. Valkealahti, T. Björkqvist, T. Korpela, P. Järventausta, Y. Majanne, M. Kojo, P. Aalto, P. Harsia, K. Kallioharju, H. Holttinen, S. Repo, Cross-Impact Analysis of Finnish Electricity System with Increased Renewables: Long-run Energy Policy Challenges in Balancing Supply and Consumption, Energy Policy 118 (2018) 504–513. doi:10.1016/J.ENPOL.2018.04.009.
URL https://www.sciencedirect.com/science/article/pii/S0301421518302246
[38] R. M. Axelrod, Structure of Decision: The Cognitive Maps of Political Elites, Princeton University Press, 1976.
URL http://www.jstor.org/stable/j.ctt13x0vw3
[39] B. Kosko, Fuzzy cognitive maps, International Journal of Man-Machine Studies 24 (1) (1986) 65–75. doi:10.1016/S0020-7373(86)80040-2.

URL https://www.sciencedirect.com/science/article/pii/S0020737386800402
[40] R. Rhyne, Technological forecasting within alternative whole futures projections, Technological Forecasting and Social Change 6 (1974) 133–162. doi:https://doi.org/10.1016/0040-1625(74)90014-6.
URL http://www.sciencedirect.com/science/article/pii/0040162574900146
[41] J. Luukkanen, Role of planning philosophy in energy policy formulation, Ph.D. thesis, Tampere University of Technology (1994).
[42] R. G. Cowell, P. Dawid, S. L. Lauritzen, D. J. Spiegelhalter, Probabilistic Networks and Expert Systems: Exact Computational Methods for Bayesian Networks, Springer Science & Business Media, 2006.
[43] S. Enzer, Cross-impact techniques in technology assessment, Futures 4 (1) (1972) 30–51. doi:http://dx.doi.org/10.1016/0016-3287(72)90023-7.
[44] F. V. Jensen, T. D. Nielsen, Bayesian Networks and Decision Graphs, Springer, 2007.
[45] S. E. Fienberg, When did Bayesian inference become "Bayesian"?, Bayesian Analysis 1 (1) (2006) 1–40. doi:10.1214/06-BA101.
URL http://projecteuclid.org/euclid.ba/1340371071
[46] A. Lehikoinen, Bayesian network applications for environmental risk assessment, Ph.D. thesis, University of Helsinki (2014).
[47] S. Dorner, J. Shi, D. Swayne, Multi-objective modelling and decision support using a Bayesian network approximation to a non-point source pollution model, Environmental Modelling & Software 22 (2) (2007) 211–222. doi:10.1016/J.ENVSOFT.2005.07.020.
URL https://www.sciencedirect.com/science/article/pii/S1364815205001817
[48] M. Rahikainen, I. Helle, P. Haapasaari, S. Oinonen, S. Kuikka, J. Vanhatalo, S. Mäntyniemi, K.-M. Hoviniemi, Toward integrative management advice of water quality, oil spills, and fishery in the Gulf of Finland: A Bayesian approach, AMBIO 43 (1) (2014) 115–123. doi:10.1007/s13280-013-0482-7.
URL http://link.springer.com/10.1007/s13280-013-0482-7
[49] S. Acid, L. M. de Campos, J. M. Fernandez-Luna, S. Rodriguez, J. M. Rodriguez, J. L. Salcedo, A comparison of learning algorithms for Bayesian networks: A case study based on data from an emergency medical service, Artificial Intelligence in Medicine 30 (3) (2004) 215–232, bayesian Networks in Biomedicine and Health-Care. doi:https://doi.org/10.1016/j.artmed.2003.11.002.
URL http://www.sciencedirect.com/science/article/pii/S0933365703001325
[50] C. Riggelsen, Learning parameters of Bayesian networks from incomplete data via importance sampling, International Journal of Approximate Reasoning 42 (1-2) (2006) 69–83. doi:10.1016/J.IJAR.2005.10.005.
URL https://www.sciencedirect.com/science/article/pii/S0888613X05000654
[51] Norsys Software Corporation, Netica, Computer software (2004).
URL http://www.norsys.com
[52] U. B. Kjærulff, A. L. Madsen, Bayesian Networks and Influence Diagrams: A Guide to Construction and Analysis, Springer New York, 2013.
[53] M. Turoff, An alternative approach to cross impact analysis, Technological Forecasting and Social Change 3 (1971) 309–339. doi:10.1016/s0040-1625(71)80021-5.
URL https://doi.org/10.1016/s0040-1625(71)80021-5
[54] N. C. Dalkey, An elementary cross-impact model, Technological Forecasting and Social Change 3 (1971) 341–351. doi:10.1016/s0040-1625(71)80022-7.
URL https://doi.org/10.1016/s0040-1625(71)80022-7
[55] J. Kane, A primer for a new cross-impact language–KSIM, Technological Forecasting and Social Change 4 (2) (1972) 129–142. doi:http://dx.doi.org/10.1016/0040-1625(72)90010-8.
[56] A. W. Blackman, A cross-impact model applicable to forecasts for long-range planning, Technological Forecasting and Social Change 5 (3) (1973) 233–242. doi:10.1016/0040-1625(73)90002-4.
URL https://doi.org/10.1016/0040-1625(73)90002-4
[57] J. E. Jackson, W. H. Lawton, Some probability problems associated with cross-impact analysis, Technological Forecasting and Social Change 8 (3).
URL https://doi.org/10.1016/0040-1625(76)90004-4
[58] I. I. Mitroff, M. Turoff, On the distance between cross-impact models: A set of metric measures for cross-impact analysis, Technological Forecasting and Social Change 8 (3) (1976) 275–283. doi:10.1016/0040-1625(76)90005-6.
URL https://doi.org/10.1016/0040-1625(76)90005-6
[59] M. F. Bloom, Time-dependent event cross-impact analysis: Results from a new model, Technological

Forecasting and Social Change 10 (2) (1977) 181–201. doi:10.1016/0040-1625(77)90044-0.
URL https://doi.org/10.1016/0040-1625(77)90044-0

[60] J. P. Martino, K.-L. Chen, Cluster analysis of cross impact model scenarios, Technological Forecasting and Social Change 12 (1) (1978) 61–71. doi:10.1016/0040-1625(78)90035-5.
URL https://doi.org/10.1016/0040-1625(78)90035-5

[61] E. Nováky, K. Lóránt, A method for the analysis of interrelationships between mutually connected events: A cross-impact method, Technological Forecasting and Social Change 12 (2-3) (1978) 201–212. doi:10.1016/0040-1625(78)90056-2.
URL https://doi.org/10.1016/0040-1625(78)90056-2

[62] Y. Kaya, M. Ishikawa, S. Mori, A revised cross-impact method and its applications to the forecast of urban transportation technology, Technological Forecasting and Social Change 14 (3) (1979) 243–257. doi:10.1016/0040-1625(79)90080-5.
URL https://doi.org/10.1016/0040-1625(79)90080-5

[63] J. R. Burns, W. M. Marcy, Causality: Its characterization in system dynamics and KSIM models of socioeconomic systems, Technological Forecasting and Social Change 14 (4) (1979) 387–398. doi:10.1016/0040-1625(79)90036-2.
URL https://doi.org/10.1016/0040-1625(79)90036-2

[64] M. Ishikawa, M. Toda, S. Mori, Y. Kaya, An application of the extended cross impact method to generating scenarios of social change in Japan, Technological Forecasting and Social Change 18 (3) (1980) 217–233. doi:10.1016/0040-1625(80)90024-4.
URL https://doi.org/10.1016/0040-1625(80)90024-4

[65] J. Brauers, M. Weber, A new method of scenario analysis for strategic planning, Journal of Forecasting 7 (1) (1988) 31–47. doi:10.1002/for.3980070104.
URL https://doi.org/10.1002/for.3980070104

[66] G. H. Jeong, S. H. Kim, A qualitative cross-impact approach to find the key technology, Technological Forecasting and Social Change 55 (3) (1997) 203–214. doi:10.1016/s0040-1625(96)00209-0.
URL https://doi.org/10.1016/s0040-1625(96)00209-0

[67] C. Choi, S. Kim, Y. Park, A patent-based cross impact analysis for quantitative estimation of technological impact: The case of information and communication technology, Technological Forecasting and Social Change 74 (8) (2007) 1296–1314. doi:10.1016/j.techfore.2006.10.008.
URL https://doi.org/10.1016/j.techfore.2006.10.008

[68] M. Pagani, Roadmapping 3G mobile TV: Strategic thinking and scenario planning through repeated cross-impact handling, Technological Forecasting and Social Change 76 (3) (2009) 382–395. doi:10.1016/j.techfore.2008.07.003.
URL https://doi.org/10.1016/j.techfore.2008.07.003

[69] D. Thorleuchter, D. V. den Poel, A. Prinzie, A compared R&D-based and patent-based cross impact analysis for identifying relationships between technologies, Technological Forecasting and Social Change 77 (7) (2010) 1037–1050. doi:10.1016/j.techfore.2010.03.002.
URL https://doi.org/10.1016/j.techfore.2010.03.002

[70] N. Agami, M. Saleh, H. El-Shishiny, A fuzzy logic based trend impact analysis method, Technological Forecasting and Social Change 77 (7) (2010) 1051–1060. doi:10.1016/j.techfore.2010.04.009.
URL https://doi.org/10.1016/j.techfore.2010.04.009

[71] V. A. Bañuls, M. Turoff, Scenario construction via Delphi and cross-impact analysis, Technological Forecasting and Social Change 78 (9) (2011) 1579–1602. doi:10.1016/j.techfore.2011.03.014.
URL https://doi.org/10.1016/j.techfore.2011.03.014

[72] V. A. Bañuls, M. Turoff, S. R. Hiltz, Collaborative scenario modeling in emergency management through cross-impact, Technological Forecasting and Social Change 80 (9) (2013) 1756–1774. doi:10.1016/j.techfore.2012.11.007.
URL https://doi.org/10.1016/j.techfore.2012.11.007

[73] E. Medina, R. D. Arce, R. Mahía, Barriers to the investment in the concentrated solar power sector in Morocco: A foresight approach using the cross impact analysis for a large number of events, Futures 71 (2015) 36–56. doi:10.1016/j.futures.2015.06.005.

[74] J. C. Duperrin, M. Godet, SMIC 74–A method for constructing and ranking scenarios, Futures 7 (4) (1975) 302–312. doi:https://doi.org/10.1016/0016-3287(75)90048-8.
URL http://www.sciencedirect.com/science/article/pii/0016328775900488

[75] P. P.-S. Chen, The Entity-Relationship model–Toward a unified view of data, in: Readings in Artificial Intelligence and Databases, Elsevier, 1988, pp. 98–111.

[76] G. Piatetsky-Shapiro, Discovery, analysis, and presentation of strong rules, Knowledge Discovery in Databases (1991) 229–238.

URL https://ci.nii.ac.jp/naid/10000000985/en/

[77] M. Hahsler, B. Grün, K. Hornik, Introduction to ARULES–Mining association rules and frequent item sets, SIGKDD Explor 2 (4) (2007) 1–28.

[78] J. Panula-Ontto, AXIOM: Advanced Cross-Impact Option Method, https://github.com/jmpaon/AXIOM (2017).
URL https://github.com/jmpaon/AXIOM

[79] R Core Team, R: A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austria, package "arules" (2014).
URL http://www.R-project.org/

Appendix A. Pseudocode description of the AXIOM model evaluation

This appendix presents the pseudocode detailing the computational procedure of evaluating an AXIOM model and generating iterations and iteration sets. Algorithm 1 presents the process of model evaluation.

Algorithm 1 AXIOM model evaluation

```
function evaluateModel(AXIOM Model m) : Configuration c
    for all unique timestep values t in m from lowest to highest t do
        ss ← statements in m that have timestep t
        shuffle(ss)                              ▷ Place statements in random order
        for all Statement s in ss do
            evaluateStatement(s)
            add s.state to c
            ns ← non-simple impacts of m whose conditions are true
            while ns.count > 0 do
                n ← random element from ns
                n.updatingFunction(m)
                check validity of m
                update c if new statements have been resolved
                remove n
                ns ← non-simple impacts of m whose conditions are true
    return c
```

The model statements are evaluated in the order determined by their timestep properties. Statements with equal timestep property values are evaluated in random order. Simple probability updates, tied to a single cause, are performed in the statement evaluation procedure. When the model state changes, the non-simple impacts whose conditions are true are executed in random order, and removed after their execution. After a non-simple update, the model validity (mainly the probability distributions of option sets of statements) is checked. A non-simple update may resolve several statements of the model, so these state changes are updated to the configuration being created in the model evaluation. The non-simple update may also make conditions of other non-simple impacts true, so the list of non-simple impacts is repopulated after a state change.

The statement evaluation procedure (Algorithm 2) *a*) assigns a state for the statement, and *b*) for each *simple* impact the assigned state has, calls the procedure to effectuate the impact. The intervention statements have a predefined state in the model being

Algorithm 2 AXIOM statement evaluation

procedure EVALUATESTATEMENT(`Statement` s)
    if s is an intervention statement **then**
        s.state $\leftarrow$ s.model.activeIntervention(s)
    else
        $r \leftarrow$ random real from the interval [0,1]
        $sum \leftarrow 0$
        for all `Option` o in s.options **do**
            $sum \leftarrow sum + o$.currentProbability
            if $r \leq sum$ **then**
                $s.state \leftarrow o$
    $is \leftarrow$ SHUFFLE(s.state.impacts)
    for all `Impact` i in is **do**
        PROBABILITYUPDATE(i)

evaluated, so they are simply assigned that predefined state; other statements are evaluated to one of their possible options according to the adjusted probability distribution of the statement's options. Impacts are placed in random order (shuffled) before being executed; this is to eliminate the effect the impact order might have on model evaluation results over the course of multiple model evaluations.

Algorithm 3 AXIOM simple probability update

procedure PROBABILITYUPDATE(`Impact` i)
    $P_{new} \leftarrow i$.UPDATINGFUNCTION(i.effect.currentProbability)
    $P_{complement} \leftarrow 1 - P_{new}$
    for all `Option` o in i.effect.statement.options **do**
        if o is i.effect **then**
            o.currentProbability $\leftarrow P_{new}$
        else
            $os \leftarrow i$.effect.statement.options where option is not i.effect
            $share \leftarrow \frac{o.\text{currentProbability}}{\text{sum of current probabilities of } \texttt{Options} \text{ in } os}$
            o.currentProbability $\leftarrow P_{complement} \times share$

The procedure of a simple impact execution is presented in Algorithm 3. The probability of the effect option of the impact is updated according to the probability updating function pointed by the impact. The probabilities of the other options under the same statement as the targeted option are updated as well, to ensure the sum of the probabilities of the option set remains equal to 1. The complement probability of the updated probability of the effect option is divided to the other options so that each option's share of the new complement probability remains equal to their share of the old complement probability.

The computation of an iteration (Algorithm 4) simply consists of performing the model evaluation multiple times and saving the resulting configurations to the iteration. The model structure, valuation and its active interventions are reset before each model evaluation during the computation of an iteration.

Algorithm 4 AXIOM iteration computation

```
function computeIteration(Model m, iterationCount) : Iteration i
    for 1 to iterationCount do
        Configuration c ← evaluateModel(m)
        add c to Iteration i
        reset m to its initial state
    return i
```

Algorithm 5 AXIOM iteration set computation

```
function computeIterationSet(Model m, iterationCount): IterationSet is
    is.add computeIteration(m, iterationCount)    ▷ Single iteration without interventions
    repeat
        m.nextInterventionCombination
        add computeIteration(m, iterationCount)
    until all possible intervention combinations of m have been processed
```

The iteration set computation (Algorithm 5) consists of computing a single iteration without active interventions, and an iteration for each possible combination of options of the intervention statements.

PUBLICATION

IV

EXIT: An Alternative Approach for Structural Cross-Impact Modeling and Analysis

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EXIT: An Alternative Approach for Structural Cross-Impact Modeling and Analysis

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Abstract

Cross-impact methods are planning, foresight and decision support tools often used in conjunction with the scenario technique. They enable systems modeling in a theory-driven way, grounded in expert judgment and understanding. This article presents the EXIT approach, a novel modeling technique and a computational method for structural cross-impact analysis. EXIT extracts insights from an expert-sourced cross-impact model, which describes the structure of direct interactions within a system. The EXIT transformation produces a relative quantification of the emergent, systemic relationships between model components, effectuating over the complex web of interactions in the system. Compared to the more established matrix multiplication approach, EXIT produces novel and more detailed analytical outputs on the basis of similar input, and offers new analytical possibilities in structural cross-impact analysis. A software implementing the EXIT transformation is freely available.

Keywords: Cross-impact analysis, Interaction analysis, Structural analysis, Systems analysis, Systems modeling, Expert methods

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1. Introduction

Cross-impact methods are planning, foresight and decision support tools often used in conjunction with the scenario technique [24, 19, 20]. They enable systems modeling in a theory-driven way, grounded in expert judgment and understanding. Cross-impact

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methods as modeling and analysis approaches fall in between empirical data-driven computational models and argumentative systems analysis, and they exhibit a high degree of disciplinary heterogeneity and focus on expert-sourced soft system knowledge [49].

The utility of cross-impact analysis is to provide deep insights into the operating logic of a system with complex interactions between its elements. A decision support-oriented utility for cross-impact models is to use them in examining the impacts of strategic choices, policy interventions or changes in the system. They are normally based on expert-sourced data on the interactions between system components, and thus enable modeling of systems that do not have ample empirical data that is required in use of traditional data-driven modeling techniques. Cross-impact analysis has become a popular technique for systems and decision analysis and well established in the fields of foresight and futures studies [24, 20, 10].

The cross-impact approach has a long history in systems analysis and various foresight applications [22, 23, 48, 15, 30, 5, 28, 39, 18, 7, 37, 40, 31, 9, 27, 8, 19, 20, 24, 29, 49, 14, 41, 47, 1, 3, 4, 32, 12, 46, 36]. The original impetus for the development was to complement the Delphi method by introducing analysis of interaction between elements of a given system [22, 23, 24, 20]. However, recent research has focused mainly on application of cross-impact analysis [13, 2, 6, 14, 21] and methodological development has dwindled in recent years. In spite of the methodological discussion and development efforts on cross-impact modeling and analysis, many approaches are somewhat opaque in their documentation and lack software tools and implementations, presenting barriers for easy utilization of the cross-impact approach in modeling and research.

This article presents the EXIT (**E**xpress **Cross**-**I**mpact **T**echnique) method for cross-impact modeling and analysis. EXIT is a structure-oriented cross-impact modeling and analysis method for extracting insights from expert-sourced system model that describes the direct interactions of the said system. The EXIT transformation aims to reveal the emergent, indirect impact network structure of the modeled system and to relate this emergent structure to the direct impact structure described by the input. The analytical objective is an improved understanding of the true relationships between the modeled system parts, forces and events. The proposed approach for structural cross-impact analysis has several advantages compared to existing approaches processing a similar input model. The EXIT approach is compared to the matrix multiplication approach, which is a well established and simple approach for structural cross-impact analysis of very similar input data.

