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Connectivity as the capacity to improve an organization's decision-making

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Abstract

This paper describes the development of a new computational model to predict the desirability of decision consequences in an organization, and the development of a prototype tool to enable real-time interaction and decision support when changes occur simultaneously. A tool, called Decision Propagation System, is developed in response to the needs of BT Group plc in understanding the most effective set of interventions in the organization where the high degree of connectivity between system components and the uncertainty in connectivity data are two critical issues. Designed on a case study of the Fields Operations Engineering, this research demonstrates that a knowledge of overlapping decision propagation paths can direct the organizational decisions towards mitigating the risk of unintended consequences.

Keywords: Complexity; Connectivity; Change propagation; Data-driven engineering design; Decision-making; Multiple domain matrix; Systems engineering.

1. Introduction

In order to improve the quality and speed of decisions, organizations need to pay more attention to what needs to be decided, by whom, and how quickly [1]. This is becoming ever-challenging as new connectivity technologies have transformed the way by which individuals in an organization communicate and influence one other. Ideally, by providing the right people with the right information, they can formulate faster and well-informed decisions at the right time, but the reality is far more complicated.

People involved in different roles have different targets and motivations which contribute to uncertainty between them. Furthermore, many decisions have to be made under uncertain circumstances, with incomplete, imprecise, or even conflicting information. The consequence of a decision often goes beyond its local impact in the organization and might globally affect other decisions, sometimes without the initial decision-maker necessarily being aware of the implications [2].

In such situations, an agent's decision (e.g., on performing a job) might affect and be affected by multiple consequences (such as customer satisfaction, productivity, and deployment cost) simultaneously, where in many cases there is a kind of overlapping impact between these consequences. Therefore, a dynamic tool is required to proactively quantify the desirability of possible consequences when they mutually affect an agent's decision. Such a tool should not only take account of the multiple channels of connectivity between decisions, but also compute the compound risk of change in elements based on the individual impact of multiple overlapping links.

This paper presents the development of such a dynamic tool called *Decision Propagation System* (*DPS*) that is built reflecting the advancements in the fields of engineering design change, graph theory, and systems engineering. It aims to support decision-makers with predictive insights to direct decisions towards designing the most effective architecture in balance with the consequences; for example, where to make changes in the organization – in roles, targets, priorities – to achieve the best compromise between total cost and customer satisfaction?

In the following, Sections 2 and 3 outline the research that led to the development of DPS. Section 4 introduces the proposed method and is followed by its implementation at BT Group (BT) in Section 5. The paper concludes in Section 6.

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2. Research methodology

Analogous to the actual engineering design processes [3], this research began with understanding the business challenges in BT to identify the modelling requirements, over a time period of six months. The original aim was to understand how to mitigate the unintended consequences of decisions through understanding the decision dynamics. However, as the result of the initial studies, a number of more fundamental research questions were raised pertaining to the:

- *Visibility of connectivity*: How to add semantic knowledge about the dependencies into the model (getting a more composite view of decisions)?
- *Nature of connectivity*: How to populate a compound risk diagram showing the most critical elements (quantifying the influence of decisions)?
- *Implications of connectivity*: What is the most efficient set of interventions in the organisation to achieve the desired set of outcomes (mitigating unintended consequences)?

The next step was to develop a range of alternative models (solution space) to address these business challenges. Examples of such models can be found in the references [4] and [2]. The former model was based on the premise that one way to predict a system's performance is to focus on the changeability of its critical elements. Therefore, the Change Prediction Method (CPM) approach [5] was used to identify the critical elements and combined with the System Dynamics to capture dynamics of those (critical) elements. In the latter research [2], a conceptual model of a Decision Propagation System was proposed, with the aim of obtaining a more composite view of decisions by focusing on multiple ways that decisions are connected to and can influence each other: for example, through their involving agents or consequences. In fact, a year of research in a close collaboration with the company was required to develop and discuss the concepts. This was an iterative process with a continuous refinement of the prototype models according to the research questions. A primary case of the Fields Force Engineering (FFE) problem was considered to assess the plausibility of the proposed models. Further investigation of the previous steps eventually led to the formulation of DPS algorithm.

After selecting the concept, the next step was to elaborate the model formulation as well as its calibration and implementation with respect to the practitioners' feedback. Over a time period of nine months, the simulation results were reported back several times to the corresponding team in the company to ensure that the research questions were fully addressed by the model. This paper concentrates on the detail formulation and implementation of the method.

