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INTRODUCTION

Modeling for policy and technology assessment: Challenges from computer-based simulations and artificial intelligence

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Abstract • Modeling for policy has become an integral part of policy making and technology assessment. This became particularly evident to the general public when, during the COVID-19 pandemic, forecasts of infection dynamics based on computer simulations were used to evaluate and justify policy containment measures. Computer models are also playing an increasing role in technology assessment (TA). Computer simulations are used to explore possible futures related to specific technologies, for example, in the area of energy systems analysis. Artificial intelligence (AI) models are also becoming increasingly important. The results is a mix of methods where computer simulations and machine learning converge, posing particular challenges and opening up new research questions. This Special topic brings together case studies from different fields to explore the current state of computational models in general and AI methods in particular for policy and TA.

***Modellierung für Politik und Technologiebewertung**:*
Herausforderungen durch computergestützte Simulationen und künstliche Intelligenz

Zusammenfassung • *Modellierung für die Politik ist zu einem integralen Bestandteil der Politikarbeit und der Technologiebewertung geworden. Dies wurde der breiten Öffentlichkeit besonders deutlich, als während der COVID-19-Pandemie Prognosen über die Infektionsdynamik auf Basis von Computersimulationen zur Bewertung und Begründung politischer Maßnahmen zur Eindämmung herangezogen wurden. Computermodelle spielen auch in der Technikfolgenabschätzung (TA) eine zunehmende Rolle. Mithilfe von Computersimulationen werden technologiegebundene Zukunftsperspektiven erkundet, beispielsweise im Bereich der Energiesystemanalyse. Auch Modelle der künstlichen Intelligenz (KI) werden immer wichtiger. Das Ergebnis ist ein Methodenmix, bei dem Computersimulationen und maschinelles Lernen zusammentreffen, was besondere Herausforderungen mit sich bringt und neue Forschungsfragen eröffnet. Dieses TATuP Special topic bringt Fallstudien aus verschiedenen Bereichen zusammen, um den aktuellen Stand von Computermodellen im Allgemeinen und KI-Methoden im Besonderen für Politik und TA zu untersuchen.*

Keywords • *computer-based modeling, technology assessment, artificial intelligence, decision-making, prognostic methods*

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Introduction

The use of models in science has long been a subject of reflection. The philosophy of science has intensively studied the role models play in science. Questions concerning the relationship between model, theory, and experiment, or the potential changes they bring to scientific practice have been addressed here (Morgan and Morrison 1999; Gelfert 2016). The study of modeling for policy, on the other hand, has only recently become a more intense subject of interdisciplinary reflection (Scheer 2013; Mansnerus 2015). Here, too, the focus is on processes of change, particularly with regard to questions like: How does decision-making change when it is based on, or at least guided by, models?

The history of modeling for policy (as distinct from the study of this history) is older. Models to guide policy questions existed in 18th century demography for example, such as equilibrium models between population size and resources (Fuhrmann 2001). This period also saw the emergence of the first models that play a role in medical policy contexts (see below). These models are primarily conceptual and mathematical in nature. In addition, there are material models, especially in technology development, but also, for example, in hydrology, such as the Large-Scale Mississippi River Basin Model, which is about 200 hectares in size and was used in the mid-20th century to predict or to reproduce past floods (Cheramie 2011). The decline of this (expensive) model in the 1970s coincides with the rise of current modeling approaches, namely computer models.

Computer models are currently mainly computer simulations and artificial intelligence (AI) methods. They are used, e.g., to study the transformation of energy markets, the effects of climate change and possible political-economic strategies for its mitigation, or urban policy design options. Mathematical techniques developed since the 18th century, such as probability theory or numerics, play an important role. However, it would be false to see computer models simply as a continuation of pen-and-paper calculations. The computer is not just a fast calculator. Rather, it changes modeling and the relationship between people and models. For information technology brings its own demands on how and what can be calculated – and in the process it changes the relationship between people (Heymann et al. 2017) causal processes) and thus promoted understanding, today there is an attempt to reduce the opacity of models (Kaminski 2018).

However, it would be equally wrong to write the history of modeling for policy primarily as a history of technology. Not only do models help to shape policy; on the contrary, it is precisely forms of political rationality such as the great planning euphoria or the 'culture of prediction' (Heymann et al. 2017) that promote modeling for policy. The connection between modeling and policy is an act of mutual adaptation, of promotion or inhibition, as well as it is a demand for understanding and a threat of misunderstanding.