The process of information extraction from a cross-impact matrix used in EXIT is previously unutilized. The process results in more detailed output on the basis of equal input information and extends the analytical possibilities of structural cross-impact analysis. An efficient computation strategy, which allows for processing large cross-impact models, is presented. The contribution of this paper is to present this new, analytically more valuable way of processing cross-impact data. It documents transparently the method for which a freely available software implementation exists. The paper adheres to design science approach, delivering an artefact in the form of EXIT method and a descriptive evaluation [45, 25, 43, 11].

2. Literature review

2.1. Overview to cross-impact analysis

Many quite different analytical techniques are called cross-impact analysis. The format of the inputs for the analysis, the computational process of transforming the inputs into some higher-order information, the nature of the outputs, and the details of the analysis of those outputs vary in the different techniques and their implementations. The development of the original cross-impact technique is attributed to Theodore Gordon and Olaf Helmer [24, 38], and this technique has largely inspired the other, more recent approaches. An important motivation for experimenting with the early cross-impact techniques was to find out "whether forecasting could be based on perceptions about how future events may interact" and enable analysis of interactions between events, which is not present in the Delphi method [24, 20, 139].

In general terms, cross-impact analysis could be described as an analytical technique for studying a system, and particularly interaction within it, consisting of several components, states, events and forces that are partially dependent on each other and therefore have influence on each other. The mentioned objects of the system are modeled as system descriptors. These system descriptors are referred to by different terms by authors of different cross-impact techniques. Gordon [24] uses the term *event*, Godet et al. [20] use the word *hypothesis*, and Honton et al. [26] use the term *descriptor*. The influence the objects of the system have on each other are given a representation in the system model. The influence can be expressed in the model as conditional probabilities [see e.g. 24, 20, 142–149], references to probability-adjusting functions [26, 35, 42], impact indices [30, 20, 90–101], or in some cases simply a boolean indicator of interaction of some kind [20, 83].

The aim of cross-impact analysis is to extract information about the indirect and total interactions between the components of the modeled system on the basis of the input information about the direct interactions. In a system with a high number of components, the chains of impacts can be long and the indirect interactions can effectuate over a complex web of mediating components. Exploring these long impact chains and interaction webs can bring forward surprising and counter-intuitive results. Cross-impact analysis can reveal that a system component that is seemingly unrelated to another component of interest is actually of central importance and conversely that the effect of some other seemingly important component might be cancelled or reversed by the system's web of interactions. It can be used to investigate the effects of changes in the system and identification of effective policy actions and interventions, and their effects in the system, with the aim of discovering policy-relevant insights.

The cross-impact analysis inputs include the system descriptors, their direct interactions and the valuations of the different properties of the descriptors and interactions. Typically, this input data is provided by people with expertise considered relevant for the modeled system or topic. Having one person to supply all the necessary input data, regardless of the method, is technically enough to build the cross-impact model. Normally, however, there are several experts, perhaps a large number of them [19, 49]. It is possible to have the experts work as a group that interacts during the process of providing the inputs; it is possible to have the experts provide the inputs via a questionnaire; or it is possible to combine these approaches in some way. An example of combining the approaches would be having the experts vote about the inputs anonymously using an online questionnaire and discuss about the results directly, then taking the vote again (observing a Delphi-like process). As the focus of this paper is not the process or facilitation of using experts in building a cross-impact model, but rather the description of a new cross-impact modeling language and the analysis of system models built with it, the questions of expert selection, model building, facilitating expert group work in model valuation and other processual intricacies are not examined in more detail. For further discussion of the use of experts in providing inputs for cross-impact modeling and analysis, see [17, 34, 19, 20, 6, 44, 2].

Cross-impact approach enables the modeling of systems that do not have a lot of statistical or empirical data available about them. As *expertise*, relevant to the modeled system or problem, is used as the source material in building the cross-impact models, many non-quantified or weakly quantified phenomena might be modeled with the approach. The expert-oriented modeling approach can be viable also in cases where lack of data makes employment of traditional modeling and simulation methods unfeasible. The cross-impact approach can be also seen as a way to process expert views and opinions in a systematic and formalized way. The collection, processing and synthesis of expert views are central methodological challenges in foresight and futures studies; cross-impact methods are tools to process and synthesize the expert-sourced data in a structured way.

2.2. Structural cross-impact analysis

The documented cross-impact methods can be divided into two categories by whether they explicitly compute probability values associated to the system descriptors or not. The methods computing probability values require more inputs and the cross-impact model construction is more time-consuming. They enable more analytical possibilities. These methods can be called *probability-focused*. The methods that do not compute probability values require less and simpler inputs and the model construction is faster. The analytical possibilities are reduced compared to methods that do compute probability values. These methods can be called *structure-focused*. The existing documented structure-focused cross-impact analysis techniques, such as MICMAC [20, 83] and its derivatives, and the ADVIAN approach by Linss and Fried [33], are based on matrix multiplication method. EXIT falls in the category of structure-focused cross-impact methods as well, but while the inputs are similar to the inputs required by the approaches based on matrix multiplication method, the computational approach is very different. EXIT can be meaningfully compared against other structure-focused cross-impact approaches, of which MICMAC appears to be the most widely used.

The structure-focused methods deliver their analytical contribution by revealing the indirect impact chains and higher-order interactions of the cross-impact model directly from the description of the direct impacts. They do not compute probability changes for the cross-impact model. Methods in this category include the MICMAC method [20, 84], the ADVIAN method [33], and the EXIT method presented in this paper. The structure-focused methods reveal the importance of system components to each other and in the overall system. The structural cross-impact modeling and analysis can be used to discover the higher-order interactions, to give an understanding of the pivotal system components, and to identify effective intervention points for strategic action and policy on the basis of that information.

The motivation for using the structure-focused methods instead of the probability-focused methods is the clearly lower cost of modeling, especially model valuation, in time and effort. The trade-off is the reduction in analytical possibilities. The cross-impact model valuation is the process of defining the necessary values of model components and their properties for analysis. This, as explained, is usually done by expert valuators in the cross-impact approach. In probability-focused methods, initial or a priori probabilities for system descriptors are required. The interactions need also be described in terms of probability changes. Defining conditional probabilities in approaches such as Gordon's method [24] or SMIC[20] is extremely challenging and time-consuming. The description of interactions is easier for model valuators if the probability adjustment function approach is used [see 26, 35, 42], but the level of complexity in valuation is still high compared to the structural cross-impact modeling approach. Valuation of a cross-impact model suitable for probability-focused approach requires, in practice, a committed team of experts for a considerable period of time. In comparison, experiments with the EXIT approach have shown that the valuation of a model suitable for structure-focused approach is possible to be completed in a single-day workshop, easing the requirement of deep expert valuator commitment to the modeling effort.

The complexity and cost of constructing cross-impact models suitable for probability-focused methods make the structure-focused approach a viable alternative in many research and modeling cases. If the main research interest is to generally understand the target system better and identify the most important components from some specific perspective, the analytical possibilities of probability-focused approaches might not be necessary or worth their cost. As the expert resources available for a cross impact modeling effort are, in practice, often limited, the complexity and time requirement of valuation phase limit the level of detail of the cross-impact model. For this reason, using an approach in which the valuation phase is easier makes it possible to *a*) build and study more expansive cross-impact models with more components, *b*) use a wider base of expertise in the valuation by involving more experts, and *c*) discuss, analyze and revise the valuation choices more thoroughly. These points improve the quality of the cross-impact model and make the resulting analysis more valuable. On these grounds, the structure-focused cross-impact methods should be preferred over the probability-focused methods, if their analytical output is sufficient for the purposes of the research.

2.3. The matrix multiplication method and methodological improvements proposed by EXIT

The structure-focused cross-impact modeling and analysis approaches, comparable to the EXIT approach, are the techniques based on matrix multiplication method. The most widely used technique in the category is the MICMAC method developed by Godet et al. [20]. The MICMAC method is, apparent by its relatively wide use, the established method for structure-focused cross-impact analysis. Recent applications of the MICMAC approach in research include work by Alizadeh et al. [2], Dubey and Ali [16], and Gorane and Kant [21]. The MICMAC method is used as a part of a larger analytical framework Godet calls "structural analysis". According to Godet, structural analysis is used to study systems consisting of interrelated elements, highlighting the structure of the relationships. The system is described using a cross-impact matrix interconnecting all the system components. Structural analysis aims to "permit analysis of the relationships and identification of the main variables" [20, 83].

The key variables are identified in structural analysis by using the MICMAC method. MICMAC is described as "a classification matrix using cross multiplication factors" [19, 26]. The MICMAC classification process takes a direct impact index matrix as input. This matrix can have impact valuations that indicate the strength and direction of the impact in the same vein as EXIT (the EXIT inputs are discussed in detail in Section 3.1). The impact matrix can also just have values 0 or 1, 0 indicating no impact from variable to another and 1 indicating an impact of some strength and direction. This simple binary presence-of-impact style is how impacts are modeled in the examples of MICMAC approach [19, 20].

The impacts variable i has on other variables are marked as elements of impact matrix on row i. This means that the impacts all other variables in the model have on variable i can be read from column i of the matrix. The customary impact markup logic is presented also in Table 2 on page 10. In a cross-impact matrix with the aforementioned properties, the sum of the impact values on a row expresses the degree of influence a variable has in the entire system. The sum of the impact values on a column tells the degree of dependence of a variable in the system. The variables can be ordered by their general influence or dependence. In the MICMAC technique, this ordering is the initial ordering. The initial ordering is based on the direct impacts expressed in the impact matrix and it does not account for any higher-order interactions.

The matrix multiplication approach to extracting information about the indirect impacts is based on squaring the direct impact matrix iteratively. When the cross-impact matrix describing the direct impacts is squared, the second-order indirect impacts are revealed [20, 93–97]. In the new matrix obtained by squaring the original direct impact matrix, the variables can again be ordered according to the row or column sums like with the direct impacts. The ordering is likely to be different in the power matrix as compared to the original. This squaring of the matrix is performed n times to reveal the $(n+1)^{\text{th}}$-order indirect impacts and the variable ordering is produced by calculating the row or column sums for each iteration.

As enough iterations have taken place, the ordering becomes stable, and the iteration can be stopped. This stable ordering, which no longer changes as the matrix is squared, is the MICMAC ordering or the *a posteriori ordering*. Godet et al. [19, 26] state that this stable ordering often emerges at iteration 4 or 5 and elsewhere an estimate is given that stability is reached at iteration 7 or 8 [20, 94]. The number of required iterations, in general, is dependent on the number of variables and the number of interactions in the cross-impact matrix.

The described matrix multiplication approach in structural cross-impact analysis produces an *a posteriori* importance (or dependence) ordering for the variables. This a posteriori ranking is based on the indirect impacts between the variables. The initial ordering of the variables is compared against the a posteriori ordering to highlight the change in the importance of variables. This method gives the prioritization of driving forces in the modeled system based on influence-dependence criteria, using the information about the indirect impacts acquired with the iterative matrix multiplication.

The matrix multiplication approach for structural cross-impact analysis is similar enough to the EXIT method in terms of the inputs and the ultimate aims of the analysis for making direct comparisons between the approaches. Both approaches start with an impact matrix describing the direct impacts in the cross-impact model. Both perform a transformation on the direct impact matrix to reveal the indirect impacts and consider the hidden or unobvious importance of the matrix variables from the perspective of these indirect impacts. However, the matrix multiplication approach has shortcomings on which the EXIT approach proposes improvements. The contribution of the EXIT method to the state of the art is highlighted by the following list contrasting the issues related to matrix multiplication approach against the methodological improvements proposed in EXIT.

1. Information about the directed pairwise influence of system components (or model variables) is not available. The rankings based on matrix multiplication approach provide information only about the overall influence or dependence of the variables in the system. The information on the relationship between individual variables is lost and only a general systemic ranking is made available. EXIT outputs information on the systemic relationship between individual variables. A system-level quantification of the influence of an EXIT hypothesis can also be made available, as Table 9 shows.

2. The matrix multiplication method only produces an ordering or ranking by importance or weight of the variables. There is no measure of how much the importance of variables might differ. A single variable or small set of variables could dominate the system and the others might be relatively insignificant, but these characteristics of the system cannot be clearly observed from the mere ranking of the variables. The EXIT transformation yields a relative quantification of the total impact of all individual system components on all other individual components, instead of a simple ordering of the components based on general system-level influence or dependence.

3. The matrix multiplication method based approaches do not consider the direction of the influence. This is a significant drawback, as strong influences pulling to different directions can cancel each other out, and only examining the magnitudes of the influences instead of their direction in terms of probability change or more abstract support or antagonism might give a very inaccurate picture of the real relationships of the variables. EXIT is able to consider the directions of the impacts and is able to reveal possible conflicting influences in the system.

4. The rankings based on matrix multiplication approach are ultimately rankings of the variables considering the indirect effects specifically. It might well be, however, that the direct impacts are the most significant for majority of variables and the indirect impacts are of great importance only for some variables. A better approach would be to somehow quantify and sum the direct and indirect impacts instead of presenting the indirect impacts specifically as the highest-order understanding that can be extracted from the cross-impact model. EXIT considers both direct and indirect impacts, instead of an alternative ranking based on indirect impacts specifically to be compared with the obvious ranking based on direct impacts. As both direct and indirect impacts are important, the cross-impact analysis technique should be able to look at both under equal terms.

This paper presents in detail the novel EXIT method for cross-impact modeling and analysis. EXIT is compared to the matrix multiplication approach, the dominant technique used in structure-focused cross-impact analysis. The matrix multiplication approach is used to answer questions about indirect interactions and the importance of different system components, in a system modeled as cross-impacts, using direct impact indices to describe the impacts. Compared to the matrix multiplication approach, EXIT operates on similar input data but provides more detailed analytical output that is less ambiguous to interpret.

This paper focuses on presenting the modeling language of EXIT and the computational transformation of the novel EXIT method clearly, and the contribution is methodological. The computation process and the analytical outputs are illustrated with a small example model. The EXIT method is implemented as a Java program. It is available at `https://github.com/jmpaon/EXIT`, with source code and documentation. The current version features a simple command line interface. The implementation efficiently performs the EXIT transformation, detailed in Section 3.3, using a combination of full computation of impacts and a stratified sampling approach, discussed in Section 3.5.

3. The EXIT approach

3.1. The EXIT model

An EXIT model is a high-level description of a system, using the EXIT modeling primitives for definition of the system characteristics. An EXIT cross-impact model consists of *(a)* a set of hypotheses, *(b)* valuations for the *direct impacts* between the hypotheses, and *(c)* a value for the *maximum impact*. Hypotheses represent system components, states, events and driving forces. Direct impacts are unmediated influences of causal nature, of an *impactor* hypothesis on an *impacted* hypothesis. The maximum impact gives a scale or interpretation to the *valuations* of the direct impacts. These three modeling primitives make up the EXIT modeling language.

3.1.1. Hypotheses

The **hypotheses** are verbalised, and ideally precise, descriptions of states of the modeled system, its components or driving forces, or events in it. The following examples of EXIT hypotheses are from an energy system model:

- New nuclear plants will be constructed by year 2030
- Average electricity price will increase 25% from current level by 2030
- Electricity consumption in 2030 will be increased from current level

A hypothesis in the model has an unknown boolean truth value, which is "revealed as the future unfolds". The hypotheses should be formulated in an unambiguous way. In the examples provided, the assumed context of the cross-impact modeling exercise provides the necessary additional details to make the hypotheses unambiguous. The verbal formulation of the hypotheses should also be such that domain experts would be able, at least in theory, to assign a probability value for them. In EXIT, probabilities for the hypotheses are not assigned, as the object of the analysis is the impact network structure. The hypotheses should nevertheless ideally be formulated in such a way that assigning probabilities is possible. The aim of such formulation of the EXIT hypotheses is to make the expert-elicited impact valuations less ambiguous. When a hypothesis is formulated in a way specific enough to be able to assign a probability, it is possible to try to valuate its probability-changing impacts on other such hypotheses. If, however, the hypotheses are formulated so that assigning a probability is very difficult due to the vagueness of the hypothesis formulation, estimating how it might influence the probabilities of other hypothesis is equally difficult. These strict requirements for hypothesis formulation can, however, be applied more loosely if it makes sense in the context or for the purpose of the analysis.

3.1.2. Direct impacts

Direct impacts are directed and non-symmetrical relationships between hypotheses. In this relationship, one hypothesis is an *impactor* hypothesis and another is an *impacted* hypothesis. In a less formal way, the direct impacts can be understood as factors of *causal* support or opposition the hypotheses have on each other. The *value* of the impact describes the direction (support or opposition) and the strength of the effect. Usually impact values are integers, but any real numbers can be used. A positive value for impact of hypothesis A (H_a) on hypothesis B (H_b) means that H_a strengthens or supports H_b. A negative value for impact of H_a on H_b means that H_a weakens or is in opposition to H_b. In EXIT, a direct impact models an assumed direct causal relationship of the impactor on the impacted hypothesis: The impactor causes the effect on the impacted. Non-causal association or dependence is not intended to be modeled in the EXIT approach with direct impacts. The direct impact of hypothesis H_a on hypothesis H_b can be written as $H_a \rightarrow H_b$.

More formally, a direct impact $H_a \rightarrow H_b$ describes a probability-changing influence of a direct causal nature of H_a on H_b. This influence is expressed as an impact value, that conveys the direction of probability change and the strength or "size" of the influence. Therefore, a direct impact can be expressed as a 3-tuple, where the first element is the impactor hypothesis, the second one is the impacted hypothesis and the third one is the impact value. The direct impact of hypothesis H_a on hypothesis H_b with a value of i can be written as $H_a \xrightarrow{i} H_b$.

The impact value is interpreted so that if an impactor hypothesis is known to be true, probability of impacted hypothesis changes according to the impact index value: Increases, if impact value is positive, decreases, if impact value is negative, at a rate determined by the impact strength. Conversely, if the impactor hypothesis is known to be false, the probability of the impacted hypothesis decreases if the impact value is positive, and increases if the impact value is negative. Impact value can be interpreted in a yet more general way: if the probability of the impactor hypothesis changes, the probability of the impacted hypothesis changes according to the impact index value. In a case of a positive impact index value, the probability of the impacted hypothesis changes to the same direction as the probability of the impactor hypothesis. In a case of a negative impact index value, a decrease in the probability of the impactor hypothesis causes the probability of the impacted hypothesis to increase. This interpretation of impact values in terms of probability changes of impactor and impacted hypotheses is shown in Table 1.