3. Research case study

The performance of Fields Force Engineering team is vital in delivering an optimal service to BT customers. In particular, the team is responsible for the forecasting, planning, scheduling, and allocation of jobs based on the customer's demands. Therefore, there might be many foreseen (e.g., new business strategy) and unforeseen (e.g., customer demand, weather condition) issues whose changes can influence the performance of FFE. These sorts of frequent changes typically result in incomplete, imprecise, or even conflicting data when planning and re-planning the system.

An additional challenge for the organization is incorporating organizational dynamics into the planning system: in this case study, there are five different roles ranging from director at the strategic level to engineers at the operational level. Each role has a specific set of objectives as well as their own motivation and varying degrees of interaction with other roles. For example, while at the operational level, maintaining work-life balance is a priority for engineers to keep them motivated, at the strategic level, director is more concerned about the big picture of the right balance between number of successful jobs, total cost, and stakeholder satisfaction.

The ideal case would presumably be when, making a decision, individuals satisfy both the local objectives of their own jobs and at the same time comply with the global objectives of the rest of the team and the entire system [6]. However, the evidence shows that the ideal case is very difficult to achieve, since there are many upstream decisions whose consequence affect the downstream decision-makers without them taking any control over the situation. For example, in the FFE case, the controller (who is responsible for prioritizing jobs) does not have any control over how many jobs are arrived, how many engineers are deployed, or how many jobs an engineer can perform per day. Therefore, the efficient management of decisions in such complex systems requires a tool to enable every decision-maker to be proactively aware of the consequences of his/her actions.

3.1. Challenges in modelling Field Engineering Systems

The need for such a tool was initially identified through a series of workshops at BT. However, a deeper investigation of the business case resulted into several challenges during the development of modelling concepts:

Data elicitation. An initial study of the business case based on the company documents identified a set of 21 key elements which were categorized into an Multiple Domain Matrices (MDM) with three layers of agents, decisions, and consequences. This data was used to build and populate the initial model, and later refined by obtaining a more detailed data from the BT experts. Eliciting data from the experts, whilst providing more resolution of the business case, was a time-consuming and error-prone process which also generated different views of the system. This posed a challenge as to how much detail was needed to understand what was happening in reality. If a deeper set of data could be obtained from the experts, would this result in a better model or a simpler picture obtained from the documents be sufficient?

Variation in expert views. during the implementation of DPS, three experts with an extensive knowledge of the case were asked to consider the entire FFE project and determine the *proportional strength* of the links between elements, based on a three-range scale: low, medium, and high. Three MDMs

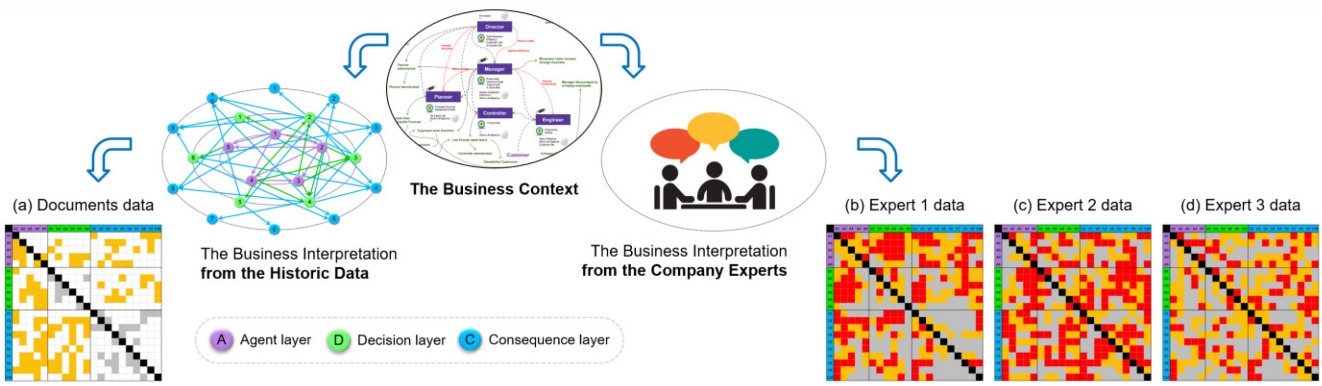

Fig. 1. Capturing Business requirements into input data: Elicitation from the historic documents (a) and from the company experts (b-d)

were generated as the result (Fig. 1, b-d) representing different views of the case: expert 2 appears to score the links more highly than the others. This raised further concerning how to resolve variation in expert views? Should they be considered individually or as an aggregated view? Further challenge would be the mapping of scaled data into probability values, e.g., should a high-priority link be valued as 0,8 or 1,0?