The prognostic turn

Modeling for policy and technology assessment has a history that dates back to emerging field of futures studies in the 1950s and 1960s. In particular, Operations Research methods, advanced by Olaf Helmer at the RAND Corporation for 'Long range forecasting', defined that the "future is no longer viewed as unique, unforeseeable, and inevitable; there are, instead, a multitude of possible futures, with associated probabilities that can be estimated and, to some extent, manipulated" (Helmer 1967, p. 2). Operations research, a military term originally used to describe groups of researchers working on large-scale projects such as radar development and surveillance, evolved in the late 1940s into a mathematical method of decision support based on control theory, game theory, linear optimization, and graph theory. Philip M. Morse, who is considered the founder of operations research, wrote in 1945: „Its object is, by the analysis of past operations, to find means of improving the execution of future operations" (Morse and Kimball 1951, p. 5). To this end, Morse had nearly 100 analysts at his disposal in the Operations Research Group founded by the U.S. Navy in 1942, who dealt with questions such as the optimal size of ship convoys or the tactics of air attacks. The success of operations research resulted from the changing situation of warfare under technological conditions. However, the management of changing situations applied not only to military but also to industrial and social conditions in general, which led to a spread of mathematical analysis and planning methods into policy processes (Greenberger et al. 1976; Seefried 2014). Policy problems "differ from operational problems in that unambiguous, rigorous representations of the problems are very difficult to construct." (Kraemer and King 1986, p. 501). Thus, Systems Analysis was developed for the analysis of complex systems under environmental conditions, again at the RAND Corporation. Here, the future came into play less as an optimization of the past than as a statistical uncertainty about the unknown effects of actions, or about unpredictable developments. This growing arsenal of analysis and prediction methods was used for establishing the field of quantitative policy analysis. Big modeling for policy projects were established in New York (Miller et al. 1988) as well as in the Netherlands for water management and storm-surge barriers (Goemans and Visser 1987).

Modeling for quantitative policy analysis became prominent when Limits to Growth was published in 1972 using Jay W. For-

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rester's World Dynamics approach developed at the Massachusetts Institute of Technology in Boston (Forrester 1971; Meadows et al. 1972). Commissioned by the Club of Rome, the study calculated the end of mankind by 2100, if no drastic policy measures would be taken. This caused worldwide media interest, which not only made 'modeling for policy' a publicly recognized topic, but anchored the 'prognostic turn' into science, society, and politics. Beside societal studies on the impact of economic growth and exploitation of nature, the increasing environmental problems of pollution, acid rains, and climate change quickly dominated the emerging 'cultures of prediction' (Heymann et al. 2017). Climate modeling, energy modeling and integrated assessment modeling (van Beek et al. 2020), gained importance in the 1970s as well as the international conferences on the increasing concerns of the Earth's condition such as the UN Conference on the Human Environment in Stockholm in 1972. In particular, the awareness of and the political dealing with the ozone hole became a role-model for the emerging global framing of model-based policy analysis and technology assessment. The 'discovery' of the Antarctic ozone hole in 1985 and the assumption that chlorofluorocarbons (CFC) are the sources of the reduction of ozone led already in 1987 to the adoption and in 1989 to the ratification of the Montreal protocol. Ironically, the ozone hole wasn't seen either in the satellite data nor in the model-based simulations before 1985. In-situ measurements, on the other hand, showed a dramatic decrease in ozone (Farman et al. 1985), which called for immediate action – although the "response of policymakers to Farman and colleagues' paper was initially cool." (Solomon 2019, p. 46) However, later models with improved atmospheric chemistry showed that a growing ozone hole would not allow humanity to enjoy full sun for more than ten minutes in 2020 without significantly increasing the likelihood of skin cancer. Although the CFC-assumption wasn't fully verified in 1987, the precautionary principle was firstly applied in the Montreal protocol on a global level. Thus, the protocol not only "prevented the ozone layer from collapsing" and gave us today's freedom of movement under the open sky, it became the "signature success story for global environmental policy" (Solomon 2019, p. 47) and shaped the framing of global climate policy until today.