While the interpretation of the direct impacts is related to probability change, the impact values do not correspond to a specific amount of probability change. The impact values simply relate the impact "sizes" or strengths to each other. The impact $H_a \xrightarrow{2i} H_b$ is twice as strong as impact $H_b \xrightarrow{i} H_c$ and has half of the strength of impact $H_c \xrightarrow{4i} H_d$. Similarly, $H_d \xrightarrow{i} H_e$ is equal in strength to $H_e \xrightarrow{-i} H_f$, but the direction of the impact is opposite. Relating the impacts to each other in terms of strength is sufficient for

Table 1: Direct impacts and their interpretation in terms of probability change of the impacted hypothesis

$\Delta P(H_a)$	$H_a \overset{+}{\rightarrow} H_b$	$H_a \overset{-}{\rightarrow} H_b$
$P(H_a)$ increases	$P(H_b)$ increases	$P(H_b)$ decreases
$P(H_a)$ decreases	$P(H_b)$ decreases	$P(H_b)$ increases

extracting structural information about the cross-impact system.

Table 2: Impact markup logic in EXIT cross-impact matrix

	H_a	H_b	H_c	H_d
H_a	$\varnothing$	$H_a \rightarrow H_b$	$H_a \rightarrow H_c$	$H_a \rightarrow H_d$
H_b	$H_b \rightarrow H_a$	$\varnothing$	$H_b \rightarrow H_c$	$H_b \rightarrow H_d$
H_c	$H_c \rightarrow H_a$	$H_c \rightarrow H_b$	$\varnothing$	$H_c \rightarrow H_d$
H_d	$H_d \rightarrow H_a$	$H_d \rightarrow H_b$	$H_d \rightarrow H_c$	$\varnothing$

The direct impacts between hypotheses can be presented in a cross-impact matrix. Table 2 presents the impact markup logic in a cross-impact matrix displaying the direct impacts in an EXIT model. The direct impact of H_a on H_b (or $H_a \rightarrow H_b$) is read from matrix entry (1,2) (row 1, column 2); The direct impact of H_d on H_c ($H_d \rightarrow H_c$) is read from matrix entry (4,3) (row 4, column 3). Table 3 in Section 3.2 presents a cross-impact matrix of an EXIT model complete with hypotheses.

It is required from a direct impact $H_a \rightarrow H_b$ that in the cross-impact model there are no intermediary hypotheses between impactor hypothesis H_a and impacted hypothesis H_b. In the real system the cross-impact model represents, there can be some intermediary mechanism or component that mediates the impact of H_a on H_b, even if this component would not be present in the model. If such intermediary system components are identified, however, it warrants consideration of modeling these components in the cross-impact model as additional hypotheses.

3.1.3. Maximum impact value

In the EXIT transformation, the indirect impacts extant in the model are related to the direct impacts. To this end, *relative impact values* are computed for both direct and indirect impacts. This process is discussed in detail in Section 3.3. A **maximum impact value** is defined for an EXIT model for computation of relative impacts. As explained in Section 3.1.2, the impact index value is the "size" or strength of the impact, interpreted relative to the other impact values. The *maximum impact value* is the greatest absolute value that the direct impacts can be valued at and the direct impact matrix is allowed to contain.

Normally the maximum impact value is a positive integer, but the maximum impact value can be any real greater than zero. As the impacts can also be negative, the opposite number of maximum impact value is the smallest impact index value allowed. It expresses the greatest possible probability-decreasing influence a hypothesis can have on another.

The EXIT approach does not force a particular interpretation of the maximum impact value. It is possible to think of an impact value equal to the maximum impact value as a fully determinate influence a hypothesis might have on another hypothesis. If this is the interpretation taken, the sum of impacts of impactors on any hypothesis in the model should not exceed the maximum impact value. This interpretation also dictates that the impacts are present only as positive values, without information about the direction of the impact: they only represent the strength of the impact. In this form, the analysis cannot consider the direction of the impact at all. In a standard case where the maximum impact value is not interpreted as a fully determinate impact, but simply as the greatest absolute impact value available for describing the impacts, this requirement does not hold. Disregarding the direction of the impacts might be useful in some applications of the cross-impact approach, but generally the direction of the impact is a very important aspect of an EXIT cross-impact model. Direct and systemic impacts can pull to different directions and cancel each other out. It is possible that the systemic impacts, when accounted for, negate the direct or obvious impact a system component has on another component. This is why consideration of the direction of the impact is generally of central importance.

3.2. Example model

Table 3: Direct impact matrix of an energy system model

		A	B	C	D	E	F	G
Electricity price will increase	A	Ø	+2.5	+1.7	+2.0	+1.6	+1.2	-1.6
Wind and solar power production will increase	B	-0.1	Ø	+2.6	+2.3	-2.1	+1.1	-0.2
Electricity storage will increase	C	-0.2	+2.2	Ø	0	-0.5	-1.0	+0.1
Market based elasticity of electricity consumption will increase	D	-1.9	+1.1	+0.1	Ø	0	-0.6	-0.1
New nuclear power plants will be constructed	E	-0.3	-1.6	-0.4	-0.4	Ø	+0.9	-0.8
Electricity transmission capacity from neighbouring countries will increase	F	-1.2	+0.1	-1.5	-0.8	0	Ø	+0.1
Subsidies for solar and wind power will increase	G	+0.2	+3.9	+1.5	+1.4	-1.0	+1.0	Ø

The EXIT approach is illustrated with a small EXIT cross-impact model representing the Finnish energy system. The model hypotheses and the direct impact valuations are presented in Table 3. The example model has seven hypotheses, which are a subset of the hypotheses of a larger EXIT model, created in a foresight-oriented energy system modeling exercise in the EL-TRAN project. The hypotheses describe the state of, and possible developments in, the Finnish energy system with a timeframe of 2017–2030. The first column of Table 3 presents the hypotheses. the impact valuations of hypotheses on other hypotheses are read row-wise; the impacts of other hypotheses on a particular hypothesis are read column-wise (see Table 2). For example, the impact of hypothesis A ("Electricity price will increase") on hypothesis E ("New nuclear plants will be constructed"), valued at +1.6, is read from matrix row 1, column 5.

The cross-impact model is expert-sourced both in its *design* (selection and formulation of included hypotheses) and *valuation* (assignment of impact values for the direct impacts). The hypotheses of the original model were selected and formulated during several expert workshops, where the central driving forces and upcoming developments were mapped from the perspective of the EL-TRAN project premises. The participants were high-level experts in electricity technology, energy economics, energy policy and other fields related to the technological, economic and political aspects of the Finnish energy system.

The valuation of the direct impacts was individually performed by 16 expert participants, each of whom supplied a cross-impact matrix via e-mail. The matrix presented in Table 3 was obtained by averaging the impact valuations of the 16 expert-sourced cross-impact matrices. This way, if the valuating experts disagreed about the direction of the impact, the mean of valuations would be close to zero and the unclear impact would be mostly eliminated from the model. Another approach would have been to bring the disagreed-upon valuations up for further discussion in an attempt to find consensus on the valuations.

The values of the direct impact matrix (Table 3) relate the direct impacts of the included hypotheses to each other. The defined maximum impact value for the model is 4. The direct impacts are thought to be unmediated in the system model: the influence of the impactor hypotheses on impacted hypotheses do not effectuate through any other modeled system component. For instance, increasing electricity price (hypothesis A) directly incentivizes (with a direct impact valued at +2.5) to increase production of electricity with solar and wind (hypothesis B) and nuclear power (E, +1.6). Increasing electricity price will also directly support increase in electricity storage capacity quite strongly (+1.7). The experts also saw that the rising price of electricity makes the increase of subsidies for solar and wind power (hypothesis G) less likely, the impact valued at −1.6. On the other hand, construction of new nuclear capacity (hypothesis E) is modeled by the experts to be a rather uninfluential factor in the energy system *directly*. Its direct impacts on electricity price, storage, or consumption elasticity have relatively low impact values. The strongest direct impact new nuclear capacity is modeled to have is on the increase of wind and solar power production (−1.6), as the increased nuclear-sourced power supply to some extent eliminates the need for increased wind and solar power production.

With the system's direct impacts modeled and their valuations presented in the direct impact matrix, the question is how to account for the numerous possible *indirect impacts* possible in the system. For instance, the strong influence of increasing electricity price (hypothesis A) on increasing wind and solar power production (hypothesis B) can be thought to *indirectly* influence the increase in electricity storage capacity (hypothesis C) through hypothesis B, as B has a strong direct impact on C. The EXIT transformation detailed in Section 3.3 describes how these indirect impacts are accounted for and related to each other in the EXIT approach.

3.3. The EXIT transformation

The basic motivation for any type of simulation and modeling is to reveal the emergent or systemic characteristics of the modeled system. In structural cross-impact modeling, this means specifically revealing the systemic role of modeled components in the system, or the systemic relationship between system parts. This is done on the basis of input data about direct impacts, by consideration of indirect impacts in the system. The EXIT approach for revealing the systemic impacts is based on *relative quantification* of all the possible impacts in the system model, direct and indirect. The sum of relative quantifications of the direct impact and all indirect impacts of H_a on H_b is the *summed impact* of H_a on H_b.

The set of possible impacts in the system are represented by the set of *impact chains* possible in the system model. Impact chains are directed sets of model hypotheses. An impact chain can also be defined as an ordered set of direct impacts, where each hypothesis included in the chain is present only once. The direct impacts are impact chains of length 2, as they consist of two hypotheses, the impactor hypothesis and the impacted hypothesis. The indirect impacts are impact chains of length $l \mid l > 2, l \leq n$, where n is the number of hypotheses in the model. The indirect impacts have, in addition to the impactor hypothesis and impacted hypothesis, one or more mediating hypotheses, which convey the impact of the impactor on the impacted hypothesis. An impact chain representing an indirect impact of H_a on H_b with y mediating hypotheses can be written as $H_a \rightarrow H_{x_1} \rightarrow H_{x_2} \rightarrow \cdots \rightarrow H_{x_y} \rightarrow H_b$, where $H_{x_1} \ldots H_{x_y}$ are the mediating hypotheses in the impact chain. Figure 1 presents the possible impact chains from impactor hypothesis H_a to impacted hypothesis H_b in an EXIT model consisting of 5 hypotheses.

The EXIT transformation does not compute the influence of *cyclic* impacts. In the matrix multiplication based approaches, cyclic impacts do have an effect on the results. This characteristic of EXIT is a logical consequence of the formal definitions of the EXIT modeling primitives, the *hypothesis* and the *direct impact*. An example of cyclic interaction would be, in the case of the system of Fig. 1, say, H_a influencing H_1 and H_1 in turn influencing H_a back. Allowing such cyclic interaction would mean that H_a would have indirect influence on itself through H_1. This would be against the definition of hypotheses as postulates or possible facts about the system state. The EXIT direct impact, in turn, is the probability-changing influence of the 'cause' hypothesis on the 'effect' hypothesis, conditional to the 'cause' hypothesis being true. This being the definition, cyclic interaction would not be logical in an EXIT model: A hypothesis being true cannot increase its own probability of being true. In EXIT, the definitions of hypothesis and direct impact are quite specific and formal, perhaps more so than in the matrix multiplication based approaches, and the definition precludes cyclic interaction. A technical or computational reason for not computing cyclic interaction is the lack of any kind of terminating condition for computing indirect impacts in a structural cross-impact model, if the cyclic interaction would be allowed: If a hypothesis could occur multiple times in an impact chains, there would be an infinite number of possible impact chains.

The relative quantification r of a direct impact $a \xrightarrow{i} b$ is computed as $\frac{i}{m}$, the ratio of the direct impact valuation i and the maximum impact value m. The relative quantification of an indirect impact $H_a \xrightarrow{i_1} H_{x_1} \xrightarrow{i_2} H_{x_2} \xrightarrow{i_3} \ldots \xrightarrow{i_{y-1}} H_{x_y} \xrightarrow{i_y} H_b$ is computed as $\frac{i_1}{m} \times \frac{i_2}{m} \times \cdots \times \frac{i_y}{m}$, the product of the relative quantifications of the direct impacts involved in the impact chain. Table 4 shows a subset of the impact chains of the example model presented in Table 3, and the computation of their relative quantifications.

In Table 4, the relative quantification of chain 3 is close to zero, as the direct impact $D \xrightarrow{+0.1} C$ included in the chain largely nullifies the impact of the chain on C. In chain 4, the negative direct impact $E \xrightarrow{-1.6} B$ reverses the direction of impact of the chain: Hypothesis A causes the probability of hypothesis E to increase, which causes the prob-

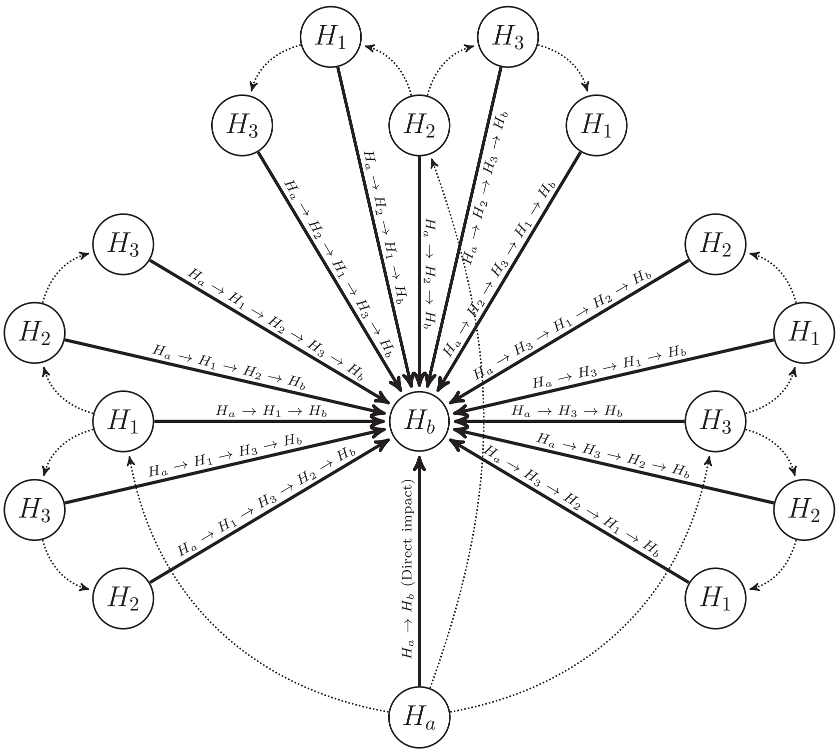

Figure 1: A directed acyclic graph of the impact of hypothesis H_a on hypothesis H_b in a system of 5 hypotheses. The nodes are model hypotheses. All edges are direct impacts, which can also be links in impact chains representing indirect impacts of H_a on H_b. Dotted edges are links in impact chains mediating the impact of H_a on H_b through H_1, H_2 and H_3 indirectly. Solid edges are the direct impacts on H_b, ultimately effectuating the impact of H_a on H_b.

Table 4: Computing the relative quantification (r) of impact chain

	Impact chain	Computation	r
(1)	$A \xrightarrow{+2.5} B$	$\frac{+2.5}{4}$	+0.625
(2)	$A \xrightarrow{+1.7} C \xrightarrow{+2.2} B$	$\frac{+1.7}{4} \times \frac{+2.2}{4} = \frac{+3.74}{4^2}$	+0.234
(3)	$A \xrightarrow{+2.0} D \xrightarrow{+0.1} C \xrightarrow{+2.2} B$	$\frac{+2.0}{4} \times \frac{+0.1}{4} \times \frac{+2.2}{4} = \frac{+0.44}{4^3}$	+0.007
(4)	$A \xrightarrow{+1.6} E \xrightarrow{-1.6} B$	$\frac{+1.6}{4} \times \frac{-1.6}{4} = \frac{-2.56}{4^2}$	−0.160
(5)	$A \xrightarrow{-1.6} G \xrightarrow{-1.0} E \xrightarrow{+3.9} B$	$\frac{-1.6}{4} \times \frac{-1.0}{4} \times \frac{+3.9}{4} = \frac{+6.24}{4^3}$	+0.098

ability of B to decrease, so the indirect impact of A on B through E turns out negative. In chain 5, the negative impact $A \xrightarrow{-1.6} G$ is reversed by the negative $G \xrightarrow{-1.0} E$, making the relative quantification of A's impact on B through G and E positive, as the positive direct impact of E on B does not again reverse the direction of the impact.

In the EXIT transformation, the relative quantification is computed for all possible impact chains for all possible impactor-impacted pairs. The summation of the relative quantifications yields a new matrix, the *summed impact matrix*: The relative quantifications of impact chains where the impactor hypothesis is H_a and impacted hypothesis is H_b are summed as the value of entry (H_a, H_b) of the summed impact matrix. The values of the summed impact matrix reflect the total impacts of all system parts on each other, when all the systemic interactions have been accounted for; its values relate the *total* impacts of hypotheses on each other, taking into consideration, in addition to the direct impacts, the higher-order interactions in the system. Table 5 presents the summed impact matrix that the EXIT transformation yields from the example model of Table 3.

Table 5: Summed impact matrix resulting from the EXIT transformation

		A	B	C	D	E	F	G
Electricity price will increase	A	Ø	+0,11	+0,16	+0,31	+0,22	+0,17	-0,40
Wind and solar power production will increase	B	-0,29	Ø	+0,68	+0,67	-0,74	-0,20	+0,20
Electricity storage will increase	C	-0,19	+0,66	Ø	+0,47	-0,51	-0,28	+0,14
Market based elasticity of electricity consumption will increase	D	-0,43	+0,27	+0,19	Ø	-0,30	-0,28	+0,17
New nuclear power plants will be constructed	E	+0,19	-0,80	-0,59	-0,65	Ø	+0,26	-0,20
Electricity transmission capacity from neighbouring countries will increase	F	-0,13	-0,28	-0,43	-0,44	+0,14	Ø	+0,05
Subsidies for solar and wind power will increase	G	-0,49	+1,31	+1,00	+1,17	-1,13	-0,26	Ø

The values of summed impact matrix are not directly comparable with the values of the direct impact matrix, as the two matrices are not in the same scale. The summed impact matrix values can only be meaningfully compared, without any further transformations, to other values in the summed impact matrix. To enable comparison between corresponding entries of the direct and summed impact matrices, both should be transformed to have the same scale.