Density of links. experience of conducting workshops with the experts revealed that, when extending the modelling scope from a *physical technical system* to a *digital-physical socio-technical system* and highlighting the mechanism by which elements influence each other (i.e., knowledge-sharing tools, organization's hierarchy), the degree of connectivity within and across layers significantly increase: for this business case, a fully connected network. A key computational challenge is therefore how to resolve the algorithmic view of change propagation in dense matrix, without simplifying the reality? The most commonly used algorithms of change propagations such as CPM [5] are based on a sparse matrix and cannot accommodate this density. This would be more problematic in multi-layer networks as each layer infers a different meaning.

Overlapping impact. it is also inferred that when making a decision, if there are two links coming to an individual (e.g., from consequences), it is more likely they are independent; but if an individual's decision is influenced through multiple links, it is more likely that they are to some degree overlapped and there might be a dominant link amongst them (with more influence). As the result, the more links coming in, the lower probability of aggregated link which implies a kind of consolidation of independence. The question is then how to reflect the impact of overlapping between multiple paths (homogeneity between elements of the same layer) when a change propagates across the system?

3.2. The need for a new approach

From an engineering change perspective, quantifying the risk of decision propagation is essentially a *multi-layer socio-technical change propagation* problem, which requires an explicit understanding of the interplay between non-technical (e.g., agents) and technical (e.g., decisions, consequences) elements. Accepting this view, it is discussed that addressing such a problem requires dealing with the tight connectivity and overlapping issues between heterogeneous elements.

Reviewing the literature of change management represents that, despite a huge repository of models for analyzing change propagation (see [7] for an overview), there has been very little attention to the propagation between the interfacing organizational and technical changes. Moreover, the current body of change prediction algorithms, mainly focusing on identifying the most influential or influenced elements, does not accommodate the density and overlapping issues. Furthermore, current models consider change propagation at a project level where changes are typically *tree*-structure; but if changes occur in the middle of a project, the propagations are more likely to be *cyclical*, and successful completion of the project relies on the iterative refinement of decisions.

In addressing these research gaps and the needs of industry sponsor, this paper introduces an alternative algorithm for predicting the compound risk of changes in a complex system where the overall system behavior depends on the changeability of the system elements and the extent to which they are connected. The proposed model should be able to accommodate the following aspects of connectivity:

- The unavoidable *subjectivity* and *variation* in expert views;
- Both unity and proportional *data* within and across layers;
- Both *tree*-like and *cyclical* dependencies across the system;
- The *density* of dependencies, belong to multiple domains;
- The impact of *overlapping* in dependencies;

4. A Decision Propagation model for systems design

4.1. Overview of the Decision Propagation System – DPS

The DPS method is based on the concept that *a system can be represented in form of its key decision variables, agents who might influence and be influenced by those decisions, and (organization- or business-related) consequences of decisions,* typically known as performance indicators. The underlying rationale is that agents in an organization make decisions and decisions generate consequences, which will in turn affect the behavior of agents. Hence, the more critical a role might be (in terms of influencing on more decisions), or the more collaborative a decision might be (in terms of involving more agents), or the more critical a decision might be (in terms of affecting more consequences), will result in a more connected network and accordingly, a more expanded propagation. The proposed algorithm used the proportional strength of the direct links between elements to compute the indirect risk. This will be accomplished in a multi-dimensional space to reflect the overlapping impact, where the number of overlapping links determines the number of dimensions.

The DPS method is primarily designed for situations where there is insufficient resolution about the business case, such as the information of the likelihood and impact values in CPM. However, if provided with a more detailed information, the method is capable of giving a more precise result. In this sense, it is an extension to the CPM in which the fundamental assumptions about the *independence* and *cyclical* propagation paths are fixed. Circumventing these issues has been the subject of several studies before such as the use of Matrix Multiplications and Bayesian networks in [9] and [10]; but, in comparison, DPS offers a *dynamic socio-technical change prediction model* at a far less computational complexity, more control over propagation paths, and better reproducibility which also requires less domain knowledge from the experts.

Structurally, the method consists of four steps: eliciting data, architecting decision views, populating risks, and learning from outputs through visualization. These steps, shown in Fig. 2, are explained in the following sub-sections:

4.2. Step 1: creating organizational model

The method begins with analyzing the business case in order to obtain an initial organizational model. It is a multi-layer network of interconnectivity between agents, decisions, and consequences. Experience of the FFE case study and company workshops suggests that, at a certain degree of abstraction, it is not too difficult for those familiar with the organization to break it down into a list of key elements. The outcome is an MDM with three layers with the same elements in rows and columns; column headings show the initiating elements and rows the influenced elements.

The value of matrix components (interconnectivity) is set to qualitatively represent the proportional strength of a connection and is delineated in form of the low, medium, and high ratings; this ranking has been a common way of describing connectivity in the literature [11]. As the output is shown in Fig. 1, two data elicitation methods have been applied in this research to determine the value of MDM based on: studying the company documents (aiming to learn probability values based on historic data) and relying on experts' knowledge (aiming to improve their judgement under uncertainty).