Model and policy: working on their alignment

If the ozone hole was the paradigm for the global challenge of the 1980s for model-based policy analysis and technology assessment, the COVID-19 pandemic is the global challenge of today. However, the beginnings of deciding health policy issues based on models can be traced back to at least the 18th century: When the number of people dying from smallpox reached a peak, variolation became known as an immunization method in England. This procedure was not without its dangers, insofar as it could itself be fatal or could contribute to the transmission of the disease. Daniele Bernoulli addressed this question on the basis of a probability calculus he had developed, in which he calculated the probabilistic life expectancy of a model population with and without variolation. In 1760, he initially published only the results (1766 then the calculations too) in which he strongly recommended variolation. Bernoulli's contemporary Jean-Baptiste Alembert strongly criticized Bernoulli's approach. An intense debate arose around this early Model for Policy (Colombo and Diamanti 2015; Dietz and Heesterbeek 2002).

Toy models, which characterized the transmission of measles such as the mixing of gas molecules in a tube, and compartment models followed at the beginning of the 20th century (Mansnerus 2015, pp. 12). Then, over the course of the 20th century, models and eventually computer models were developed that examined measles infection or smallpox vaccination strategies, for example, to prepare policy recommendations (Grüne-Yanoff 2017).

More recently, COVID-19 simulations have even come to the attention of a broader audience. In Germany, the Federal Institute for Population Research (BiB) had begun to predict the load of intensive care units in Germany on the basis of a computer simulation. This project exemplifies the work required on the alignment. Indeed, the BiB soon discovered that the model developed to inform policymakers about the predicted situation in intensive care units in German hospitals, in order to derive a basis for COVID-19 measures, was becoming too computationally intensive. Thereby, a start was made with the Federal High-Performance Computing Center (HLRS) at the University of Stuttgart. HLRS had previously hosted several major modeling for policy research projects, such as HiDALGO, in which one of the pilots was to predict the escape movements of people in crisis situations facing war or natural disasters. It quickly turned out that the code developed did not run efficiently on the computers there. As Ralf Schneider noted in a lecture given in the seminar 'Modeling for Policy' at RWTH Aachen on 11.05.2021, a re-implementation of the model became necessary. This revealed a first form of necessary alignment: The way of thinking and coding of the researchers at BiB and the simulation scientists at HLRS had to be aligned under time pressure. The following observations go back to discussions we had with the simulation scientists there: About 20 % of the German population was then represented in the model, and the model was fed with actual data from 401 local counties (Klüsener et al. 2020). The results were forwarded weekly to the RKI and the Federal Ministry of Health. Here, a second alignment became necessary. This concerned the alignment of scientists and politicians. The question arose of whether to work with scenarios and, if so, in what way. The concern on the part of the simulation scientists was in particular that the results would be interpreted in the sense of a weather forecast.

Since the project showed how time-consuming (in a situation that required fast information) this alignment is already among scientists, a follow-up project was created: Computational Immediate Response Center for Emergencies. From our point of view, this project aims to facilitate and stabilize the required epistemic and policy alignment.

Added-value and limitations of computer-based models for policy

We will now take a step further in the reconstruction of how and to what extent this alignment can be achieved: "Policy-making in pluralistic societies is bound to principles of forward-thinking, decision-orientation and evidence-based rationales." (Scharpf 1973) Policies result from a process in which problems to be solved are identified, policy objectives and solutions are then formulated and finally decided by the legislator. Policy interventions are thus key aspects of a decision-based understanding of policy-making (Scheer et al. 2021, p. 7). Computer based models and (lately) AI are to a great extent compatible with these three policy-making features. Decisions about prognostic futures have to be made despite all the complexity of the sociotechnical system, possible path dependencies and uncertainties as well as non-knowledge about (un-)intended economic, ecological and societal consequences of these decisions. The genesis of scientific system, orientation and action knowledge for possible futures plays a central role as an input provider for boundary conditions and impact chains and is confronted with analytical and methodological challenges. However, there are several features of computer-based models and AI that are highly compatible with policy-making. Key characteristics of computer simulations can be synthesized into the following specific capabilities (for the following points and considerations see Scheer 2017, pp. 105–107):

- Display cause-impact chains: Simulations show the effects and outcomes of complex and multidimensional cause-impact relations.
- Reduction of complexity: From a system perspective computational modeling reduce, represent and visualize real-world phenomena, interrelations and statuses.
- Comparison of options: Computer simulations are able to demonstrate and compare several options and courses of action for future developments.
- Intervention effects: With computational modeling the effect and impact of several policy actions, instruments and interventions can be calculated and displayed.
- Formats of results: Simulation results are highly aggregated technical calculations transforming time-depended system states into easily accessible formats of pictures, diagrams and numbers.
- Trial without error: Computer simulations are virtual trial and error operations for finding optimal solutions where the error is not costly and painful.