The summed impact matrix does not have a defined maximum impact value, like the direct impact matrix has. A theoretical maximum impact value for the summed impact matrix exists, and is dependent on the maximum impact value of the direct impact matrix and the number of hypotheses in the model. This theoretical maximum impact value is, however, not well suited to be used as the assumed maximum impact value of the summed impact matrix, as it is, in all practical cases, bound to be very high in comparison to the summed impact values. A sensible approach to making the matrices comparable is to normalize both matrices. This could be done in different ways, but the recommendation of the authors is to divide the matrix entry values by the mean of

Table 6: Normalized direct and summed impact matrices

		Normalized direct impacts								*Normalized summed impacts*						
		A	**B**	**C**	**D**	**E**	**F**	**G**		**A**	**B**	**C**	**D**	**E**	**F**	**G**
Electricity price will increase	**A**	∅	+2.8	+1.9	+2.2	+1.8	+1.3	-1.8	**A**	∅	+0.3	+0.5	+0.9	+0.6	+0.5	-1.1
Wind and solar power production will increase	**B**	-0.1	∅	+2.9	+2.6	-2.3	+1.2	-0.2	**B**	-0.8	∅	+1.9	+1.9	-2.1	-0.6	+0.6
Electricity storage will increase	**C**	-0.2	+2.5	∅	0	-0.6	-1.1	+0.1	**C**	-0.5	+1.8	∅	+1.3	-1.4	-0.8	+0.4
Market based elasticity of electricity consumption will increase	**D**	-2.1	+1.2	+0.1	∅	0	-0.7	-0.1	**D**	-1.2	+0.8	+0.5	∅	-0.8	-0.8	+0.5
New nuclear power plants will be constructed	**E**	-0.3	-1.8	-0.5	-0.5	∅	+1.0	-0.9	**E**	+0.5	-2.2	-1.6	-1.8	∅	+0.7	-0.6
Electricity transmission capacity from neighbouring countries will increase	**F**	-1.3	+0.1	-1.7	-0.9	0	∅	+0.1	**F**	-0.4	-0.8	-1.2	-1.2	+0.4	∅	+0.1
Subsidies for solar and wind power will increase	**G**	+0.2	+4.4	+1.7	+1.6	-1.1	+1.1	∅	**G**	-1.4	+3.7	+2.8	+3.3	-3.2	-0.7	∅

the absolute values of all matrix entries (or the average distance of values from zero). After this normalization, the 'unit' of the cross-impact matrix is the *cross-impact unit*, the average impact of an average impactor on an average impacted hypothesis in the system. When both direct and summed impact matrices are normalized, their values can be directly compared between matrices. The effects of the systemic and emergent interactions can be observed from the difference between the normalized summed impacts and the normalized direct impacts.

The summed impact matrix values reflect a more 'real' valuation of the interaction between the system components, as the systemic effects are appraised alongside the obvious direct impacts. Comparing the summed impact valuations to the direct impact valuations can reveal surprising systemic properties, such as *a*) relationships that are seemingly important but whose effects are cancelled out by other systemic effects, *b*) relationships that are hidden and revealed only through mapping of the indirect impacts, or *c*) relationships that are reversed as the indirect impacts are considered: the total impact of a hypothesis on another might be opposite to the obvious logic of the direct interaction.

Table 6 presents the normalized direct and summed impact matrices. The consideration of indirect impacts in the system changes the picture of the interactions considerably: 14 (33%) of the 42 directed pairwise impacts change more than one cross-impact unit either positively or negatively. For instance, while the direct impacts of hypothesis A ("Electricity price will increase") are substantial on all other hypotheses, the indirect impacts significantly curtail the direct impacts. The strong positive direct impact of price increase on growing solar and wind power production is almost completely neutralized by the impacts A has B through the other system components. While the impacts of A do not change their direction after computation of indirect impacts (A still supports hypotheses B–F and restrains G), the impacts are greatly weakened. On the basis of the direct impacts only, the increasing electricity price appears to be a strong driver in the system, but in the systemic perspective, its influence is quite limited. The impact of A on G ("Subsidies for solar and wind power will increase") is the only total impact that exceeds one cross-impact unit (with a value of -1.1).

On the other hand, the summed impact values of hypothesis G ("Subsidies for solar and wind power will increase") on other hypotheses are considerably higher than the direct impact valuations. While the subsidies on solar and wind do appear to be a quite strong driver in the energy system directly, their influence on several developments such as increase of electricity storage, market-based elasticity of electricity consumption, and construction of new nuclear capacity, is further amplified by the indirect impacts. In the light of the example model of the energy system, increasing solar and wind subsidies restrains the electricity price increase, but this effect is enacted indirectly, as the direct impact is close to neutral.

Some relationships change in their nature altogether, going from supporting to restraining or vice versa, when the higher-order interactions are computed. Increased wind and solar power production (hypothesis B) and increased subsidies on solar and wind power (hypothesis G) are modeled to directly support the increase of electricity transmission capacity from neighboring countries (hypothesis F), but their systemic impacts change the total impact into negative. Section 3.4 presents further transformations which can be used in facilitating analysis of the EXIT output.

3.4. Facilitation of interpretation and analysis

The difference of the summed impacts and direct impacts for each directed hypothesis pair equals the indirect impacts of each directed hypothesis pair. Table 7 presents a difference matrix, where the direct impact matrix has been subtracted from the summed impact matrix. The difference matrix can be useful in observing for which interactions the higher-order, systemic interactions change the relationship considerably. In the example model, the relative quantification of all indirect impacts is less than the relative quantification of the direct impact for 23 (55%) of the modeled relationships and less than 50% of the direct impact in 16 (38%) of the relationships, so for the majority of cases, the direct influence is still dominant even after consideration of the emergent, systemic interactions. On the other hand, 19 (45%) of the relationships are such that the sum of the indirect impacts is greater than the direct impact. Three relationships, namely (C,D), (D,E), and (F,E) only effectuate indirectly through the system's impact network, as there is no direct impact in these relationships. From analytical standpoint, the relationships that have substantial indirect impacts might often be interesting for further analysis.

Information about the differences between the direct and summed impact matrices can also be summarized with a matrix, where the nature of the effect of the indirect impacts and emergent relationships between the hypotheses is represented with an appropriate symbol. The utility of such matrix is to highlight how the higher-order interactions change the relationship of system components. Table 8 presents a summary matrix with the differences between direct and summed impacts are classified into seven categories, listed in the table legend.

As the compared matrices have been normalized to cross-impact unit scale, a threshold of $\frac{1}{3}$ cross-impact units can be used to define what amount of change is deemed significant and what range of impact values is considered to be a small or insignificant impact. The threshold and the way the understanding of the impact of a hypothesis on another changes as the indirect impacts are discovered are used in classifying the relationships. In the summary matrix of Table 8, *a*) cases where absolute differences between direct and summed impacts are smaller than the threshold are classified in the "no

Table 7: Difference matrix of summed and direct impact matrices

		A	B	C	D	E	F	G
Electricity price will increase	A	Ø	-2.5	-1.5	-1.4	-1.2	-0.9	+0.7
Wind and solar power production will increase	B	-0.7	Ø	-1.0	-0.7	+0.3	-1.8	+0.8
Electricity storage will increase	C	-0.3	-0.6	Ø	+1.3	-0.9	+0.3	+0.3
Market based elasticity of electricity consumption will increase	D	+0.9	-0.5	+0.4	Ø	-0.8	-0.1	+0.6
New nuclear power plants will be constructed	E	+0.9	-0.4	-1.2	-1.4	Ø	-0.3	+0.3
Electricity transmission capacity from neighbouring countries will increase	F	+1.0	-0.9	+0.5	-0.3	+0.4	Ø	0
Subsidies for solar and wind power will increase	G	-1.6	-0.7	+1.1	+1.7	-2.0	-1.9	Ø

Table 8: Summary matrix on the nature of the emergent relationships

		A	B	C	D	E	F	G
Electricity price will increase	A	Ø	↳	↘	↘	↘	↘	↘
Wind and solar power production will increase	B	↧	Ø	↘	↘		↺	↥
Electricity storage will increase	C		↘	Ø	↥	↗		
Market based elasticity of electricity consumption will increase	D	↘	↘	↥	Ø	↧		↥
New nuclear power plants will be constructed	E	↥	↗	↗	↗	Ø		↘
Electricity transmission capacity from neighbouring countries will increase	F	↘	↧	↘		↥	Ø	
Subsidies for solar and wind power will increase	G	↧	↘	↗	↗	↗	↺	Ø

Absolute difference smaller than ⅓ CIU (cross-impact unit)	No significant change	(empty)
Significant direct impact, total impact close to 0	Systemic neutralization	↳
Direct impact close to 0, total impact negative	Negative activation	↧
Direct impact close to 0, total impact positive	Positive activation	↥
Impacts have same sign, total impact smaller than direct	Systemic curtailment	↘
Impacts have same sign, total impact greater than direct	Systemic boost	↗
Impact sign changes when indirect impacts are computed	Systemic negation	↺

significant change" class, b) cases where the impact changes from positive or negative to neutral are classified as "systemic neutralization", as the systemic effects largely cancel out the direct impacts, c) cases where the impact changes from neutral to negative are classified as "negative activation", as the directly neutral relationship becomes negative through the impact network, d) cases where the impact changes from neutral to positive are classified as "positive activation", e) relationships that retain the direction of their influence after discovery of indirect impacts, but where the influence is weakened by systemic effects, are classified in the "systemic curtailment" class, f) relationships that retain the direction of their influence but where the influence is strengthened by systemic effects, are classified in the "systemic boost" class, and g) relationships for which the systemic effects overpower the direct impact, switching the direction of the influence, from positive to negative or from negative to positive, are classified as "systemic negation".

For 8 (19%) relationships in the model, there is no significant change when the indirect impacts are accounted for. One relationship (impact of electricity price increase on increase of wind and solar power production) is systemically neutralized. 10 (24%) of the relationships are neutral in the light of direct impacts, but are systemically activated to have either positive or negative impact. 21 (50%) of the relationships remain supporting or restraining as the direct impacts indicate, but are boosted or curtailed more than the threshold of $\frac{1}{3}$ cross-impact unit. Two relationships (impacts of increasing wind and solar production (B) and increasing subsidies for solar and wind power (G) on (F) electricity transmission capacity) are reversed by the systemic effects: both directly support the increase of electricity transmission capacity from neighboring countries but systemically restrain the development.

Table 9: Systemic influence and dependence in the energy system model.

		Influence		Dependence	
		Direct	Summed	Direct	Summed
Electricity price will increase	A	11.8	3.9	4.3	4.8
Wind and solar power production will increase	B	9.4	7.8	12.7	9.6
Electricity storage will increase	C	4.5	6.3	8.7	8.5
Market based elasticity of electricity consumption will increase	D	4.2	4.5	7.7	10.4
New nuclear power plants will be constructed	E	4.9	7.5	5.8	8.5
Electricity transmission capacity from neighbouring countries will increase	F	4.1	4.1	6.5	4.1
Subsidies for solar and wind power will increase	G	10.0	15.0	3.2	3.2

The MICMAC approach for structural cross-impact analysis produces a ranking of the model descriptors based on systemwide influence or dependence, reflecting the overall 'impactingness' or 'impactedness' of the system components. This is done on the basis of direct impacts and also after the iterative matrix multiplication, with the idea of observing how the ordering of the descriptors changes. If a similar analytical output is required, it can be extracted from the EXIT model by summing the absolute values of rows or columns, for both direct and summed impact matrices. In EXIT, the sum of absolute row values can be understood to reflect the systemwide influence of each hypothesis. Similarly, the sum of absolute column values reflects the systemwide dependency. This information for the example energy system model is presented in Table 9.

The influence-dependence quantification shows the relative sidelining of the influence of electricity price in the systemic outlook. Also the intensification of the influence of subsidies can be easily observed from the figures of Table 9. Compared to the matrix multiplication approach, the information could be seen as of higher value as a quantification is provided of the influence and dependence, instead of mere ordering. However, important aspects of the information provided by the EXIT transformation is lost if the influence-dependence values of the hypotheses are used as the analytical focal point. The influence-dependence valuations only provide a summary of the general role of the components of the system, and the directed pairwise impact valuations offer far more insight into the relationships in the modeled system.

3.5. Estimation strategies for large EXIT models

The number of impact chains that can be formed from a cross-impact matrix is dependent on the number of hypotheses. The total number of possible impact chains in a cross-impact model with $n \mid n > 1$ hypotheses is $\sum_{k=0}^{n-2} \frac{n!}{k!}$, while the total number of impact chains longer than 2 hypotheses (the number of impact chains that represent indirect impacts) is $\sum_{k=0}^{n-3} \frac{n!}{k!}$. As the number of hypotheses in the cross-impact model grows, the number of possible impact chains grows exponentially.

For models with 10 or less hypotheses, full computation of indirect impacts is fast, but as the number of hypotheses grows, calculating the relative impacts of all possible impact chains quickly becomes unfeasible due to computational cost. An efficient strategy for accurate estimation of the summed impacts without full computation is needed to process big cross-impact models. The possibilities for estimation of summed impacts are the following:

1. **Cutting computation of indirect impacts at a specified chain length.** Computing impacts fully for all impact chains that are shorter than a given threshold is a straightforward approach and accounts for the most important indirect impacts if the chain length threshold is big enough (say, 7-8 hypotheses). Each individual uncomputed impact chain will most likely have a low relative impact value. For example, in a cross-impact system where 5 is the defined maximum impact value, a very strong 8-hypothesis impact chain consisting of direct impacts all having absolute value of 4 ($H_1 \overset{\pm\frac{4}{5}}{\to} H_2 \overset{\pm\frac{4}{5}}{\to} H_3 \overset{\pm\frac{4}{5}}{\to} H_4 \overset{\pm\frac{4}{5}}{\to} H_5 \overset{\pm\frac{4}{5}}{\to} H_6 \overset{\pm\frac{4}{5}}{\to} H_7 \overset{\pm\frac{4}{5}}{\to} H_8$) would have an absolute relative impact of $(\frac{4}{5})^8 \approx 0.168$. While this is still a quite significant relative impact, impact chains as strong as this are highly improbable in normal cross-impact models. Most likely the relative impact of an average 8-hypothesis impact chain is close to zero. If the average direct impact value in a 8-hypothesis impact chain would be 3, a very high average impact, the relative impact of the impact chain would be only $(\frac{3}{5})^8 \approx 0.017$, and with an average direct

impact of 2.5, the relative impact of such chain would be as low as $(\frac{2.5}{5})^8 \approx 0.004$. Hence, full computation of only shorter impact chains is sufficient for approximation of summed impacts in many cases.

2. **Pruning the search space using a threshold value for relative impact of chains.** Another solution for approximation of summed impacts, satisfactory in most cases, is to only compute the impact chains which are significant, having a impact value higher than a significance threshold value defined by the analyst. If only significant chains are considered, only a fraction of the set of possible impact chains need to be examined. The threshold value should be a real in the range $]0,1[$. If threshold is 0, all chains that have a relative impact different from 0 are significant; if threshold is 1, no chains are seen as significant. In practice, a suitable threshold value is close to 0.

   Any impact chain in an EXIT model can be thought to have a (possibly empty) set of *immediate expansions*. The set of immediate expansions for an impact chain c includes the impact chains that are longer than c by one hypothesis, which is in the cross-impact model but not in the chain c. For instance, the chain $H_1 \overset{-2}{\rightarrow} H_4 \overset{-3}{\rightarrow} H_2$ formed from a cross-impact model of 5 hypotheses would have the immediate expansions $H_1 \overset{-2}{\rightarrow} H_4 \overset{-3}{\rightarrow} H_2 \overset{-3}{\rightarrow} H_3$ and $H_1 \overset{-2}{\rightarrow} H_4 \overset{-3}{\rightarrow} H_2 \overset{+1}{\rightarrow} H_5$. The immediate expansions of an impact chain have, in turn, their immediate expansions, which are also *non-immediate expansions* of the original chain. The immediate expansions of any impact chain can have, at most, the same relative impact as the impact chain they expand. This means that if the relative impact of an impact chain is lower than the threshold, all its expansions will also have relative impacts lower than the threshold.

   When calculating the summed relative impacts for a cross-impact model, it is possible to start with the direct impacts and compute a particular impact's immediate expansions only if the relative impact of the direct impact exceeds the threshold. The same principle is then applied recursively on the immediate expansions. This way only impact chains that can possibly have an impact greater than the threshold are considered. The impact chains that have a relative impact below the threshold are not examined in the computation, greatly reducing the computational cost. For big cross-impact models, the computation can still be very slow when a low threshold value is used.

3. **Using a sampling-based approach.** The estimation of summed impacts can also be based on sampling the population of possible impact chains. As the number of chains of a given length for a cross-impact system is known, this information can be used for sample stratification. The number of impact chains of length L between H_a (impactor) and H_b (impacted) is, in a system of n hypotheses, $\frac{(n-2)!}{((n-2)-L)!}$. The number of intermediary chains of any length from H_a to H_b in such system is $\sum_{L=2}^{n} \frac{(n-2)!}{((n-2)-L)!}$.

   In estimating the summed impact of H_a on H_b, a sample is drawn for each intermediary chain length that is possible in the system. This means that in a system of of n hypotheses, samples are drawn from the sets of chains between H_a and H_b with $1, 2, \ldots, n-2$ intermediary hypotheses (producing $n-2$ samples). For each sample, a sample mean is computed and it is multiplied by the number of possible impact chains of that length. For each impactor-impacted pair (H_a, H_b) the total relative impact of H_a on H_b is approximately $\sum_{L=2}^{n} \bar{x}_L \times \frac{n!}{(n-L)!}$, where $\bar{x}_L$ is the sample mean of relative impacts of chains of length L: the estimated summed impact between H_a and H_b is the sum of the weighted sample means and the relative direct impact.

In any cross-impact model, the overwhelming majority of possible impact chains will be long impact chains which involve more than half of the hypotheses in the model. For instance, in a cross-impact system of 15 hypotheses, more than 90% of the possible impact chains are longer than 10 hypotheses; in a system of 20 hypotheses, only (1.02×10^{-5}) % of possible impact chains will consist of 10 or less hypotheses. The relative impacts of these long chains will be very small in comparison to the relative impacts of shorter chains. However, as there are great numbers of these small impacts in the vast uncomputed set of possible impact chains, any possible structure in these high-order impacts might have noticeable impact on the results; if the positive and negative impacts of these long impact chains do not cancel each other out, the estimates of summed impacts derived by approaches 1 or 2 might be inaccurate. The sampling-based approach to estimation, when large samples ($n > 10^6$) are used, provides more than sufficiently accurate estimates even for big cross-impact models, considering the somewhat rough and approximate nature of the expert-sourced input data. The sampling-based approach is able to estimate the summed impacts in linear time, making it a feasible approach for estimation of summed impacts in large (15+ hypotheses) cross-impact models.

The EXIT approach to estimation is to fully compute short impact chains and estimate the impacts of longer impact chains based on the stratified sampling approach. In the EXIT implementation, the definition of a short chain is dependent on the user-defined sample size k. The sample size defines, in the estimation of the summed impact of hypothesis H_a on H_b, how many impact chains of each possible chain length are sampled. If the number of possible chains of length L is smaller or equal than the user-defined sample size k (and therefore it is faster to do the full computation instead of drawing the sample) the chain length L is short and the full computation is performed. Otherwise the impacts of impact chains between H_a on H_b of length L are estimated by computing a sample mean of the relative impacts of a sample of size k of such chains in the system. The user can also force a minimum full computation length.