4.3. Step 2: framing decision propagation paths

The input data obtained in the first step embodies the flow of decision-making in the whole lifecycle of an organization's change. At this step, however, the user needs to define the focus of modelling: architecting the entire network (mapping organizational dynamics) or an instantiation of it (representing

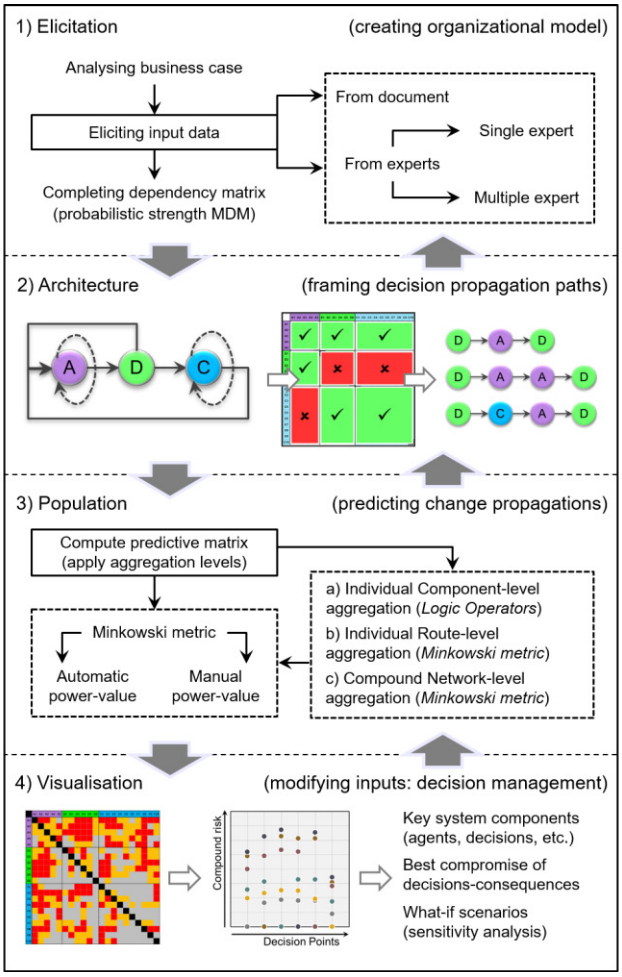

Fig. 2. The Decision Propagation System method

a specific business situation). Considering the modelling context as a complete network, consequently, the model contains so many branches that they cannot be fully independent of the others. This has two implications: (a) there must be some degree of commonality or overlap between network branches; and (b) there should be a set of pruning strategies to confine the number of expected propagation paths. Two strategies are consequently applied in this step:

- *Static Pruning* (carried out at *design time* as part of the MDM configuration): we prune all paths that do not follow our assumptions about decision-making flow, by neutralizing the corresponding boxes in the MDM (Fig. 2, step 2);
- *Dynamic Pruning* (carried out at *run time* when the propagation algorithm is run): we prune all paths whose length exceeds three steps. It is considered to be sufficient to track the flow of a change across layers back to the same layer where the change was originated, e.g., to capture the cyclical change propagation.

Differentiating propagation paths in DPS eventually enables the user to identify the most critical paths and the elements. The current change propagation models mostly emphasize what element affects what and do not account for how (through which elements or paths) this will be done.

4.4. Steps 3: predicting change propagation

Framing propagation paths in the previous step determines all feasible routes through which any two elements in the MDM are connected together. An example of those routes between two decision points is shown in Fig. 3 (top). Accordingly, in each route scenario, a propagation tree (limited to *three* steps) can be derived from the network, where there might be a number of paths (in each route) to connect the two (initiating and affecting) elements. In the example of Fig. 3 (top-left), it is shown that there are four paths that connect D_a to D_b through the consequences. DPS then uses the strength value of direct links between elements to compute the risk (R) of a change: it is a combination of probability and impact:

$$Risk\ (R_{ab}) = Probability\ (P_{ab}) \times Impact\ (I_a) \qquad (1)$$

4.4.1. Computing Compound Probability

The compound probability is an average value that a change in an element will propagate to a change in another one. There are a number of algorithms for aggregating change probabilities, yet none of them found to have the potential to address the previously outlined challenges in a single frame. This paper presents a systematic aggregation method for