Computer simulations are science-based instruments for producing knowledge on upcoming future developments. Hence, simulations are an essential addition to the policy impact assessment toolbox and are able to advise policy-makers with relevant information. Using computer simulations, complex real-world systems are reduced to their structural system functions, are replicated in a simplified system 'copy' as a digital twin, and are visible through various visualization techniques. A substantial advantage of simulation is to run system dynamics over time and display various complex system statuses at a specific date where researchers and decision-makers have an interest in. Thus, scientific modeling is a future research and foresight knowledge instrument which may serve as a basis for decisions. The future observing feature of simulations matches perfectly with the forward-looking need of policy-making.

Computed quantitative results in pictures and numbers tend to obscure underlying uncertainties and suggest a level of accuracy which is often not adequate to reality.

Another added value is the comparative character of modeling with relatively easy to do configurations once the principal model is set up. Simulations and scenarios are closely linked in modeling. With slightly changing initial and framework conditions through parameter settings in simulations, modelers are able to compare different scenarios of possible future system developments. With modifications of influencing factors (e.g., parameters) modelers are able to analyze impact and effect of specific (policy) interventions with a trial-and-error method – using a virtual environment without a serious real-world damage. Thus, simulations combine the abilities to run through several alternatives with a clear focus which marks the differences, and the observation of its results and impacts in order to find an optimal solution.

However, computer simulations have their limitations when it comes to policy advice and decision-making. Simulations are often seen as opaque, and thus policy decisions based on simulations are vulnerable and may take center-stage in political dispute over solutions and strategies. The backbone of simulations, that is complexity reduction, comparison of options and policy intervention, are frequently based on oversimplified system functions, starting point assumptions and cause-impact relationships. What is often neglected in simulations are one-time effects and contingencies of human action. On the other side,

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computed quantitative results in pictures and numbers tend to obscure underlying uncertainties and suggest a level of accuracy which is often not adequate to reality. Against this background, it is not surprising to see that computer simulations are heavily criticized in the policy arena. The main features of simulation critique are a lack of trust in models and modelers, spurious accuracy of simulation results, and inadequacy of the computing process itself which is usually not understandable by the audience.

Model-driven and AI-driven policy analysis and TA

History as well as case studies show that policy analysis is driven by the use of computer-based models and simulations from the very beginning on. However, also technology assessment (TA) is increasingly using modeling and simulation techniques as assessment tools for an anticipatory, "hermeneutic approach" (Grunwald 2022). As policy requirements for technology designs become more demanding – in particular, in terms of sustainability – TA turns from an ad-hoc approach into a prognostic task. Due to the complexity of today's technology designs, prognostic TA "by hand, however, is time-consuming and seems inappropriate" as the case of conceptual aircraft and system research demonstrates (Gradel et al. 2022, p. 281). Therefore, prognostic in-silico TA based on modeling and simulation is required to meet the ambitious political aims of the European Commission's Green Deal (European Commission 2021). "Model-based safety assessment (MBSA) […] uses models to describe the fault behavior of a system. Consequently, safety analyses (e.g., the synthesis of fault trees) can be performed partly automatized with these models." (Gradel et al. 2022, pp. 281–282).