4. Discussion

This paper presents the EXIT approach for cross-impact analysis. EXIT improves on the existing structure-focused cross-impact methods that process expert-sourced system models to extract insights about the emergent, higher-order and indirect interactions from the system of direct impacts described in the model. EXIT method is positioned among other cross-impact approaches and compared against the approaches based on multiplication method, which is discussed in Section 2.3. The improved analytical capabilities of the EXIT approach, as compared to the matrix multiplication approaches, and the additional information extracted from the cross-impact model input are explained in Section 2.3. The enhanced analytical power, the transparent documentation of the approach and the freely available software implementation make EXIT a strong candidate for structural cross-impact analysis where the main interest lies in the structure of the system and the role and importance of the system components in light of higher-order interactions. The previously unutilized way of the extraction of information and insights on the higher-order impacts in the cross-impact system is the main contribution and has been detailed in Section 3.

The broader framework of EXIT method includes several phases that are of critical importance to the cross-impact modeling and analysis. These include identifying the expertise relevant to the study, finding the experts with this expertise, securing their commitment to participate, organizing their work in both selecting the cross-impact model hypotheses and valuating the impacts between the hypotheses and ultimately analysis of the results. These challenges and the best practices concerning them are, however, discussed in existing literature [see e.g. 34] and fall outside the scope and focus of this paper introducing the EXIT approach and detailing the EXIT modeling language and the process of information extraction from models built using the language.

In Section 3.2, the use of EXIT in systems modeling has been illustrated with a small example model, based on a larger modeling exercise of the Finnish energy system. For practical purposes of clear presentation of the EXIT approach and its methodological and computational details, the example model presents only a subset of the components of the original system model. The EXIT transformation, which quantifies the systemic and emergent impacts on the basis of description of the system's direct impacts, is of the greatest utility when the analysed models are relatively large, consisting of a big number of components. In a more extensive model, the impact chains are longer and the analysis of the impact network can bring forth results and insights which are difficult, if not impossible, to access without a systematic computational approach like EXIT. While increasing the number of components in the model obviously means more work for the experts providing the model valuations, the cognitive cost of describing the direct interactions in the simple modeling primitives used in EXIT remains comparatively low, especially when compared to probability-oriented cross-impact approaches. Design and valuation of extensive cross-impact models is, while certainly labour-intensive, completely feasible using the described approach.

Generally, the modeling approach of using experts as a principal information source in describing system characteristics has many interesting possibilities. It makes modeling of systems and problem domains that are characterized by lack of empirical data and difficulties of quantification more natural or possible in the first place. Especially foresight-oriented modeling about phenomena whose modeling cannot be based on yet-nonexistent empirical data will benefit from development of approaches and tools that enable modeling of these domains for which the traditional data-driven approaches are not well suited. It also makes incorporating less quantifiable aspects of systems easier, helping to avoid the omission of possibly essential system features and resulting limited strategic and policy scope, resulting from methodological limitations in modeling. In light of the challenges that occur in attempting to understand the uncertainty of impacts and interactions of driving forces in complex systems, structural cross-impact analysis and the EXIT approach have great potential to enhance the understanding of the importance of the systemic and higher order interactions that may significantly improve the foresight ability of futures techniques.

[1] Agami, N., Saleh, M., El-Shishiny, H., sep 2010. A fuzzy logic based trend impact analysis method.

Technological Forecasting and Social Change 77 (7), 1051–1060.
URL https://doi.org/10.1016/j.techfore.2010.04.009

[2] Alizadeh, R., Lund, P. D., Beynaghi, A., Abolghasemi, M., Maknoon, R., 2016. An integrated scenario-based robust planning approach for foresight and strategic management with application to energy industry. Technological Forecasting and Social Change 104, 162 – 171.

[3] Bañuls, V. A., Turoff, M., nov 2011. Scenario construction via delphi and cross-impact analysis. Technological Forecasting and Social Change 78 (9), 1579–1602.
URL https://doi.org/10.1016/j.techfore.2011.03.014

[4] Bañuls, V. A., Turoff, M., Hiltz, S. R., nov 2013. Collaborative scenario modeling in emergency management through cross-impact. Technological Forecasting and Social Change 80 (9), 1756–1774.
URL https://doi.org/10.1016/j.techfore.2012.11.007

[5] Blackman, A., jan 1973. A cross-impact model applicable to forecasts for long-range planning. Technological Forecasting and Social Change 5 (3), 233–242.
URL https://doi.org/10.1016/0040-1625(73)90002-4

[6] Blanning, R. W., Reinig, B. A., 1999. Cross-impact analysis using group decision support systems: an application to the future of Hong Kong. Futures 31 (1), 39–56.

[7] Bloom, M. F., jan 1977. Time-dependent event cross-impact analysis: Results from a new model. Technological Forecasting and Social Change 10 (2), 181–201.
URL https://doi.org/10.1016/0040-1625(77)90044-0

[8] Brauers, J., Weber, M., jan 1988. A new method of scenario analysis for strategic planning. Journal of Forecasting 7 (1), 31–47.
URL https://doi.org/10.1002/for.3980070104

[9] Burns, J. R., Marcy, W. M., sep 1979. Causality: Its characterization in system dynamics and KSIM models of socioeconomic systems. Technological Forecasting and Social Change 14 (4), 387–398.
URL https://doi.org/10.1016/0040-1625(79)90036-2

[10] Cagnin, C., Costa, O. D., Döry, T., Gilson, D., Könnolä, T., Pierantozzi, V., Scapolo, F., Schoen, A., Warnke, P., Witney, T., 2016. FOR-LEARN: Online foresight guide: Cross-impact analysis. Available online at http://forlearn.jrc.ec.europa.eu/guide/2_scoping/meth_cross-impact-analysis.htm, accessed 29.10.2016.

[11] Cash, P., Stanković, T., Štorga, M. (Eds.), 2016. Synthesizing Knowledge in Design Research. Springer, Ch. Experimental Design Research: Approaches, Perspectives, Applications, pp. 233–252.

[12] Ceric, A., 2016. Analysis of interactions between it and organisational resources in a manufacturing organisation using cross-impact analysis. Journal of Enterprise Information Management 29 (4), 589–611.

[13] Chander, M., Jain, S. K., Shankar, R., 2013. Modeling of information security management parameters in indian organizations using ism and micmac approach. Journal of Modelling in Management 8 (2), 171–189.

[14] Choi, C., Kim, S., Park, Y., oct 2007. A patent-based cross impact analysis for quantitative estimation of technological impact: The case of information and communication technology. Technological Forecasting and Social Change 74 (8), 1296–1314.
URL https://doi.org/10.1016/j.techfore.2006.10.008

[15] Dalkey, N. C., jan 1971. An elementary cross-impact model. Technological Forecasting and Social Change 3, 341–351.
URL https://doi.org/10.1016/s0040-1625(71)80022-7

[16] Dubey, R., Ali, S. S., 2014. Identification of flexible manufacturing system dimensions and their interrelationship using total interpretive structural modelling and fuzzy MICMAC analysis. Global Journal of Flexible Systems Management 15 (2), 131–143.

[17] Enzer, 1971. Delphi and cross-impact techniques. Futures 3 (1), 48 – 61.

[18] Godet, M., jan 1976. Scenarios of air transport development to 1990 by SMIC 74—a new cross-impact method. Technological Forecasting and Social Change 9 (3), 279–288.
URL https://doi.org/10.1016/0040-1625(76)90012-3

[19] Godet, M., Bourse, F., Chapuy, P., Menant, I., 1991. Futures Studies: A Tool-box for Problem Solving. Futuribles (series). GERPA Prospective.

[20] Godet, M., Coates, J., Unesco, 1994. From Anticipation to Action: A Handbook of Strategic Prospective. Future-oriented studies. Unesco Publishing.

[21] Gorane, S., Kant, R., 2013. Supply chain management: modelling the enablers using ISM and fuzzy MICMAC approach. International Journal of Logistics Systems and Management 16 (2), 147–166, pMID: 56158.

[22] Gordon, T., Hayward, H., 1968. Initial experiments with the cross impact matrix method of forecasting. Futures 1 (2), 100 – 116.

[23] Gordon, T. J., 1969. Cross-impact matrices: An illustration of their use for policy analysis. Futures 1 (6), 527–531.

[24] Gordon, T. J., 1994. Cross impact method. Tech. rep., United Nations University Millennium Project.

[25] Hevner, A., March, S. T., Park, J., Ram, S., 2004. Design science in information systems research. MIS quarterly 28 (1), 75–105.

[26] Honton, E., Stacey, G., Millett, S., 1984. Future Scenarios: The BASICS Computational Method. Economics and policy analysis occasional paper. Battelle Columbus Division.

[27] Ishikawa, M., Toda, M., Mori, S., Kaya, Y., nov 1980. An application of the extended cross impact method to generating scenarios of social change in japan. Technological Forecasting and Social Change 18 (3), 217–233.
URL `https://doi.org/10.1016/0040-1625(80)90024-4`

[28] Jackson, J. E., Lawton, W. H., jan 1976. Some probability problems associated with cross-impact analysis. Technological Forecasting and Social Change 8 (3), 263–273.
URL `https://doi.org/10.1016/0040-1625(76)90004-4`

[29] Jeong, G. H., Kim, S. H., jul 1997. A qualitative cross-impact approach to find the key technology. Technological Forecasting and Social Change 55 (3), 203–214.
URL `https://doi.org/10.1016/s0040-1625(96)00209-0`

[30] Kane, J., 1972. A primer for a new cross-impact language – KSIM. Technological Forecasting and Social Change 4 (2), 129 – 142.

[31] Kaya, Y., Ishikawa, M., Mori, S., aug 1979. A revised cross-impact method and its applications to the forecast of urban transportation technology. Technological Forecasting and Social Change 14 (3), 243–257.
URL `https://doi.org/10.1016/0040-1625(79)90080-5`

[32] Lee, H., Geum, Y., 2017. Development of the scenario-based technology roadmap considering layer heterogeneity: An approach using cia and ahp. Technological Forecasting and Social Change 117, 12 – 24.
URL `http://www.sciencedirect.com/science/article/pii/S0040162517300823`

[33] Linss, V., Fried, A., 2010. The advian classification–a new classification approach for the rating of impact factors. Technological Forecasting and Social Change 77 (1), 110–119.

[34] Linstone, H., Turoff, M., 1977. The Delphi Method: Techniques and Applications. Addison-Wesley, available online at `http://is.njit.edu/pubs/delphibook/`.

[35] Luukkanen, J., 1994. Role of planning philosophy in energy policy formulation. Ph.D. thesis, Tampere University of Technology, tampere University of Technology publications # 129.

[36] Mamdouh, A. M., Ahmed, A. E.-H. N., Saleh, M. M., Agami, N. E., 2015. Dynamic cross impact analysis with markov chain. In: Industrial Engineering and Operations Management (IEOM), 2015 International Conference on. IEEE, pp. 1–9.

[37] Martino, J. P., Chen, K.-L., jun 1978. Cluster analysis of cross impact model scenarios. Technological Forecasting and Social Change 12 (1), 61–71.
URL `https://doi.org/10.1016/0040-1625(78)90035-5`

[38] Matic, G., Berry, M., 2013. Design research techniques: Cross-impact analysis as a research pattern.
URL `http://designresearchtechniques.com/casestudies/cross-impact-analysis-as-a-research-pattern/`

[39] Mitroff, I. I., Turoff, M., jan 1976. On the distance between cross-impact models: A set of metric measures for cross-impact analysis. Technological Forecasting and Social Change 8 (3), 275–283.
URL `https://doi.org/10.1016/0040-1625(76)90005-6`

[40] Nováky, E., Lóránt, K., aug 1978. A method for the analysis of interrelationships between mutually connected events: A cross-impact method. Technological Forecasting and Social Change 12 (2-3), 201–212.
URL `https://doi.org/10.1016/0040-1625(78)90056-2`

[41] Pagani, M., mar 2009. Roadmapping 3g mobile TV: Strategic thinking and scenario planning through repeated cross-impact handling. Technological Forecasting and Social Change 76 (3), 382–395.
URL `https://doi.org/10.1016/j.techfore.2008.07.003`

[42] Panula-Ontto, J., November 2016. AXIOM Method for Cross-Impact Modeling and Analysis. Master's thesis, University of Tampere, available online at http://tampub.uta.fi/handle/10024/100041.

[43] Prat, N., Comyn-Wattiau, I., Akoka, J., 2015. A taxonomy of evaluation methods for information systems artifacts. Journal of Management Information Systems 32 (3), 229–267.

[44] Seker, S. E., 2015. Computerized argument delphi technique. IEEE Access 3, 368–380.
[45] Siau, K., Rossi, M., 2011. Evaluation techniques for systems analysis and design modelling methods– a review and comparative analysis. Information Systems Journal 21 (3), 249–268.
[46] Thorleuchter, D., den Poel, D. V., 2014. Quantitative cross impact analysis with latent semantic indexing. Expert Systems with Applications 41 (2), 406 – 411.
URL http://www.sciencedirect.com/science/article/pii/S0957417413005538
[47] Thorleuchter, D., den Poel, D. V., Prinzie, A., sep 2010. A compared r&d-based and patent-based cross impact analysis for identifying relationships between technologies. Technological Forecasting and Social Change 77 (7), 1037–1050.
URL https://doi.org/10.1016/j.techfore.2010.03.002
[48] Turoff, M., jan 1971. An alternative approach to cross impact analysis. Technological Forecasting and Social Change 3, 309–339.
URL https://doi.org/10.1016/s0040-1625(71)80021-5
[49] Weimer-Jehle, W., may 2006. Cross-impact balances: A system-theoretical approach to cross-impact analysis. Technological Forecasting and Social Change 73 (4), 334–361.
URL https://doi.org/10.1016/j.techfore.2005.06.005

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PUBLICATION

V

Cross-Impact Analysis of Finnish Electricity System with Increased Renewables: Long-run Energy Policy Challenges in Balancing Supply and Consumption

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Cross-Impact Analysis of Finnish Electricity System with Increased Renewables: Long-run Energy Policy Challenges in Balancing Supply and Consumption

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Abstract

Climate change and global economic pressures are strong drivers for energy economies to transition towards climate-neutrality, low-carbon economy and better energy and resource efficiencies. The response to these pressures, namely the increased use of renewable energy, creates a set of new challenges related to supply-demand balance for energy policy and electricity system planning. This study analyses the emergent problems resulting from the renewable energy response. These complex aspects of change in the electricity system are analysed with a cross-impact model based on an expert-driven modeling process, consisting of workshops, panel evaluations and individual expert work. The model is then analyzed using a novel computational cross-impact technique, EXIT. The objective of the study is to map the important direct drivers of change in the period 2017–2030 in electricity consumption and production in Finland, construct a cross-impact model from this basis, and discover the emergent and systemic dynamics of the modeled system by analysis of this model.

Keywords: electricity system, cross-impact analysis, renewables, transition, low-carbon

1. Introduction

This paper describes a problem-oriented study of the future electricity system and energy policy of Finland, motivated by the research aims of the EL-TRAN project (see

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`https://el-tran.fi/in-english/`). The EL-TRAN consortium works to fundamentally rethink the energy system in Finland, in an attempt to help resolve policy challenges involved in a transition to a resource efficient, climate neutral electricity system. The initial phase of such a transition is currently underway in Finland. It is a response to global megatrends and roadmaps, including climate change, the Paris agreement to limit the global warming, increasing competition for fossil fuels among Asia's emerging economies, and European Union (EU) visions such as the 2050 Roadmap to a Resource Efficient Europe and the low-carbon objectives of the Energy Roadmap 2050 [see 35, 58, 17].

These roadmaps make it necessary for Finland, as well as other EU member states, to rethink long-run targets and policies in the domain of energy. The policy challenges call for a new approaches to energy research, such as systems thinking approaches that respond to the inability of normal disciplinary science to deal with multidimensional complex problems as outlined by the Intergovernmental Panel on Climate Change (IPCC) [40]. There is need to develop and organize interdisciplinary international studies, which recognize these new long-run challenges of energy policy in the context of global energy sector changes [1, 2, 30, 37, 59].

In addition to decades of prominent technical global energy and emission studies through complex scenario analysis such as Nakicenovic et al. [42], scenario analysis methods have often been used by policy makers and in strategic foresight as an instrument to manage uncertainty and to support the shaping of long-term policies and decision-making [15, 16, 6]. Cross-impact methods have been used in conjunction with energy scenario construction [see e.g. 4, 39, 60]. The cross-impact approach can be seen as a systems modeling approach, using mainly expert-sourced data in lieu of statistical or empirical data in model construction. Cross-impact methods, as modeling and analysis approaches, fall in between empirical data-driven computational models and argumentative systems analysis. They exhibit a high degree of disciplinary heterogeneity and focus on expert-sourced soft system knowledge [61], making them exceptionally applicable in foresight-oriented modeling.

Typically, complex systems are very challenging to analyse [see 5]. The process of building a cross-impact model of such complex systems has the advantage of partitioning and modularizing the complexity. Instead of trying to intuitively assess the dynamics and operating logic of the entire system and its interaction web, the human expertise mobilized for the modeling can be used to assess individual system aspects and components and their bilateral relationships. Starting from a conceptual-level and argumentative system model, the cross-impact approach provides a tool for going further, proceeding towards a more formal and systematic model of the analysed system. A more formal system model can then undergo a computational transformation to reveal non-obvious, emergent characteristics of the system. Cross-impact modeling is also a way to go beyond argumentative systems analysis in modeling cases where data-driven models are not feasible due to lack of empirical data and difficulties in quantification of essential system characteristics.

The cross-impact approach can be thought to be relatively strong, compared to the data-driven approaches, when there is a lot of variety and heterogeneity in the utilized theoretical or methodological approaches. The cross-impact methods provide possibilities to analyse systems, which have too complex interactions to be meaningfully analysed by mere qualitative reasoning [61, 25, 24, 6, 56, 39]. Several different modeling languages and computational processes of varying complexity have been proposed for the analysis of complex interactions between system components and processes, based on mostly expert-sourced data. These approaches have shared characteristics and overlapping utilization areas, but are referred to by various labels by different authors. Labels such as structural analysis[19, 20], morphological analysis[51], and cross-impact analysis[24, 23, 26, 61] all refer to approaches for doing expert-based systems modeling.

In this study, we utilize the *Express Cross-Impact Technique (EXIT)* [49] [see also 47, 50] in foresight-oriented analysis of the Finnish energy system. EXIT takes a model of statements or *hypotheses* describing a hypothetical or future state of the modeled system, and the valuations of the direct supporting or negating interactions between the hypotheses as its input. From this information, the EXIT computational process mines the valuations for *indirect* impacts in the system model. Together, the direct (input) interactions and the indirect (computed) interactions can be used to valuate the *emergent* or *systemic* interactions between the hypotheses describing the system, accounting for the influence the different system parts and processes have on each other through the system's complex web of interactions. This information helps understand the system and the relationships of its parts better and serves to identify those that are pivotal. Identification of the most important parts with highest systemic leverage is useful in invervention point evaluation in strategic decision-making. The EXIT input data can be collected in expert workshops or in a multi-stage expert survey process. The EXIT approach can help organisations and agencies in the boundary work between policy, strategy and knowledge about the future [54].