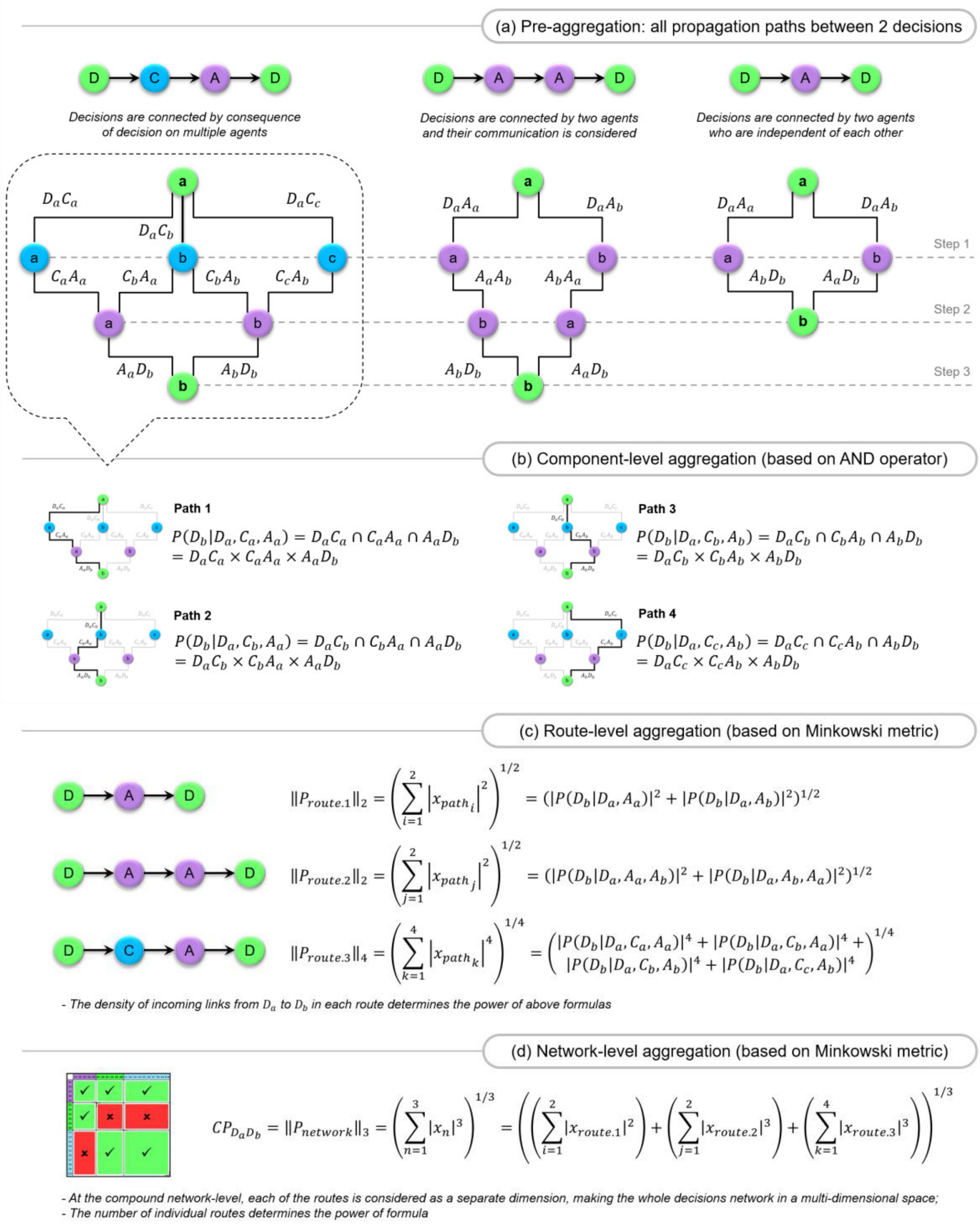

Fig. 3. A multi-layer aggregation method for computing the compound probability

computing the compound probability. It is comprised of three levels pertaining to the aggregation of (1) *direct links* in a single path, (2) *multiple paths* in a single route, and (3) *multiple routes* in the network. These steps are exemplified in Fig. 3 for a simplified network with 2 decision points, 2 agents, and 3 consequences. Of central importance to the proposed method is the aggregation engine. Inspired by the generalization of distance metrics in a multi-dimensional space, we found the *Minkowski* metric sufficiently agile to calculate the aggregation power of overlapping links, while being applicable to a dense network. It is in fact the most commonly used proximity metric in graph theory that is used in this research to give a *non-linear* approximation of the relative probability between elements. For a real number $p \in \mathbb{R}$ ($where\ p$ is the number of dimensions), the p-norm of Minkowski measure is defined as below, where n refers to the number of incoming links to an element and may be or not equivalent to the power of formula (p):

$$\|x\|_p = (|x_1|^p + |x_2|^p + \cdots + |x_n|^p)^{\frac{1}{p}} \tag{2}$$

(a) Pre-aggregation. Given the probabilistic MDM as the input, the algorithm first generates the three-step propagation trees for all the elements, such as the ones illustrated in Fig. 3 (top) for D_a. Unlike many change prediction models, the DPS method differentiates the *route-type* (by which the elements are connected) and the *path-number* within each route (by which an element might be affected). In the given example, there are in total three routes that connect the decisions D_a and D_b ($D \to A \to D$; $D \to A \to A \to D$; $D \to C \to A \to D$); each route contains 2, 2, and 4 paths, respectively.

