MULTI-MODEL ECOLOGIES FOR ADDRESSING MULTI-SCALE, MULTI-PERSPECTIVE POLICY PROBLEMS

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ABSTRACT

Many key societal problems share a set of common features – multiple interacting temporal and spatial scales, multiple valid perspectives, changing requirements and unquantifiable uncertainties. These characteristics substantially stress our cognitive and computational resources, limiting our capacity to effectively address these problems. We introduce an approach for dealing with the inherent complexity of such problems. At the core of this approach is the notion of a *multi-model ecology* – an interacting and constantly evolving system of models, datasets, interfaces and humans tasked with enhancing the ability of decision makers to effectively address a complex policy problem. The multi-model ecology approach entails the systematic fragmentation and gradual reconstitution of a problem's multiple components and dimensions in an evolving participatory context. We describe an implementation of this approach currently in progress – focused on electricity infrastructure vulnerability to climate change – and identify several key areas of research for developing this approach further.

INTRODUCTION

There exists a unique class of problems characterized by multiple relevant temporal and spatial scales, multiple valid perspectives, changing requirements and unquantifiable uncertainties (hereafter referred to as MMCU problems). Problems of this class – including climate change adaptation, sustainability, urban poverty, etc. – share aspects of other theoretical notions such as wicked problems (Churchman 1967), deep uncertainty (Lempert et al. 2003) and post-normal science (Funtowicz and Ravetz 1993). MMCU problems are not new and neither is the idea of using quantitative models to address them. Still, they continue to vex scientists and policy makers for several reasons – interactions between different temporal and spatial scales are challenging to conceptualize and formally represent, multiple valid perspectives are difficult to reconcile, and changing requirements and unquantifiable uncertainties mean that no solution is permanent nor optimal.

In an ideal technocratic world, scientists would develop all-encompassing models generating definitive projections upon which policy and strategy decisions could unhesitatingly be based. When it comes to MMCU problems, however, no model can capture more than a minute fraction of the potentially relevant components and relationships – every model is based on tenuous assumptions. Still, the modeling and simulation (M&S) community often treats decision makers as rational agents operating in a tractable environment – expecting that the right scientific input will lead to the right decisions. The reality is that, in dealing with MMCU problems, there are no rational decisions – the available information is too much, too incomplete and too uncertain.

In the wake of Lee's criticisms of the large-scale, monolithic policy models of the 1960s (Lee 1973), the M&S community advanced an array of techniques and approaches to cope with the inherent complexity of policy problems. At the same time, the policy and strategy communities have begun to recognize the limitations of a purely rational and strictly evidence-based approach to decision making (Freiberg and Carson 2010; Nutley et al. 2003). Against the background of these developments, a pertinent question is how the diverse approaches of the modeling and simulation community can be brought together in a coherent manner to more effectively address MMCU problems. The purpose of this paper is to introduce such an approach.

We define a *multi-model ecology* as an interacting

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and constantly evolving system of models, datasets, interfaces and humans tasked with enhancing the ability of decision makers to effectively address a MMCU problem. The notion of multi-model ecologies builds on existing modeling and simulation approaches, including microworlds (Morecroft 1988; Papert 1980), exploratory modeling and analysis (Bankes 1993) and multi-resolution modeling (Davis and Tolk 2007). Its novelty lies in the links drawn between the the M&S process, its components and the realities of complex policy decisions.

The next section of this paper lays the foundation of the multi-model ecologies approach, describing related research from the M&S field as well as psychology and policy. From this starting point, we proceed with a more extensive introduction to the multi-model ecologies approach and highlight its applicability to MMCU problems. Finally, we demonstrate the application of this approach based on a multi-model ecology currently in development, addressing the issue of electricity infrastructure vulnerability to climate change. We conclude with recommendations for future research.

BACKGROUND AND RELATED RESEARCH

The 1960s saw the advent of large-scale, monolithic computer models as prescriptive policy tools. This approach was famously criticized by Lee (1973), who pinpointed a range of shortcomings in the large-scale urban models of that period - hypercomprensiveness, grossness, hungriness, wrongheadedness, complicatedness, mechanicalness and expensiveness. While these criticisms by no means halted the development of large-scale models for addressing complex policy issues, they highlighted the need for alternatives to a monolithic, prescriptive approach.