The aims of the study described in this paper were to

1. Recognising emerging challenges related to increasing wind and solar penetration, formulate a specific, compact set of system descriptors relevant to the near-term future of the Finnish energy system

2. Model and valuate the direct interactions of this set of essential system descriptors using the EXIT modeling language, based on an expert group process supplying the necessary inputs

3. Discover the internal dynamics of the modeled system, using the EXIT computational process to valuate the indirect impacts extant in the system, and to gain understanding of the systemic relationships between the descriptors and the emergent system characteristics

4. Identify the critical system aspects from the perspective of the EL-TRAN project premise, to support and facilitate the process of defining different paths for strategic policy actions in the long-run electricity market policy in Finland

The study is also a trial of the EXIT cross-impact approach in the high-level modeling case of a complex energy system. It demonstrates the use of the EXIT approach in this domain, using a relatively small and high-level set of system descriptors. The built system model, and the transformation performed on it, illustrate the possibilities of investigating the emergent and systemic properties of systems in a cross-impact setting. The trial study lays a basis for more extensive modeling efforts in the domain, using the same approach.

2. Methodology

The modeling and analysis of the Finnish energy system undertaken in this study is based on the EXIT approach, which falls into the category of cross-impact analysis approaches. The cross-impact approach could be described as a high-level systems modeling approach, with emphasis on utilizing expert-sourced inputs, and capacity to use heterogeneous theoretical and methodological approaches in the definition of the characteristics of the model. The different cross-impact modeling and analysis methods diverge in terms of their modeling languages and the nature of their analytical output. What is referred to as cross-impact analysis is really a family of methods for modeling and analyzing systems and problem complexes. The best-known methods are Gordon's cross-impact method[24, 22, 23], SMIC[19, 20], BASICS[26] (see also [36]), MICMAC[19, 20], KSIM[31], and the cross-impact balances approach[61]. The cross-impact approach has been utilized and further methodologically developed in many projects and studies, and it already has a relatively long history in systems analysis and various foresight applications [see 21, 22, 57, 13, 31, 8, 28, 41, 18, 9, 38, 44, 32, 11, 27, 10, 19, 20, 23, 29, 61, 12, 45, 55, 3, 6, 7].

The cross-impact method used in this study, the EXIT method ([49], see also [47, 50]), is a computational technique for processing a model consisting of expert input about the direct impacts that different events, phenomena, drivers and forces have on each other. The computational aspiration of EXIT is to use the information of the model to compute how the network of effects works, and how the system descriptors affect each other *systemically*, over the complex network of effects. An event, phenomenon, driver or force considered in a particular cross-impact analysis setting can be called in a more generic fashion a *system descriptor*, a *cross-impact item*, or a *hypothesis*, as is done in EXIT. The method is useful for comparing the cross-impact items in terms of the magnitude of their total (direct + indirect) effect on any particular cross-impact item included in the model. As direct impacts between items are an input to the analysis, the added value of the calculation is the consideration of the indirect impacts, effectuating over the multi-nodal impact chains.

Table 1: Example cross-impact matrix

	H_a	H_b	H_c	H_d
H_a	∅	+3	+1	−2
H_b	+1	∅	0	+4
H_c	0	+3	∅	−1
H_d	−2	+1	+1	∅

Formally, the components of the EXIT model are *(a)* the cross-impact items or *hypotheses* representing events, phenomena, drivers and forces, *(b)* the cross-impact matrix that describes the direct impacts the items have on each other as impact indices, and *(c)* an absolute value for the maximum impact. The hypotheses have descriptions that should be estimable, in terms of their probability, by the experts contributing to the cross-impact modeling. In practice, the description of a hypothesis should be verbalized in the form of a statement or a claim about the future (or hypothetical state of the system). A statement has a yet-unknown truth value. Formulation of such a statement could be "The energy consumption in Finland will grow from 2017 levels by 2030".

The direct impact valuations of the model can be presented in a cross-impact matrix (see Table 1). The impacts *of* a particular hypothesis are read row-wise in the matrix, so that the impacts of item H_a (Hypothesis a) on other hypotheses are read from the first row; The impacts *on* a particular hypothesis are read column-wise from the matrix, so that the impacts of other hypotheses *on* hypothesis H_a are read from the first matrix column. We can use the notation $H_a \rightarrow H_b$ to represent the direct impact of hypothesis a on hypothesis b. The markup logic of direct impacts is illustrated in Table 2.

The maximum impact value is used to interpret the impact index values; it is simply the greatest allowed or used impact index value in the cross-impact model. In the example cross-impact model, the maximum impact value is 4. The range of the impact index values in the example model is therefore $[-4, +4]$. Impact index value $+4$ means a strong positive effect on the probability of the impacted hypothesis, while impact index value -4 would mean an equally great negative effect. The strengths of the other used impact values are interpreted in a linear fashion: impact with an index value of $+2$ would represent an impact of half the strength of $+4$. While the impacts are understood to mean probability-changing influences, the impact index values do not correspond to specific, defined changes in probabilities of the impacted hypotheses. They simply relate the impacts in the model *to each other* in regards to strength and direction. This level of modeling detail is enough to extract structural information and insights about the system from the system model, and the modeling process remains fairly easy.

Table 2: Impact markup logic in the example cross-impact matrix

	H_a	H_b	H_c	H_d
H_a	$\varnothing$	$H_a \rightarrow H_b$	$H_a \rightarrow H_c$	$H_a \rightarrow H_d$
H_b	$H_b \rightarrow H_a$	$\varnothing$	$H_b \rightarrow H_c$	$H_b \rightarrow H_d$
H_c	$H_c \rightarrow H_a$	$H_c \rightarrow H_b$	$\varnothing$	$H_c \rightarrow H_d$
H_d	$H_d \rightarrow H_a$	$H_d \rightarrow H_b$	$H_d \rightarrow H_c$	$\varnothing$

Impact valuations for the direct impact matrix should be supplied by experts individually, or a panel of experts jointly. The direct impacts are valuated so that only the direct causal association of impactor hypothesis on the impacted hypothesis is considered. The indirect impacts are computed by the software implementing the EXIT method on the basis of the expert-supplied direct impacts.

The cross-impact methods comparable to EXIT in terms of inputs, namely MICMAC [19, 20] and MICMAC-inspired ADVIAN [34], are based on matrix multiplication method. In the matrix multiplication method, the cross-impact matrix is squared and the cross-impact items are ordered on the basis of their systemwide influence or dependence: this is calculated as the row sum of each item (for influence) or the column sum of each item (for dependence). The power matrix is iteratively squared as long as the ordering of items changes as a result of squaring the matrix. When a stable ordering is reached, the iteration is stopped [20]. In the matrix multiplication approach, this stable ordering is the new ordering that now reflects the influence or dependence of the cross-impact items system-wide, based on the indirect impacts specifically (instead of total systemic impact). While this approach gives an interesting cue about the non-obvious, systemic significance of the investigated system components, it loses most of the information that could be gained through an expert process that results in the kind of cross-impact model that is fed to MICMAC and EXIT. The EXIT method is based on a completely different approach to accounting for the indirect impacts in the system model: the computation of relative impacts of impact chains. The set of possible impact chains in the system model represents the set of possible causal impacts in the system, direct and indirect.

Table 3: Impact chains and computation of relative impact

Impact chain	Computation	Relative impact (r)
$\mathrm{H}_a \xrightarrow{-2} \mathrm{H}_d$	$r_1 = \frac{-2}{4^1}$	-0.5
$\mathrm{H}_a \xrightarrow{+3} \mathrm{H}_b \xrightarrow{+4} \mathrm{H}_d$	$r_2 = \frac{+3\times+4}{4^2}$	$+0.75$
$\mathrm{H}_a \xrightarrow{+1} \mathrm{H}_c \xrightarrow{-1} \mathrm{H}_d$	$r_3 = \frac{+1\times-1}{4^2}$	-0.0625
$\mathrm{H}_a \xrightarrow{+3} \mathrm{H}_b \xrightarrow{0} \mathrm{H}_c \xrightarrow{-1} \mathrm{H}_d$	$r_4 = \frac{+3\times0\times-1}{4^3}$	0
$\mathrm{H}_a \xrightarrow{+1} \mathrm{H}_c \xrightarrow{+3} \mathrm{H}_b \xrightarrow{+4} \mathrm{H}_d$	$r_5 = \frac{+1\times+3\times+4}{4^3}$	$+0.75$
$\mathrm{H}_a \rightarrow \cdots \rightarrow \mathrm{H}_d$	$r_1 + r_2 + r_3 + r_4 + r_5$	$+0.9375$

The relative impact of an impact chain of n hypotheses (consisting of the impactor hypothesis, impacted hypothesis and $n-2$ mediating hypotheses) is computed as $r = \frac{\sum_e^n i_e}{m^{n-1}}$, where r is the relative impact of the chain, n is the number of hypotheses in the chain, e is an hypothesis in the chain, i is an impact index value of hypothesis e, and m is the maximum impact value defined for the cross-impact model. Using this approach on the cross-impact model presented in Table 1, the total relative impact of H_a on H_d ($\mathrm{H}_a \rightarrow \cdots \rightarrow \mathrm{H}_d$) can be computed as the sum of the relative direct impact of H_a on H_d ($\mathrm{H}_a \rightarrow \mathrm{H}_d$) and all relative indirect impacts between H_a and H_d possible in the cross-impact model ($\mathrm{H}_a \rightarrow \mathrm{H}_b \rightarrow \mathrm{H}_d$, $\mathrm{H}_a \rightarrow \mathrm{H}_c \rightarrow \mathrm{H}_d$, $\mathrm{H}_a \rightarrow \mathrm{H}_b \rightarrow \mathrm{H}_c \rightarrow \mathrm{H}_d$, and $\mathrm{H}_a \rightarrow \mathrm{H}_c \rightarrow \mathrm{H}_b \rightarrow \mathrm{H}_d$).

Table 3 presents the impact chains from H_a to H_d possible in the cross-impact model presented in Table 1 and the computation of the relative impact for these impact chains. The result of computation of the total relative impact for all hypothesis pairs in the cross-impact model yields a new matrix called summed impact matrix. Table 5 presents a normalized summed impact matrix that results from the computation of summed impacts for the cross-impact model presented in Table 4, followed by the normalization operation discussed at page 7. The values of the summed impact matrix reflect the pairwise relationships of the hypotheses of the cross-impact model, when all the systemic interactions have been accounted for.

In a small cross-impact model, such as the example model of Table 1, relative impacts of all possible impact chains can easily be computed even by hand, but when the number of hypotheses grows, the number of possible impact chains grows fast. In a larger model, with more than 13–15 hypotheses, full computation of relative impacts of possible impact chains becomes unfeasible due to the size of the search space, and an estimation strategy is needed. For advanced estimation strategies, see [47] and [50]. The results presented in

Section 4 of this study have been obtained by full computation of all the impact chains extant in the 10-hypothesis cross-impact system presented in Section 3.

3. Data

The EXIT cross-impact approach was used to investigate the internal dynamics of the near-future development of the Finnish energy system. The analytical focus was on the balance of the electricity supply, electricity transmission system, and electricity demand, in the case of increased amount of intermittent supply of wind and solar power. An EXIT cross-impact model was built in an expert process for the analysis. The cross-impact items or hypotheses in the model were generated in three consecutive expert workshops. A choice of framing the modeling to 10 hypotheses was made, based on the opinion of the experts in the workshops. This meant valuation of 90 directed pairwise interactions for the model valuation phase. A set of 30 variables would have, in comparison, meant valuation of 870 directed pairwise interactions. A larger set of included variables would have enabled inclusion of several interesting aspects of the studied system. However, as the cross-impact modeling effort was not the sole purpose of the expert workshops and practical concerns limited the access to the expert resource, a framing choice for modeling had to be made. The final selection of the included hypotheses was made, in alignment with the expert-driven nature of the modeling approach, on the basis of the expert feedback arising the workshops.

The number of experts participating in this part of the study was 61. This is a relatively big expert group to deliberate the considered system components, aspects and forces, and the inclusion and exclusion of model hypotheses. However, there is no justified recommendation about the number of experts who should take part in this process. The quality of the experts, their expertise coverage of the modeled domain and the quality of the facilitation of the work are more important for robust outcomes from an expert-judgement approach, rather than the number of participants. The direct impacts between the selected key electricity sector items were discussed in another larger expert workshop including researchers from universities and research institutes, energy industry, NGOs and energy administration. The participants were high-level experts in electricity technology, energy economics, energy policy and other fields of expertise of the modeled socio-techno-economic energy system.

16 of the experts individually valuated the direct interactions in the cross-impact model by supplying a cross-impact matrix via e-mail. Mean of the 16 expert valuations of each cross-impact matrix entry was used as the impact valuation of the final EXIT model. This way, if the valuating experts disagreed about the direction of the impact, the unclear impact would be mostly eliminated from the model. The maximum impact value of the 16 individually valuated models was 4, so that the range of direct impact valuations is $[-4, +4]$, -4 being a strong negative impact and $+4$ a strong positive impact, and the strengths of other valuations interpreted linearly (see Section 2). The time horizon in the study was defined as the year 2030: The hypotheses and their interactions were considered in a temporal frame ranging from 2017 to 2030.

Table 4 presents the cross-impact model of 10 hypotheses and their direct impact valuations, made by the 16 experts. The presented direct impact matrix has been normalized by dividing each matrix entry value by the mean of absolute values in the matrix (or the average distance from zero). In this normalized matrix, the unit for the values can

Table 4: Valuated, normalized direct impact matrix of the Finnish energy system model. Direct impact of A on C is read from row 1, column 3 of the matrix.

		A	B	C	D	E	F	G	H	I	J
Electricity price will increase	A	∅	+2.5	+1.7	+2.0	+1.6	-1.8	+0.9	+1.2	+1.1	-1.6
Wind and solar power production will increase considerably	B	-0.1	∅	+2.6	+2.3	-2.1	+0.1	+2.9	+1.1	+1.5	-0.2
Electricity storage will increase considerably	C	-0.2	+2.2	∅	0.0	-0.5	+0.4	-1.5	-1.0	-0.5	+0.1
Market based elasticity of electricity consumption will increase	D	-1.9	+1.1	+0.1	∅	0.0	-0.1	-1.2	-0.6	-0.4	-0.1
New nuclear power plants will be constructed	E	-0.3	-1.6	-0.4	-0.4	∅	+1.3	-0.8	+0.9	-0.4	-0.8
Electricity consumption will increase	F	+2.1	+1.9	+1.0	+1.6	+1.9	∅	+1.9	+1.7	+1.3	+0.6
Electricity price fluctuations will increase	G	+1.0	-0.4	+2.7	+3.2	-0.3	-0.1	∅	+1.0	+1.9	-0.2
Electricity transmission capacity from neighbouring countries will increase	H	-1.2	+0.1	-1.5	-0.8	0.0	+0.5	-1.3	∅	-0.6	+0.1
Fluctuations in electricity consumption will increase	I	+1.9	-0.3	+2.3	+2.3	-0.8	+0.1	+2.9	+0.8	∅	-0.1
Subsidies for solar and wind power will increase	J	+0.2	+3.9	+1.5	+1.4	-1.0	+0.2	+1.8	+1.0	+1.0	∅

be understood to be the *cross-impact unit*, the average impact of an average impactor on an average impacted hypothesis in the model. Normalization of the both direct impact matrix (input matrix) and the summed impact matrix (output matrix) is necessary to bring their valuations into the same scale and enable comparisons between matrices.

The system descriptors in EXIT modeling can represent events, precisely defined system states or trends or drivers. The system descriptors in the model presented in this paper represent general high-level drivers or trends. They are not explicated as precise descriptions of the future state of the system at the end of the temporal horizon (year 2030), but rather as deviations from the present state or the "expected" development. The modeling exercise aims to discover the emergent, systemic interactions: The EXIT transformation reveals the level of support or antagonism the drivers have on each other. The cross-impact model hypotheses presented in Table 4 are short labels for the hypotheses. The detailed content of each hypothesis was formulated in the workshops preceding the model valuation. The following list explains the model hypotheses in more detail and presents the argumentation for their modeled direct impacts as formulated by the expert group in the valuation workshop.

(A) Electricity price will increase. This hypothesis describes a general upward trend in electricity prices in the modeling exercise time frame from current price levels. Currently electricity price in Finland from consumer perspective is relatively low, compared to the EU average. The electricity price for industry is also relatively low, and energy-intensive industries benefit from the co-ownership of power generation model, being able to use electricity at cost price.

Increasing electricity price quite obviously incentivizes to increase electricity production, with a strong positive direct impact on wind and solar power production increase (+2.5) and nuclear power capacity increase (+1.6). Increasing price also incentivizes other electricity investments, such as increase in electricity storage

(+1.7). Conversely, the increasing price strongly curtails (−1.8) growth of electricity consumption. Price hikes are also modeled to support market based elasticity increase (+2.0), as especially a very significant electricity price hike would make many consumers ready to be more elastic in their consumption. Increasing electricity price are modeled to be antagonistic to increasing subsidies for solar and wind power (−1.6), as policymakers are expected to see the subsidies as less necessary in a high electricity price scenario. Overall, electricity price is a very strong direct driver in the system model and has an impact of about one cross-impact unit or more in all the other hypotheses.

(B) Wind and solar power production will increase considerably The wind power capacity is relatively low compared to the rest of the nordic countries. The share of wind power was 3.6% of the total electricity consumption in Finland in 2016 [53]. The potential for growth in the wind power capacity is considerable, and the expert group argued that it is feasible that the capacity might be more than doubled by 2030 under favourable regulatory and subsidy policy conditions.

Increasing wind and solar power production strongly supports increasing electricity price fluctuations (+2.9). The fluctuating electricity price is one of the problems linked to the main theme of the EL-TRAN project, the increasing use of larger amounts of intermittent power sources in the Finnish electricity system. Wind and solar power production is also modeled to have strong direct support for with the increase of electricity storage (+2.6) and increasing market based elasticity of consumption (+2.3). The expert valuators argued that the increasing intermittent electricity production will force investments and require advancements in electricity storage technology, and be coupled with more tolerance of the consumers to exercise market based elasticity in their consumption decisions.

Increasing wind and solar power production is also modeled to be a clear trade-off against construction of new nuclear power plants, with a negative direct impact of −2.1: if the additional electricity demand will be covered mostly with wind power generation there is little need for new nuclear capacity. Experts argued that if the expansion of wind (and solar) capacity would turn out to be very significant in magnitude, it would also support the expansion of the electricity transmission capacity to neigbouring countries (+1.1), with the idea of selling the excess electricity to the Nordic electricity market during peak production times.