(b) Component-level aggregation. At the first aggregation level, the model utilizes the AND logic operator and multiplies the direct links within each path, starting from the top. It is based on the concept of path searching in that if for example C_a is a consequence of D_a which can affect A_a, then D_a can indirectly affect A_a with an impact that is less than a direct impact between them.

(c) Route-level aggregation. When aggregating the direct links at the component-level, there is an assumption about the independence of multiple paths that belong to the same route. However, in reality, the links coming to a decision (D_b) might involve the same element (e.g., two paths going through C_b) which can be contributed to an overlapping impact. Therefore, the next level aggregates multiple propagation paths of the same route. In the example of Fig. 3(c), all the changes are propagated through consequences and agents. Mathematically, the model considers each individual path in a separate dimension, and the density of paths between initiating and affected elements determines the power of Minkowski formula. In the given example, this number is respectively equal to 2, 2, and 4 for routes ending to D_b.

(d) Network-level aggregation. This phase aggregates all the routes by which the two elements are connected together. At this point, the model considers the entire network in a multi-dimensional space in which a change in an upstream decision (D_a) affects a downstream decision (D_b) by different routes, through the involving agents, communication between agents, or impact of consequences on the agents. Hence, the number of possible routes between two elements regulates the power of Minkowski formula. Finally, the model normalizes the compound probability values to ensure that they lie within the range of $(0,1)$.

4.4.2. Computing Compound Impact

There are several ways to quantify impact of a change. Focusing on connectivity, this paper proposes that one way to measure the impact of an element is through adjacency metrics: looking at the intensity of changes that an element exerts on (activity) or receive from (passivity) its immediate neighbours. Hence, inspired by the Centrality metrics in Network Science [12], we define the measure of *Criticality* (Cr) as the fraction of the cumulative strength of outgoing links from an element over the cumulative strength of incoming links to that element. As the criticality can take any positive value, *Feature Scaling* is then used to restrict the values between the arbitrary points of a (lower strength bound) and b (upper strength bound), as the formulas show:

$$Criticality\ (Cr_i) = \frac{Weighted\ sum\ of\ value\ of\ outgoing\ links}{Weighted\ sum\ of\ value\ of\ incoming\ links} \tag{3}$$

$$Impact\ (I_i) = \left(a + \frac{(Cr_i - Cr_{min}) \times (b-a)}{(Cr_{max} - Cr_{min})}\right) \tag{4}$$

A higher value of impact implies that if change occurs, the element has more influence on the other elements, whilst being less influenced by the others. Fig. 4 displays the computation of impact values for a trivial example with 4 elements.

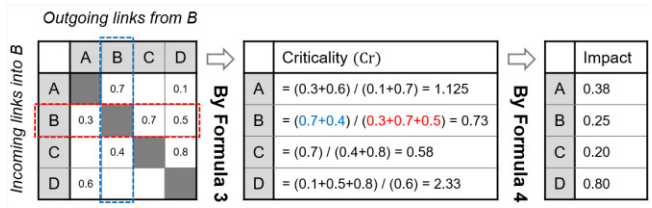

Fig. 4. Example of computing impact in DPS; the values are bounded within the range of [0.2,0.8]

4.5. Step 4: decision management

Once the compound risk matrix has been derived, a variety of charts and diagrams may be used to visualize the resultant data. The primary outcome of the model would be a risk plot. It can be tailored to show the mutual risk between agents, decisions, and consequences in parallel. The initial analysis enables the user to identify the critical elements and the low-risk leverages, i.e., the sensitivity that consequences show to each decision and agent. More iterations may be applied by the user to evaluate and compare the impact of change in initial data pertaining to for example different decision-making strategies, multiple expert views, or different translation of connectivity data (strength values). The following section outlines the implementation of DPS.