Insight into possible directions for such alternatives has come from subsequent scientific developments concerning the cognitive processes underlying decision making in complex environments. Multiple studies have highlighted the relevance of "non-rational" decision strategies, particularly intuition, in strategic decision making (Khatri and Ng 2000; Woiceshyn 2009). Subsequent research has elucidated the process behind the use of intuition in decision making. Analogical reasoning, as this process is called, involves the "mapping" of knowledge from a source context of prior experience to a current "target" context – a process which is restricted by the richness of the mental models that map a decision maker's previous experiences (Gary et al. 2012; Gavetti et al. 2005).

This is one reason why MMCU problems pose such an obstacle to decision makers. Effective learning requires specific conditions – in particular, accurate and immediate feedback between the situational conditions and the appropriate response (Tversky and Kahneman 1986). The long timeframes of many MMCU problems and the enormity of variables involved lead to a lack of feedback concerning the effectiveness of previous decisions. This leaves decision makers with limited opportunity to develop their mental models, and subsequently the intuitive mechanisms that would allow them to make effective decisions. Even worse, decision makers may not be aware of this – Kahneman (2011) suggests that when insufficient mental models exist, individuals will gleefully and unwittingly draw from marginally similar experiences that do not serve as adequate guides to the situation at hand.

In line with these findings, research in the policy community has begun to question the assumption that policy should always be based on a rational analysis of available evidence (Freiberg and Carson 2010). Limitations on the rationality of decision makers mean that the links between research, knowledge and policy are "always likely to remain loose, shifting and contingent" (Nutley et al. 2003). Against the background of these limitations, Sanderson (2009) recommends a shift in emphasis from *evidence-based policy making* to *intelligent policy making* – policy making that emphasizes learning and experimentation, and draws from "reserves of experience, intuition, tacit knowledge and all the hidden skills and capacities that technical rationality has relegated to obscurity". It is these hidden skills and capacities on the part of decision makers that the M&S community is well-positioned to develop.

One area of M&S that pushes in this direction is the "microworlds" approach, first proposed by Papert (1980). This approach, originally developed for application in managerial situations, stresses the development of decision makers' mental models – enhancing their contextual understanding and (in theory) enabling them to make better strategic decisions. The key advantage of the microworlds approach lies in its capacity to compress time and space using dynamic simulation, especially system dynamics.

The microworlds approach facilitates learning on the part of decision makers by compressing time and space. But it does not explicitly address the challenges of problem situations that cannot be neatly captured within a single, unified representation of reality – e.g. problems spanning multiple scales of time, space and organization, and problems characterized by multiple valid conceptualizations of reality. Beginning with the work of (Oeren 1991), the modeling and simulation community has begun to address this topic under the banners of multisimulation and multi-perspective, multi-resolution and multi-aspect modeling (Tekinay et al. 2010; Yilmaz et al. 2007). Such approaches entail the modular representation of systems within a set of interoperable models that capture reality from multiple angles and at multiple levels of fidelity.

Where multisimulation and multi-perspective/-resolution/-aspect modeling enable capturing reality from multiple angles, the technique of exploratory modeling and analysis (EMA) is used to explore the assumptions space of a model. The aim of EMA is to facilitate the identification of *robust* policy options – options which perform well across a range of possible futures – or *hedging* strategies – strategies to prevent the most adverse consequences (Lempert et al. 2004). In theory, the combination of EMA with, for instance, multi-resolution modeling can allow for the exploration of both parametric and structural uncertainties (Davis and Tolk 2007) – helping to provide decision makers with a holistic understanding of the consequences of the uncertainties associated with a problem.

As the paragraphs above have demonstrated, the M&S community has developed a number of techniques – e.g. microworlds, multisimulation and EMA - that address shortcomings of a monolithic, prescriptive approach to using models to address complex policy problems. In the following sections, we discuss how aspects of these techniques can be brought together in the context of a coherent approach to address MMCU problems.

MULTI-MODEL ECOLOGIES

A multi-model ecology is an interacting and constantly evolving system of models, datasets, interfaces and humans tasked with enhancing the ability of decision makers to effectively address a MMCU problem. The multi-model ecology approach entails the systematic fragmentation and gradual reconstitution of a problem's multiple components and dimensions in an evolving participatory context. This approach is particularly suited to addressing MMCU problems for several reasons.

1. Multi-model ecologies facilitate the capture of multiple system levels, multiple timescales and multiple perspectives.

Models in a multi-model ecology are constructed with different scopes, resolutions and perspectives. Independently, each model provides a partial picture of the components and relationships underlying the problem at hand. Together, they provide a multi-dimensionsional representation of the relevant system(s). Drawing hints from the fields of multisimulation and multi-perspective/resolution/aspect modeling, models in a multi-model ecology are not independent entities, but modules in a larger whole. Each of these models/modules has a clearly defined scope, purpose, resolution and set of inputs/outputs, and rests on a particular set of assumptions.