(C) Electricity storage will increase considerably Electricity storage, in the context of the presented model, conceptually covers battery storage technologies, but also pumped-storage hydroelectricity facilities used in load balancing. The pumped-storage hydroelectricity allows the use of intermittent energy sources to be saved when they are available and can be seen as an important enabler for the use of intermittent renewable energy sources.

In the valuation workshop, the expert informants discussed the mechanism of emerging trends influencing the system by showing a techno-economic solution to be feasible. In this way, the electricity storage solutions can support directly investment in solar and wind power production, even when their actual role in the system in the timeframe 2018–2030 would be small. The strongest direct impact the increase of electricity storage has is on increasing wind and solar power production (+2.2). Electricity storage will also naturally reduce price fluctuation (−1.5) and reduce need for increasing transmission capacity (−1.0).

(D) Market based elasticity of electricity consumption will increase Hypothesis D describes a change in the consumer behaviour and expectations, that would make the higher-than-present price fluctuations more palatable for consumers and change their readiness to alter the level of electricity consumption based on the electricity price. This can be thought to be accompanied by providing consumers information on the price changes more efficiently through communications technology.

Increased market elasticity is modeled to strongly hinder the rise of electricity price (−1.9), and curtail the electricity price fluctuations (−1.2), as demand becomes more elastic to price, going down when price goes up and not supporting the higher electricity price. Market elasticity also supports increased wind and solar power generation (+1.1), as these intermittent forms of electricity production are likely to be more palatable to the consumers if the market based elasticity of consumption is higher.

(E) New nuclear power plants will be constructed The new unit 3 of Olkiluoto nuclear power plant with a nameplate capacity of 1600 MW is currently under construction and is expected to be in operation before 2020. The construction of another new nuclear power plant in Pyhjoki is expected to commence in 2018, with a commission date in 2024. The older units in Loviisa are planned to be decommissioned before 2030. Hypothesis E refers to decisions to increase capacity by construction of additional new units in the time frame 2018-2030. While these new units will likely not be commissioned in the time frame of the cross-impact model, the decisions, if made, will impact the rest of the modeled system by e.g. changing the investment outlook for other types of power generation units.

New nuclear power capacity is an alternative to wind and solar power from the perspective of new energy investments, and if reasonably priced nuclear sourced electricity is available, there is not much incentive to invest in solar and wind power capacity. The direct impact of new nuclear power plants on wind and solar power is −1.6. Construction of new nuclear power plants also supports increase in overall electricity consumption, being synergetic with further investments of energy-intensive industries in Finland.

(F) Electricity consumption will increase Hypothesis F simply describes an upward trend in overall electricity consumption. The electricity consumption in Finland in the period 2008–2016 has been in the range of 81.3–87.7 TWh [53], with no clear trend of increase. The presence of energy-intensive heavy industry in Finland is an important determining factor for the electricity use trend. The share of industry of the total electricity use is slightly less than 50% [53]. The forestry, paper and pulp industry in turn uses about 50% of that share, or 25% of the total electricity consumption. The future presence of paper and pulp industry, chemical and steel industries will greatly influence the trend of consumption.

Increasing electricity consumption is a strong direct driver in the system overall, with positive impacts on all other hypotheses, averaging +1.6 cross-impact units.

It supports strongly electricity price increase (+2.1) and new capacity for both nuclear and renewable energy (+1.9 and +1.9). Increasing consumption has a direct causal effect on increased production in addition to the impact coming through the price signal: policymakers will determine public investments on energy infrastructure based on consumption and forecasts of consumption. The impact on increasing solar and wind subsidies (+0.6) is positive but small, and the experts saw that there is not much need for subsidies when the consumption is increasing: new capacity will be built anyway. In the current electricity market conditions, where the price of electricity is quite low, there is a much greater need for subsidies as the price does not give much incentive to invest in any kind of power generation, renewable or not. Increasing electricity consumption is also modeled to increase price fluctuation (+1.9). The argumentation is that in conditions of high demand and intermittent supply the price fluctuations will increase. The increasing consumption can be baseload-type consumption, or more intermittent. In the case of intermittent consumption, the high consumption phase will increase price fluctuation, as it is unclear how the demand can be met in different situations.

(G) Electricity price fluctuations will increase Hypothesis G describes a change trend in the electricity system where electricity price fluctuations of magnitude great enough to start influencing consumer behaviour and investment decisions. Currently the price of electricity is very stable and fluctuation is low.

Increasing price fluctuations quite naturally support increased consumption fluctuations (+1.9). Price fluctuations are also strong drivers for electricity storage increase (+2.7) and increase of market-based consumption elasticity (+3.2). High price fluctuation creates incentive for electricity retailers to invest in storage to be able to sell during price peaks. Consumers are also likely to consider the timing of their electricity use in an electricity market with high price fluctuation.

(H) Electricity transmission capacity from neighbouring countries will increase Finland is integrated into the Nordic electricity market, and imports electricity from Russia. The average share of net imports of total electricity consumption was about 18% in the period 2008–2016 [53]. At the mentioned period, the highest annual share of net imports was more than 22%. The general trend for transmission capacity is that it is increasing, albeit slowly. The motivation for increasing the transmission capacity can obviously be, in addition to importing electricity, exporting it. In a scenario of building a lot of additional nuclear power generation capacity, the vision could be that the electricity is exported to Nordic or Central European markets. Hypothesis H describes a trend of investments on transmission capacity and a higher rate of increase in the capacity for the period 2018–2030.

Transmission capacity increase inhibits the electricity price increase (−1.2), as the demand can more easily be met by importing more electricity from abroad. For the same reason it also inhibits electricity price fluctuations, as price hikes will encourage neighbouring countries to export their electricity to Finland. Increase in transmission capacity is modeled as quite strong constraining factor to electricity storage increase (−1.5), as the demand for storage would be smaller.

(I) Fluctuations in electricity consumption will increase Hypothesis I describes a trend of relative increase in electricity consumption fluctuation. A significant amount of energy-intensive industry operates in Finland. In case of a development where Finland is not attracting much further investments in heavy industry, the constant base load of electricity consumption declines, lowering the electricity consumption and increasing the consumption fluctuation in relative terms.

Higher electricity consumption fluctuation is also a strong driver for storage increase (+2.3) and electricity consumption increase (+2.3). High consumption fluctuation gives a signal for the retailers to invest in electricity storage, to be able to supply electricity during peak consumption. Consumption fluctuations also increase electricity price (+1.9) and electricity price fluctuations (+2.9). Preparing for the increasing fluctuations obviously means investing in the power generation capacity in order to be able to respond to the higher demand, raising the electricity price. Also, as price will fluctuate higher during high demand and on average, the electricity price will therefore be higher.

(J) Subsidies for solar and wind power will increase Currently, wind power is subsidized with a system of guaranteed price: electricity distribution companies are obligated to buy the produced wind-sourced electricity at a set price. The current subsidy policy defines a minimum and maximum capacity and a limit on power output, which limits the application area of the subsidies, effectively limiting the guaranteed price subsidy policy to medium to big operators. Additionally, there are direct investment subsidies, which enable smaller operators to produce wind power and be compensated. The subsidy policy is a central driver for the growth in wind power capacity. Hypothesis J refers to a development where the wind power subsidy policy changes into a more favourable direction for further wind power investments through a combination of reduction of regulatory limitations, increase of the guaranteed price, and increase of the direct investment subsidy. Similar policies can be implemented for solar power, although it was seen by the expert informants to be of secondary importance in the Finnish case.

Increasing subsidies for solar and wind power are a strong direct driver overall in the system, like the increase in electricity price. It has average to strong direct impacts on all other hypotheses than electricity price increase and increase in electricity consumption. Increasing subsidies were modeled to also directly support electricity storage and market based consumption elasticity, as storage infrastructure was seen as a likely target of investment subsidies as well, and consumption elasticity was assumed to be supported by changes in the regulatory framework. Subsidies were argued, also based on research [43] to be the strongest driver for increasing wind and solar power production (+3.9). If a strategy emphasizing renewables in electricity production, and heavily subsidizing them, is chosen, new permits for additional nuclear power plants are likely not granted. By this argumentation, the direct impact of increased subsidies for solar and wind power are antagonistic to the construction of new nuclear power plants (−1.0).

The presented system model is high-level and macro in its characteristics. The hypothesis count is low, resulting in fairly high abstraction level. The causal chains are not fully opened in the model, as some mediating links in the causal mechanisms of the system are not explicitly present in the model. The influence of these system components is implicitly considered by the experts in model valuation but not modeled. A cross-impact model opening the causal chains of the modeled system fully by modeling all the mediating components relevant to the system in a very atomic way would be ideal, but would also require a more sustained expert group involvement and result in a slower and more work-intensive valuation phase. In a high-level model with a small number of system descriptors, the positive impact valuations for some seemingly causally non-related system descriptors might reflect some indirect causation through system components not included in the high-level system model. Ideally, the valuating experts should only consider direct causation in the direct impact valuation. When some mediating system component that is not included in the model arises in their thought process, this component should preferably be added to the model. However, this sort of iterative mode for the system modeling was not feasible in the EL-TRAN cross-impact modeling case due to time and resource constraints.

It should also be noted that this high-level model of the electricity system presents the causalities as linear and symmetric. For some system descriptors, the causality could be thought to be activated only at a certain level of change: for instance, the level of increase in wind power production is meaningful to the causality on increase in electricity transmission capacity. A small increase in wind power will probably not have a great deal of impact on the transmission capacity, whereas a major increase would. The same observation could be made about the impact of electricity price increase: some impacts associated to it can be thought to only occur at a specific level or magnitude of price increase. It could also be thought that the causalities are not necessarily symmetric, in the sense that a price decrease in electricity will not really have the opposite impacts to price increase. To take the described conditionalities and non-symmetrical causality properties into account in a cross-impact model, a more complicated system modeling language such as AXIOM [46] would have to be employed.

4. Results

4.1. Quantification of systemic impacts

The EXIT software implementation [48] was used to compute the relative impacts of impact chains (see Section 2). This transformation gives a valuation for the directed total, systemic impacts between the model hypotheses, on the basis of the model of the direct causal relationship reported by the direct impact matrix, presented in Table 4. The resulting *summed impact matrix* is normalized in the same way as the direct impact matrix (see Section 3). The normalized summed impact matrix is presented in Table 5.

The values of the summed impact matrix reflect the total (direct + indirect) impact of the model hypotheses on each other. In a case of a successful mapping of direct causalities of the modeled system, the summed impact values derived from the model should reflect the emergent, systemic relationship between the system parts. The summed valuations for the causal relationships take into account, in addition to the direct impacts, the complex network of indirect impacts and aim to provide a better understanding of the true relationships between the system components. Additional utilities of discovery of the systemic impacts are revealing hidden relationships, unintended consequences, and neutralized or reversed causal relationships.

Table 5: Normalized summed impact matrix. Summed (total) impacts of A on C are read from row 1, column 3 of the matrix.

		A	B	C	D	E	F	G	H	I	J
Electricity price will increase	A	∅	+0.7	+0.9	+1.3	+0.2	-0.9	-0.5	-0.1	+0.1	-1.1
Wind and solar power production will increase considerably	B	-0.6	∅	+3.3	+3.6	-1.8	-0.2	+1.4	-0.1	+0.9	+0.1
Electricity storage will increase considerably	C	0.0	+1.5	∅	+0.8	-0.9	+0.1	+0.3	-0.4	+0.4	+0.2
Market based elasticity of electricity consumption will increase	D	-1.4	+0.3	-0.5	∅	-0.3	+0.2	-0.6	-0.8	-0.4	+0.6
New nuclear power plants will be constructed	E	+0.1	-1.4	-1.8	-1.8	∅	+0.8	-0.9	+0.6	-0.7	-0.3
Electricity consumption will increase	F	+0.6	+2.4	+3.2	+4.2	-0.1	∅	+1.6	+1.7	+1.5	-0.3
Electricity price fluctuations will increase	G	-0.1	+1.2	+2.2	+3.0	-0.9	0.0	∅	+0.1	+1.1	-0.2
Electricity transmission capacity from neighbouring countries will increase	H	-0.5	-0.9	-1.9	-1.6	+0.5	+0.5	-0.6	∅	-0.4	+0.4
Fluctuations in electricity consumption will increase	I	+0.3	+1.7	+2.6	+3.1	-1.0	-0.1	+1.6	+0.1	∅	-0.5
Subsidies for solar and wind power will increase	J	-0.3	+3.9	+4.6	+4.9	-2.5	0.0	+2.6	+0.8	+1.9	∅

The difference matrix in Table 6 derived from Table 4 and Table 5 shows the difference between the direct impacts Table 4 and the summed (direct + indirect) impacts Table 5. From the perspective of emergent system properties, which the cross-impact analysis aims to reveal, relationships of particular interest can be those that change the most as a result of the discovery of indirect impacts. These are the pairwise relationship where the difference in the greatest. The differences with an absolute value greater than one cross-impact unit are highlighted in Table 6.

Accounting for the indirect impacts change the impact valuations considerably (i.e. more than one cross-impact unit) in 24 of the 90 directed pairwise impacts. If a change in the valuation of one cross-impact unit or more is the threshold of significance for the change, consideration of the indirect impacts changes the picture of overall influence on other hypotheses especially for electricity price (A, 5 significant valuation changes) and increasing electricity consumption (F, 4 significant valuation changes). Also the changes in the magnitude of valuations of impacts of increasing wind and solar power subsidies (J) are noteworthy.

For about 37% of the relationships in the cross-impact system, the indirect impacts are greater than the direct impacts. The absolute mean of the indirect impact in the system is 0.78, and absolute median 0.6: the direct impacts dominate the relationship of most system components. About 34% of the relationships remain more or less the same as the indirect impacts are accounted for. 20% of the relationships are supported and strengthened by the indirect impacts. 19% are hindered or curtailed, but remain influencing in the same causal direction. About 14% are neutralized, meaning that a directly positive or negative impact is cancelled out by the indirect impacts, bringing the total impact close to zero. 9% are systemically activated, so that the relationship between model components is only manifested in the indirect impacts. Three relationships are reversed in terms of the direction of their causality, meaning that a directly positive

Table 6: Difference matrix derived from summed and direct impact matrices. Matrix values report the sum of all *indirect* impacts between hypotheses. Indirect impacts of A on C are read from row 1, column 3 of the matrix.

		A	B	C	D	E	F	G	H	I	J
Electricity price will increase	A	∅	-1.8	-0.8	-0.7	-1.4	+0.9	-1.4	-1.3	-1.0	+0.5
Wind and solar power production will increase considerably	B	-0.5	∅	+0.7	+1.3	+0.3	-0.3	-1.5	-1.2	-0.6	+0.3
Electricity storage will increase considerably	C	+0.2	-0.7	∅	+0.8	-0.4	-0.3	+1.8	+0.6	+0.9	+0.1
Market based elasticity of electricity consumption will increase	D	+0.5	-0.8	-0.6	∅	-0.3	+0.3	+0.6	-0.2	0.0	+0.7
New nuclear power plants will be constructed	E	+0.4	+0.2	-1.4	-1.4	∅	-0.5	-0.1	-0.3	-0.3	+0.5
Electricity consumption will increase	F	-1.5	+0.5	+2.2	+2.6	-2.0	∅	-0.3	0.0	+0.2	-0.9
Electricity price fluctuations will increase	G	-1.1	+1.6	-0.5	-0.2	-0.6	+0.1	∅	-0.9	-0.8	0.0
Electricity transmission capacity from neighbouring countries will increase	H	+0.7	-1.0	-0.4	-0.8	+0.5	0.0	+0.7	∅	+0.2	+0.3
Fluctuations in electricity consumption will increase	I	-1.6	+2.0	+0.3	+0.8	-0.2	-0.2	-1.3	-0.7	∅	-0.4
Subsidies for solar and wind power will increase	J	-0.5	0.0	+3.1	+3.5	-1.5	-0.2	+0.8	-0.2	+0.9	∅

influence turns out negative when indirect impacts are considered, or vice versa.

The EL-TRAN project investigates the problematique of increasing amount of intermittent electricity supply in the energy system, systemic coping mechanisms for the intermittent supply and the steering and policy options to reduce the emerging problems related to the intermittent electricity production. From this perspective, items of special interest are increasing wind and solar power (hypothesis B), electricity storage (hypothesis C), and subsidies on wind and solar power (hypothesis J).

4.2. Systemic influence and dependence of increasing intermittent electricity production

Overall, the systemic impacts of increased solar and wind power turn out to be largely aligned with the direct impacts, with differences mostly in the magnitude of impacts. Increasing wind and solar power production is modeled to be a strong direct driver for increase in electricity storage and increasing market based elasticity. The indirect impacts compound to both of the relationships, significantly strengthening them: the total impact of increased wind and solar power on increased electricity storage is +3.3 and on increased market based consumption elasticity +3.6. Expansion in solar and wind power production can be seen as synergetic with especially electricity storage, but also increased market based elasticity of consumption: development of electricity storage techniques, most likely pumped storage facilities, is required to make the increased wind power generation viable.

The intermittent electricity production remains also a driver for the increasing electricity price fluctuations. However, this impact is greatly moderated by the indirect impacts (from +2.9 to +1.4). Increased wind and solar power directly supports quite strongly the increase of electricity storage, increase of market based elasticity in consumption and electricity transmission capacity, which in turn have a negative relationship on increase of price fluctuations.

The positive relationship on increased electricity transmission capacity is systemically neutralized. The increased electricity storage, synergetic with the increased wind power, ends up reducing the need for investment in transmission capacity.

4.3. Systemic dependence of electricity storage and market based consumption elasticity

Electricity storage and elasticity of consumption are the main strategies for making an increased reliance on intermittent renewable sourced electricity production possible. It is important to discover their chief drivers and antagonists from the systemic perspective. Both are systemically reactive drivers, that do not have very significant impacts on other components of the system. For electricity storage, the most influential direct driver in the model is the increase of electricity price fluctuations, followed by the increasing wind and solar power production. Price and consumption fluctuations are other important drivers. Subsidies on solar and wind power are a positive driver, but less important than electricity price and consumption.

In the systemic perspective, electricity price turns out to be relatively unimportant driving factor for electricity storage. Also the importance of price fluctuations is decreased. The level of subsidies on solar and wind power is clearly the most influential supporting driver for electricity storage systemically. The systemic effects greatly buttress the effect of subsidies. The electricity consumption level, directly only a driver of average importance, appears as a strong driver for electricity storage. New nuclear power plants and increased electricity transmission capacity from neighbouring countries are the most important systemic antagonists for increased electricity storage. New nuclear capacity appears rather insignificant factor directly to the storage increase, but systemically it proves to be a strong hindering factor. This relationship is activated mainly through indirect impacts.