5. Implementation and discussion

The implementation of DPS was an iterative process with regular evaluation and calibration after each development phase. The primary validation was undertaken with reference to the BT's FFE system. A prototype support tool has been developed in Microsoft Excel (due to its compatibility and portability across different operating systems) to enable real-time interaction and decision support (Fig. 5). It is a data-driven platform that provides ready access to the underlying change prediction model in a way that encourages decision makers to explore the mutual sensitivity between Consequences, and also the sensitivity that Consequences have to each Decision and Agent (via the output risk plot and matrix).

The DPS dashboard has been tailored based on the sponsors' preferences in such a way that embraces a number of views relating to the: impact of elements (bar charts); compound risk on the Consequences (risk plot/matrix); risk variance between multiple propagation routes (tree boxes); and sensitivity analysis engine (combined bar charts) which provide an extensive range of narratives to compare variation in expert views. This integrated platform enables the user to build, populate, re-evaluate, and refine the data until reaching a level of relative stability in the outcomes. Each of the icons in the XL-DPS ribbon has been designed to address a specific aspect of model building, populating, and analysis, based on the challenges that have been identified during the workshops with partners.

The implementation of DPS began with the historic data that was obtained from the company documents. It was based on the assumption that all the links of the same type (e.g., agents' influence on decisions as shown in the left-middle box in the input MDM) have the same priority. The focus of the initial implementation has largely been on creating and testing a range of what-if business scenarios that could potentially affect the model behavior; for example, to what extent do changes in the organization-related consequences (such as work-life balance and productivity) effect the business-related consequences (such as public image and total cost), and what are the key decisions to mitigate that risk?

After endorsing the plausibility of the model, a range of workshops was held with BT experts to obtain more detailed connectivity data using the FFE case as an end-to-end project. This resulted in a deeper investigation of the challenges that were discussed earlier in section 3.1. For example, as far as related to the data elicitation approaches, Fig. 6 shows the apparent difference in behavior of the model based on a sparse (historic data) dataset and a more dense (expert 1) dataset. Accordingly, the figure signifies the critical role of the density and interdependence of the connections across the system, and the validity of the model's assumptions relating to the proportional strength of the connections and the need for clarity in displaying the details of the model.

Further investigations, using the sensitivity analysis panel, compared the experts' views in terms of the compound risk between consequences: this is displayed by the Stacked Risk bars in Fig. 5 (right) together with the Clustered bars representing the Variance between them. The results explicitly identify the connections at which there is more consensus between the experts. As a result, the focus of further refinements can be shifted towards the areas with a higher degree of variation to find out the source, thus helping to