As illustrated by the schematic in Figure 1, models in a multi-model ecology may interact with one another, with human decision makers, with datasets or with several of the above. Models may dynamically link with one another during runtime, or more statically in sequence. They may also be completely independent of other models in the ecology, receiving input from datasets or interfaces, and generating output to other datasets or interfaces. *Datasets* in a multi-model ecology store both the data inputs to models as well as the data outputs. They may link with models or with interfaces, allowing them to be directly viewed by human decision makers or processed into other forms. *Interfaces* are the links between models or datasets and the mental models of human decision makers. The key aspect of models, datasets and interfaces in multi-model ecologies is their flexible relationship with other entities. Taking a hint from the role of programs in the GNU/Linux operating system (Gancarz 2003), entities in a multi-model ecology can be seen as "filters" for processing and transforming data, and can be linked with other filters in different ways to serve different purposes. The aim in such cases is not "pure composability" (Davis and Tolk 2007) – strict plug-and-play capability – but the cultivation of a set of resources that can be configured and reconfigured to interact with one another in different ways, whether statically, dynamically, directly or indirectly.

The human components of a multi-model ecology include decision makers, domain experts and developers. *Developers* are the programmers and software engineers behind the implementation of models and the maintenance of datasets. *Experts* are the holders of specialized domain knowledge, essential in constructing models and datasets, and evaluating their validity. *Decision makers* are the ultimate users of the ecology. Involved individuals may at times wear different hats, depending on their relevant expertise – e.g. a developer or decision maker knowledgeable in domain aspects may at time play the role of domain expert.

2. Multi-model ecologies support systematic and comprehensive exploration of the assumptions space.

Each of the components in a multi-model ecology rests on a bed of assumptions. The assumptions underlying a model are determined by the concep-

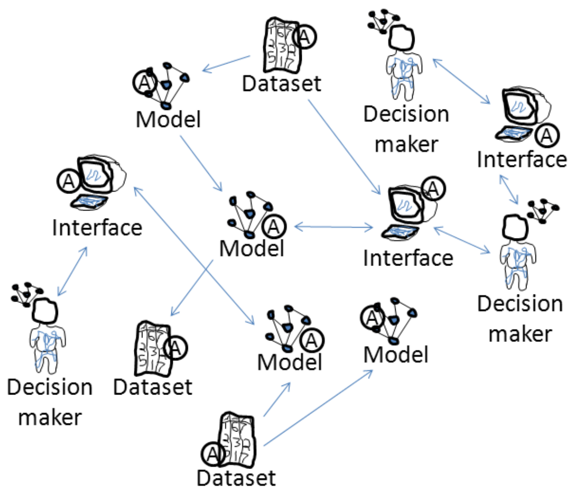

Figure 1: Schematic of a hypothetical multi-model ecology, including models, datasets, interfaces and human decision makers. An encircled “A” refers to the assumptions associated with a component. Domain experts and developers are excluded from the schematic.

tualization of the system being represented, by the scope and fidelity of the model and by the modeling technique being employed. Models based on established theory – such as many physical systems models – may rest on a solid foundation of generally accepted assumptions, whereas models based on less established theory and/or participative processes – e.g. many models of social systems – may sit on an array of tenuous and subjective assumptions. The datasets and interfaces in a multi-model ecology also rest on assumptions. The assumptions underlying a dataset may have to do with the manner in which the data was collected – via questionnaires, direct observation, etc. – or with the assumptions of the model from which the data was generated. The assumptions underlying an interface have to do with the way data is presented to human users and the manner in which users are able to interact with data and models.

Assumptions are an inevitable part of the components of a multi-model ecology, essential remnants of abstraction and simplification processes. Most important in a multi-model ecology approach is that these assumptions are clearly tracked and documented. Drawing from exploratory modeling and analysis, vigilant tracking of assumptions opens up possibilities for deliberate and systematic exploration of the assumptions space underlying a particular configuration of models, datasets and interfaces. Interface tools such as the EMA workbench (Kwakkel 2012) can help to translate the results of this exploration into a form readily understandable to decision makers, helping them to comprehend the consequences of different sets of assumptions, including both parametric and structural uncertainties.