In particular, in Health Technology Assessment (HTA) models have been used to better understand and predict the outcome of policy changes. Again, sustainability – here the UN's Sustainable Development Goals (SDGs) calling for achieving a universal health coverage – is the main driver for the use of prognostic methods (Kingkaew et al. 2022). Interestingly, HTA is also leading in the application of AI methods, although this trend is nascent. "In health care, with the increasing use of information systems and access to large amounts of data, the application of AI tools might facilitate the evidence base of policy decisions. Specifically, in the field of HTA, researchers can rely on health systems data such as administrative claims or electronic health records to generate evidence on health outcomes to support decisions of policy makers and inform patients about the utilization practice, effectiveness, or costs of technologies." (Tachkov et al. 2022, p. 2) While AI technologies are on the forefront of healthcare, for instance for automatic diagnostics, drug development, care robotics, and data management (Davenport and Kalakota 2019), the use AI in healthcare applications still has to be assessed beyond technical performance. In particular, IBM's Watson Oncology failure in 2017 displayed an 'AI chasm' between laboratory conditions and clinical application. Thus, "it becomes clear that regulatory and decision-making organizations as well as HTA agencies are facing unprecedented complexity: evaluating and approving so-called disruptive technologies, especially AI, requires taking several issues into consideration altogether." (Alami et al. 2020, p. 6). A comprehensive TA framework for evaluating technology that uses AI is still lacking.

The contributions in this Special topic

Against the outlined backdrop of the history of model- and AI-based policy analysis and technology assessment this TATuP Special topic 'Modeling for Policy' collects seven papers from scholars of TA, sociology and philosophy of science and technology. We called for contributions that investigate whether and, if so, how decisions change, if they are made on the basis of AI and computer models. Do options for action, evaluations, forecasts or justifications change when policy making decisions are made on the basis of models? In addition, on a second level, to what extent does this change technology assessment, insofar as computer-based models are used to assess technologies? Does it change the courses of action considered in TA? These questions are of interest as AI models and simulations models present a dual challenge for technology assessment.

Firstly, these prognostic methods are used in the object domain of TA. Secondly, TA makes use of these methods itself. In our view, this raises far-reaching epistemic as well as normative questions for TA. This dual challenge concerns, for example, the transparency of TA: the opacity of the models is inherited as a possible opacity of TA. Questions also arise about the robustness of models, especially in novel domains, which then appear as questions about the evaluation of values in TA: is reliability something more important than comprehensibility? Although, the contributions explore different questions and cases, all contributions explore the alignments and frictions, tensions and convergences of models and policies.

Anja Bauer and Daniela Fuchs ask in their paper 'Modeling for nano risk assessment and management: The development of

In Health Technology Assessment models have been used to better understand and predict the outcome of policy changes.

integrated governance tools and the potential role of technology assessment' for critical reflection these tools from the outside as well as from inside by actively engaging in their development processes. Based on the case of the SUNDS tool both authors show that the tool manifests conceptual shifts from risk to innovation governance.

Lou Therese Brandner and Simon David Hirsbrunner are looking at an entirely different field. Their paper 'Algorithmic fairness in investigative policing: Ethical analysis of machine learning methods for facial recognition' askes fundamental questions about fairness in AI based policing using facial

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recognition by addressing the AI chasm. Furthermore, they argue that quantitative fairness methods can distract from how discrimination and oppression translate into social phenomena.

Jens Hälterlein investigates the important case of 'Agent-based modeling and simulation for pandemic management.' He shows that decisions based on these simulations influenced the course of the pandemic and that the use of computer simulations can be understood as a co-production of knowledge about the recent COVID-19 pandemic.

Catharina Landström explores stakeholder involvement in water management in her paper 'Why won't water managers use new scientific computer models? The co-production of a perceived science-practice gap.' She asks, if more stakeholder involvement would lead to an increased uptake of scientific models in water management?

Lilla Horvath, Erich Renz and Christian Rohwer are reflecting on the advantages of 'Combining behavioral insights with artificial intelligence for technology assessment.' As policy decisions concerning technology applications can have far-reaching societal consequences rationality-enhancing procedures are essential. TA will face this challenge.

Titus Udrea, Leo Capari and Anja Bauer examine how models can structure epistemic communities in order to better assess the knowledge claims and evidence politics of computer modeling. Therefore, their paper 'The Politics of Models: Socio-political discourses in modeling of energy transition and transnational trade policies' compares two modeling communities, energy transition and transnational trade.

Johannes Weyer, Fabian Adelt and Marlon Philipp explore 'Pathways to sustainable mobility. Modeling the impact of policy measures' using the example of the Ruhr region and the mobility of the people living there. Simulation experiments show significant differences in the behavior of actor types and in their response to policy interventions. Thus, modeling can help policymakers when planning and designing measures whose goal is sustainable transformation.

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