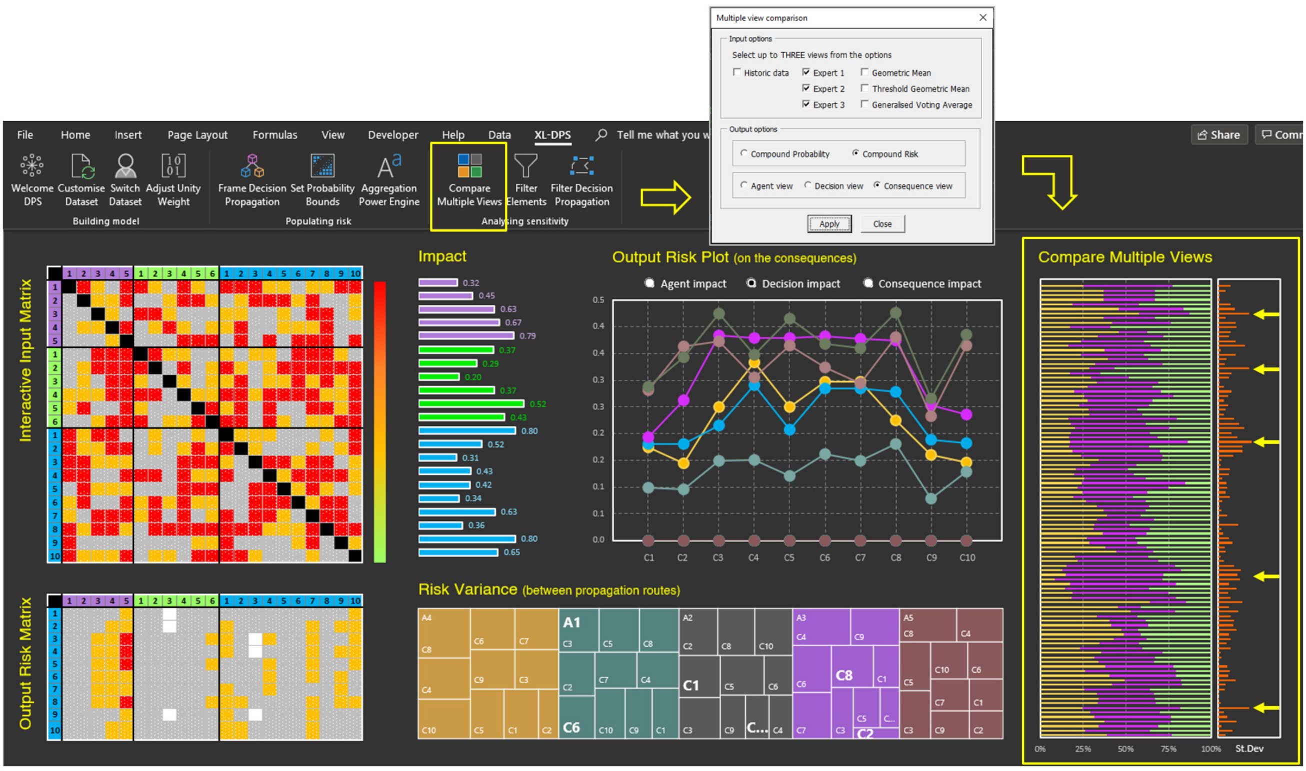

Fig. 5. A data-driven real-time computer support prototype for DPS: a screenshot of the model run in case of Expert 2; each Scatter line in the Output Risk Plot stands for the compound risk of a particular agent on consequences; each line in Stacked bar at far right shows a risk of propagation between two consequences

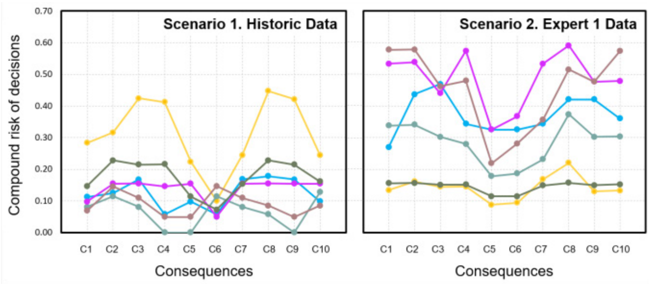

Fig. 6. Impact of using different data elicitation techniques on the risk of decisions on consequences

achieve a convergent answer in less time and effort.

Therefore, the rich DPS ribbon supported by a multi-view dashboard can provide the user with numerous ways of capturing, interpreting, and visualizing a model. The population panel in XL-DPS enables the configuration of propagation architecture, the translation of connections into probability values, and setting up the aggregation engine. The primary result presented earlier is in fact based on *automatic* computation of the Minkowski power where the density of incoming links determines the power of formula. In this case, each propagation path is considered as a separate dimension and hence, the degree of overlap between multiple paths is equal to their number. However, this might not be always the case. To address this sort of uncertainty, the aggregation engine in DPS is developed to work in two modes: *automatic* and *manual*. In the latter case, the power of Minkowski metric for each propagation route is manually entered by the user, and the power engine icon allows the user to evaluate the impact of using different power values until reaching the stability in the outcomes.

Finally, the analysis panel provides a mean for analyzing the impact of *multiple simultaneous changes* on the outcome, when for example some elements or a particular propagation route are excluded from the computation. As pointed out by the practitioners, it is an effective way of analyzing the global impact of local unforeseen issues, e.g., absence of a particular role and its associated decisions. At the end of the initial implementation, the research questions (Section 2) and the associated modelling challenges (Section 3.1) were reviewed with the BT team. The primary workshops confirmed the credibility of the results and that the proposed method has properly addressed all the modelling challenges. Populating the FFE model based on the ultimate (most-dense) scenario confirmed that the DPS mathematical engine has the capability to deliver the compound risk of making decisions in highly connected and overlapped networks without saturation.

6. Conclusions

Grounded in the connectivity inside and across organizations, new business requirements necessitate the need for rethinking about the decision-making and decision modelling processes. Making well-informed decision in such situations requires a proactive approach to quantify the desirability of its possible consequences. In response to the needs of industry and the research community, this paper has proposed the development of a new way of capturing, interpreting, and visualizing probabilistic connections in complex systems. The implementation of a new change propagation algorithm has accommodated the density of connections; and the design of a novel dashboard acts as an interface to the model and enables real-time interaction and decision support.

The potential impact of this research to support process improvement is significant – particularly in the light of ever more connected products and manufacturing processes. Not only for engineering and business sectors which often make interconnected decisions, but also for the academic community which have few tools capable of supporting connected decision propagation with overlapping spheres of influence.

The experience from the primary case study (partially illustrated in this paper) represents the relative success of the proposed method in tackling an organization's challenges in dealing with socio-technical change predictions. At present, the method is under evaluation in BT and being evolved to facilitate its utility with respect to the different business contexts such as healthcare and infrastructure systems design.

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