The pairwise relationship between electricity storage and market based elasticity of electricity consumption is weak in both direct and total impacts. However, the systemic dependence on drivers of market based elasticity of consumption has a very similar profile as increasing electricity storage. The level of subsidies for solar and wind power is clearly the most important driver, followed by the level of electricity consumption. Both hypotheses appear very volatile, in the sense of having a high dependence on most other system descriptors. For both, the high dependence is mostly systemic, manifested by the impacts of drivers being indirectly strengthened in other cases than electricity price.

4.4. Systemic role of subsidies on wind and solar power

In the analysed system model, solar and wind power subsidies are modeled to be a very independent factor in the system, largely unaffected by the other system descriptors. The most important direct drivers are electricity price and new nuclear capacity, which have an antagonistic direct relationship with subsidy level. Accounting for the indirect impacts does not change the picture of the dependence of subsidy level dramatically, and it remains a very independent policy variable, most strongly dependent on electricity price, that relationship being that rising prices work against increasing subsidies, as subsidies are not needed in a high electricity price scenario.

Systemically, the impacts of level of subsidies on renewable electricity production do not undergo systemic reversals or neutralizations, but influence according to the same logic that modeled direct impacts indicate. In many relationships, the impact of subsidy level is strongly reinforced and the indirect impacts imply that the wind and solar power subsidies support the main enabling developments of increased intermittent electricity production, the increase of electricity storage and consumption elasticity, as well. Overall, the subsidy level is systemically a central driver.

4.5. Key findings

The most important conclusions of the cross-impact analysis of the Finnish energy system are:

- Revealing the systemic effect of increasing wind and solar power production highlights its importance system-wide, as this development remains a key factor even as the indirect impacts are accounted for: there are no emergent systemic effects that would undermine its importance.
- Increasing electricity price is systemically a much less important determinant than what its direct impacts would seem to indicate
- Subsidies for solar and wind appear to be systemically even more important than direct impacts would seem to indicate, and based on the cross-impact analysis, subsidy level appears to be a high-leverage intervention point, with a great deal of systemic impact supporting their direct impacts. Growing electricity consumption and increasing consumption fluctuations are also influential in the systemic perspective.
- Development towards increased wind and solar power production is systemically tightly coupled with increased electricity storage and greater market-based elasticity of electricity consumption.
- Based on the modeled structure of the relationship between the energy system development trends, further investments on nuclear power plants and a greater reliance on wind power appear to be somewhat mutually exclusive, and bifurcation into a more nuclear power based system arrests the systemic prerequisites for increasing wind power production significantly
- Systemically, there are not many drivers supporting increased electricity transmission capacity from neighbouring countries. Most of the direct supporting impacts are largely systemically neutralized and a significant expansion in the transmission capacity seems unlikely as it is not aligned with the possible future development scenarios of the Finnish electricity system.

In synthesising the outcomes of the large increase in low-carbon energy transition studies globally, Kirby and OMahony [33] concluded that they are converging towards a common set of conclusions:

1. The low-carbon transition is technically and economically feasible
2. Transition comes with multiple co-benefits
3. Replacement of fossil energy systems with renewables, increased electrification of energy consumption and strong pursuit of energy efficiency, are identified as the necessary elements of technological change.

Delucchi and Jacobson [14, 1154] proposed that the barriers to global technological transition are not economic or technical, but predominantly social and political. This is consistent with what is known about transition, which according to the IPCC must begin with sustainable development pathways [52], also predominantly social and political challenges. The Finnish cross-impact analysis in this study does not disagree with these conclusions, but in prominent new findings, it also suggests that energy price is less important, and nuclear energy will hamper the development of renewables. This places social and political factors in the future transition of the Finnish energy system front-and-centre, suggesting that there is agency to choose.

5. Discussion

It is often necessary to prepare robust scenarios in areas where quantification is difficult. The cross-impact approach provides an interesting and valuable tool for assessing the future developments of the energy and electricity system. It enables inclusion of several multidimensional assessment categories in the analysis, that are not easily modeled with traditional quantitative methods, and have complex interconnections which are difficult to grasp intuitively or with argumentative logic. Our analysis in this study was based on a compact set of key factors of electricity demand, electricity supply and electricity network. Understanding the complex interlinkages and systemic relationships between these key factors are grand challenges for long-run policy design [42, 40]. Our cross-impact analysis provides new insights into the internal dynamics of the Finnish energy system, based on expert evaluation of cross-impacts.

The main challenge in utilizing the cross-impact approach is, without question, the modeling of the system. The selection and exact formulation of the hypotheses or cross-impact items is crucial, and a notable modeling challenge. The question about model framing and bounding of the inclusion of possibly-important system components is there, as in all modeling. Having an extensive set of hypotheses describing the modeled system is ideal in the sense that the direct causal effects can be modeled with more clarity and precision, and without a great deal of ambiguity and possibilities for differentiated interpretations of the hypotheses. However, a larger set of hypotheses will conversely mean more work in the model valuation phase. Successful cross-impact modeling requires a compromise between high abstraction and overloading of content in the hypotheses, making individual impact valuations difficult and possibly ambiguous (as in a model with a small number of hypotheses) and a possibly overwhelming number of pairwise impacts to valuate (as in a model with a high hypothesis count). The modeling can be quite labour intensive for the experts involved, and an important factor of success is securing their commitment to the effort. The selection of hypotheses and appropriate facilitation of the valuation process are necessary preconditions for implementation of the technique.

Considering further development of the presented cross-impact model, an important improvement would be to model more specific policy instruments as system descriptors. This will enhance the ability to draw clear conclusions and policy-relevant recommendations. It will obviously also increase the difficulty and time requirements of the model valuation. The number of system descriptors in the presented model is quite low and the abstraction level remains high. A more atomic presentation of the system would likely result in less ambiguity in the valuation phase and more uniform understanding of causalities, albeit at a greater time cost in modeling. In an interaction model exhibiting a high level of abstraction, it is possible that in the valuation of a single direct impact of a hypothesis on another, some indirect influence will "bleed" into the direct impact valuation. This is unavoidable in a high-level model and does not necessarily compromise the value of the model, as in all causal models there are some unmodeled intermediary components, that are simply left out because explicitly including them is unnecessary considering the aims of the analysis: any model is always a compromise between practicality and conceptual precision.

This study tested the process of defining the hypotheses for the model and valuating their interactions using expert workshops and questionnaires. The results of the study showcase the analytical aspect of the EXIT cross-impact approach and its possibilities. The experiences and the results that can be extracted from the presented model warrant a more extensive modeling endeavor, resulting in a larger, more complex and more finely grained model, with greater potential for highly actionable analytical outputs.

References

[1] Aalto, P., 2011. Organizing interdisciplinary international studies: from puzzlement to research programmes. In: International Studies. Springer, pp. 66–91.

[2] Aalto, P., Korkmaz Temel, D., 2012. Towards a wider European energy security society: From vulnerability and viability to sustainability. Global and Regional Problems: Towards Interdisciplinary Study, 79–104.

[3] Agami, N., Saleh, M., El-Shishiny, H., 2010. A fuzzy logic based trend impact analysis method. Technological Forecasting and Social Change 77 (7), 1051–1060. URL `https://doi.org/10.1016/j.techfore.2010.04.009`

[4] Al-Saleh, Y., 2009. Renewable energy scenarios for major oil-producing nations: The case of Saudi Arabia. Futures 41 (9), 650–662.

[5] Andersson, C., Törnberg, A., Törnberg, P., 2014. Societal systems–complex or worse? Futures 63, 145–157.

[6] Bañuls, V. A., Turoff, M., 2011. Scenario construction via Delphi and cross-impact analysis. Technological Forecasting and Social Change 78 (9), 1579–1602. URL `https://doi.org/10.1016/j.techfore.2011.03.014`

[7] Bañuls, V. A., Turoff, M., Hiltz, S. R., 2013. Collaborative scenario modeling in emergency management through cross-impact. Technological Forecasting and Social Change 80 (9), 1756–1774. URL `https://doi.org/10.1016/j.techfore.2012.11.007`

[8] Blackman, A., 1973. A cross-impact model applicable to forecasts for long-range planning. Technological Forecasting and Social Change 5 (3), 233–242. URL `https://doi.org/10.1016/0040-1625(73)90002-4`

[9] Bloom, M. F., 1977. Time-dependent event cross-impact analysis: Results from a new model. Technological Forecasting and Social Change 10 (2), 181–201. URL `https://doi.org/10.1016/0040-1625(77)90044-0`

[10] Brauers, J., Weber, M., 1988. A new method of scenario analysis for strategic planning. Journal of Forecasting 7 (1), 31–47. URL `https://doi.org/10.1002/for.3980070104`

[11] Burns, J. R., Marcy, W. M., 1979. Causality: Its characterization in system dynamics and KSIM models of socioeconomic systems. Technological Forecasting and Social Change 14 (4), 387–398. URL `https://doi.org/10.1016/0040-1625(79)90036-2`

[12] Choi, C., Kim, S., Park, Y., 2007. A patent-based cross impact analysis for quantitative estimation of technological impact: The case of information and communication technology. Technological Forecasting and Social Change 74 (8), 1296–1314. URL `https://doi.org/10.1016/j.techfore.2006.10.008`

[13] Dalkey, N. C., 1971. An elementary cross-impact model. Technological Forecasting and Social Change 3, 341–351. URL `https://doi.org/10.1016/s0040-1625(71)80022-7`

[14] Delucchi, M. A., Jacobson, M. Z., 2011. Providing all global energy with wind, water, and solar power, Part II: Reliability, system and transmission costs, and policies. Energy policy 39 (3), 1170–1190.

[15] Enzer, 1971. Delphi and cross-impact techniques. Futures 3 (1), 48 – 61.

[16] Enzer, S., 1972. Cross-impact techniques in technology assessment. Futures 4 (1), 30 – 51.

[17] EU Commission, 2011. Roadmap to a resource efficient europe. Tech. rep., EU Commission.

[18] Godet, M., 1976. Scenarios of air transport development to 1990 by SMIC 74 — A new cross-impact method. Technological Forecasting and Social Change 9 (3), 279–288.
URL `https://doi.org/10.1016/0040-1625(76)90012-3`

[19] Godet, M., Bourse, F., Chapuy, P., Menant, I., 1991. Futures Studies: A Tool-box for Problem Solving. Futuribles (series). GERPA Prospective.

[20] Godet, M., Coates, J., Unesco, 1994. From Anticipation to Action: A Handbook of Strategic Prospective. Future-oriented studies. Unesco Publishing.

[21] Gordon, T., Hayward, H., 1968. Initial experiments with the cross impact matrix method of forecasting. Futures 1 (2), 100 – 116.

[22] Gordon, T. J., 1969. Cross-impact matrices: An illustration of their use for policy analysis. Futures 1 (6), 527–531.

[23] Gordon, T. J., 1994. Cross impact method. Tech. rep., United Nations University Millennium Project.

[24] Gordon, T. J., Hayward, H., 1968. Initial experiments with the cross impact matrix method of forecasting. Futures 1 (2), 100–116.

[25] Helmer, O., 1981. Reassessment of cross-impact analysis. Futures 13 (5), 389400.

[26] Honton, E., Stacey, G., Millett, S., 1984. Future Scenarios: The BASICS Computational Method. Economics and policy analysis occasional paper. Battelle Columbus Division.

[27] Ishikawa, M., Toda, M., Mori, S., Kaya, Y., 1980. An application of the extended cross impact method to generating scenarios of social change in Japan. Technological Forecasting and Social Change 18 (3), 217–233.
URL `https://doi.org/10.1016/0040-1625(80)90024-4`

[28] Jackson, J. E., Lawton, W. H., 1976. Some probability problems associated with cross-impact analysis. Technological Forecasting and Social Change 8 (3), 263–273.
URL `https://doi.org/10.1016/0040-1625(76)90004-4`

[29] Jeong, G. H., Kim, S. H., 1997. A qualitative cross-impact approach to find the key technology. Technological Forecasting and Social Change 55 (3), 203–214.
URL `https://doi.org/10.1016/s0040-1625(96)00209-0`

[30] Kaivo-oja, J., Luukkanen, J., Panula-Ontto, J., Vehmas, J., Chen, Y., Mikkonen, S., Auffermann, B., 2014. Are structural change and modernisation leading to convergence in the CO_2 economy? Decomposition analysis of China, EU and USA. Energy 72, 115–125.

[31] Kane, J., 1972. A primer for a new cross-impact language – KSIM. Technological Forecasting and Social Change 4 (2), 129 – 142.

[32] Kaya, Y., Ishikawa, M., Mori, S., 1979. A revised cross-impact method and its applications to the forecast of urban transportation technology. Technological Forecasting and Social Change 14 (3), 243–257.
URL `https://doi.org/10.1016/0040-1625(79)90080-5`

[33] Kirby, P., OMahony, T., 2018. Planning future pathways: Implications and outcomes of scenario studies. In: The Political Economy of the Low-Carbon Transition. Springer, pp. 115–141.

[34] Linss, V., Fried, A., 2010. The ADVIAN classification–A new classification approach for the rating of impact factors. Technological Forecasting and Social Change 77 (1), 110–119.

[35] Lund, P. D., 2007. The link between political decision-making and energy options: assessing future role of renewable energy and energy efficiency in finland. Energy 32 (12), 2271–2281.

[36] Luukkanen, J., 1994. Role of planning philosophy in energy policy formulation. Ph.D. thesis, Tampere University of Technology, tampere University of Technology publications # 129.

[37] Luukkanen, J., Panula-Ontto, J., Vehmas, J., Liyong, L., Kaivo-oja, J., Häyhä, L., Auffermann, B., 2015. Structural change in Chinese economy: Impacts on energy use and CO_2 emissions in the period 2013–2030. Technological Forecasting and Social Change 94, 303–317.

[38] Martino, J. P., Chen, K.-L., 1978. Cluster analysis of cross impact model scenarios. Technological Forecasting and Social Change 12 (1), 61–71.
URL `https://doi.org/10.1016/0040-1625(78)90035-5`

[39] Medina, E., Arce, R. D., Maha, R., 2015. Barriers to the investment in the concentrated solar power sector in Morocco: A foresight approach using the cross impact analysis for a large number

of events. Futures 71, 3656.
[40] Metz, B., 2007. Climate change 2007: mitigation of climate change: contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.
[41] Mitroff, I. I., Turoff, M., 1976. On the distance between cross-impact models: A set of metric measures for cross-impact analysis. Technological Forecasting and Social Change 8 (3), 275–283. URL https://doi.org/10.1016/0040-1625(76)90005-6
[42] Nakicenovic, N., Alcamo, J., Grubler, A., Riahi, K., Roehrl, R., Rogner, H.-H., Victor, N., 2000. Special Report on Emissions Scenarios (SRES), A Special Report of Working Group III of the Intergovernmental Panel on Climate Change. Cambridge University Press.
[43] Nicolini, M., Tavoni, M., 2017. Are renewable energy subsidies effective? evidence from europe. Renewable and Sustainable Energy Reviews 74, 412–423.
[44] Nováky, E., Lóránt, K., 1978. A method for the analysis of interrelationships between mutually connected events: A cross-impact method. Technological Forecasting and Social Change 12 (2-3), 201–212.
URL https://doi.org/10.1016/0040-1625(78)90056-2
[45] Pagani, M., 2009. Roadmapping 3G mobile TV: Strategic thinking and scenario planning through repeated cross-impact handling. Technological Forecasting and Social Change 76 (3), 382–395. URL https://doi.org/10.1016/j.techfore.2008.07.003
[46] Panula-Ontto, J., November 2016. AXIOM Method for Cross-Impact Modeling and Analysis. Master's thesis, University of Tampere, available online at http://tampub.uta.fi/handle/10024/100041.
[47] Panula-Ontto, J., 2016. EXIT Method for Cross-Impact Analysis, available at https://www.researchgate.net/publication/319679034_EXIT_method_for_cross-impact_analysis.
[48] Panula-Ontto, J., 2017. EXIT: Express Cross Impact Technique. Software available at https://github.com/jmpaon/EXIT.
[49] Panula-Ontto, J., Luukkanen, J., Kaivo-oja, J., Majanne, Y., Vehmas, J., 2016. Complex energy futures. the use of Express Cross-Impact Technique (EXIT) with participatory expert workshops to analyse complex systems and interactions. In: Conference proceedings of 2016 International Conference on Advances on Clean Energy Research, ICACER 2016, At Bangkok, Thailand. ICACER.
[50] Panula-Ontto, J., Piirainen, K., 2017. EXIT method for cross-impact analysis, unpublished.
[51] Ritchey, T., 2006. Problem structuring using computer-aided morphological analysis. Journal of the Operational Research Society 57 (7), 792–801.
URL http://dx.doi.org/10.1057/palgrave.jors.2602177
[52] Sathaye, J., Najam, A., Cocklin, C., Heller, T., Lecocq, F., Llanes-Regueiro, J., Pan, J., Petschel-Held, G., Rayner, S., Robinson, J., et al., 2007. Sustainable development and mitigation. In: Climate Change 2007: Mitigation of Climate Change. Cambridge University Press, pp. 691–743.
[53] Statistics Finland, 2017. Statistics finland database.
URL http://www.tilastokeskus.fi/tup/statfin/index.html
[54] Steen, M. V. D., Twist, M. V., 2013. Foresight and long-term policy-making: An analysis of anticipatory boundary work in policy organizations in the Netherlands. Futures 54, 3342.
[55] Thorleuchter, D., den Poel, D. V., Prinzie, A., 2010. A compared R&D-based and patent-based cross impact analysis for identifying relationships between technologies. Technological Forecasting and Social Change 77 (7), 1037–1050.
URL https://doi.org/10.1016/j.techfore.2010.03.002
[56] Thorleuchter, D., Poel, D. V. D., 2014. Quantitative cross impact analysis with latent semantic indexing. Expert Systems with Applications 41 (2), 406411.
[57] Turoff, M., 1971. An alternative approach to cross impact analysis. Technological Forecasting and Social Change 3, 309–339.
URL https://doi.org/10.1016/s0040-1625(71)80021-5
[58] Van den Bergh, J. C., Bruinsma, F. R., 2008. Managing the transition to renewable energy: theory and practice from local, regional and macro perspectives. Edward Elgar Publishing.
[59] Vehmas, J., Kaivo-oja, J., Vehmas, J., et al., 2016. Sustainability cycles in China, India, and the world? Eastern European Business and Economics Journal 2 (2), 139–164.
[60] Vögele, S., Hansen, P., Poganietz, W.-R., Prehofer, S., Weimer-Jehle, W., 2017. Building scenarios for energy consumption of private households in Germany using a multi-level cross-impact balance approach. Energy 120, 937–946.
[61] Weimer-Jehle, W., 2006. Cross-impact balances: A system-theoretical approach to cross-impact analysis. Technological Forecasting and Social Change 73 (4), 334–361.
URL https://doi.org/10.1016/j.techfore.2005.06.005