3. Multi-model ecologies foster the development of rich mental models on the part of decision makers.

The ultimate purpose of a multi-model ecology is to facilitate learning on the part of decision makers – to enhance the mental models that serve as a basis for policy decisions. Research has shown that processes of analogical transfer may be enhanced by supporting the ability of decision makers to explore multiple variations of a problem situation, and allowing them the possibility to systematically test hypotheses (Gary et al. 2012). The structure of a multi-model ecology – the presence of multiple, flexibly interlinked models, datasets and interfaces – facilitates this by exposing decision makers to numerous variations of the problem situation. Learning on the part of decision makers may come from systematic interaction with interfaces, but it may also emerge from interactions with domain experts and developers in the context of participatory model development processes, which can help to surface the tacit assumptions of decision makers. These assumptions can then be incorporated into one or more models in the ecology, allowing their consequences to be explored and compared with alternative sets of assumptions.

4. Multi-model ecologies evolve as knowledge of the problem and the needs of decision makers change.

A multi-model ecology is not designed from the top down, but emerges over time as a consequence of interactions between decision makers, experts and developers. Its development is ultimately driven by the changing needs of involved decision makers. At times, it may also be spurred by the exploratory efforts of domain experts and developers seeking to incorporate new knowledge and come to terms with various approaches to capturing the relevant aspects of the problem. Different models, datasets and interfaces within an ecology may develop at different rates and according to different methodologies. Some models may be developed using participatory approaches, allowing decision makers to heavily influence the assumptions underlying the model's structure. Others may be implemented chiefly by experts and developers, with the underlying assumptions based on established theory. Still others may be adopted or adapated from external sources. As a result of the development of new models, datasets and interfaces, and the maturation and obsolescence of existing ones, the composition of a multi-model ecology changes gradually over time, driven both by the changing requirements of the problem and the availability of new knowledge.

A MULTI-MODEL ECOLOGY IN DEVELOPMENT

This section introduces a multi-model ecology currently in development. The MMCU problem addressed by this ecology is the vulnerability of electricity infrastructures to climate change. Climate change is anticipated to have a variety of impacts on electricity infrastructures (Rothstein et al. 2008). By affecting the range of environmental conditions under which these infrastructures must operate, and the frequency with which extreme conditions may occur, climate change poses multiple threats to these systems, from a gradual degradation of their integrity to sudden and catastrophic blackouts. The problem of electricity infrastructure vulnerability to climate change is characterized by several aspects that categorize it as a MMCU problem: (1) the electricity infrastructure spans multiple organizational and geographic scales; (2) climate change plays out over decades, while weather-induced disturbances may unfold over a period of hours, minutes or even seconds; and (3) Climate change is characterized by unquantifiable uncertainties, and multiple perspectives exist concerning e.g. the dynamics underlying the long-term development of the electricity infrastructure.

Given the decision-makers involved, the current geographic focus of this multi-model ecology is the Netherlands. Amongst these actors, there is a deficit of knowledge concerning the severity of this problem and the necessity of actions to address it. The purpose of the ecology is not to prescribe immediate actions on the part of decision makers, but to enhance their mental models in a manner that can enable them to better incorporate this threat into their decisions.

Composition and evolution of the ecology

Driven by the needs of decision makers, the first task in developing the multi-model ecology was to capture key relationships between weather variables and components of the electricity infrastructure in an initial model of *weather-infrastructure interactions* (item 1 in Figure 2) – based on a combination of known physical relationships (e.g. between power line resistivity and temperature) and statistically identified relationships (e.g. between weather variables and electricity demand (Hekkenberg et al. 2009)). A preliminary version of this model has been implemented in the numerical simulation environment MATLAB.

Given the focus of involved decision makers at the level of the national transmission network, this model was then linked with a preliminary dataset of the components of the Dutch transmission network (item 2). This dataset is housed in a web-based platform called Enipedia (Anonymous 2013; Davis 2012), which uses semantic wiki technology to enable the collabortive cultivation of power industry data. This RDF-based platform allows for the extraction of targeted portions of the dataset using SPARQL queries. By embedding tailored SPARQL queries in the code of our weather-infrastructure interactions model, we establish a runtime link between this model and the web-based dataset.

The aim of the weather-infrastructure interactions model is not only to capture the relationships between weather variables and the performance of infrastructure components, but also the effects of changes in component performance on the network as a whole. Key to enabling this was establishing a runtime link between the weather-infrastructure interactions model and a pre-existing MATLAB-based power flow model (item 3) (Zimmerman et al. 2011). Power flow models are a mature class of models for analyzing power systems in steady state operation, outputting power flows through the lines in a power system under provided supply and demand conditions. Establishing this link required translating the semantic base of the weather-infrastructure interactions model into the language of the power flow model, a process which engendered several important assumptions.

This combination of components (items 1, 2 and 3) provided us with a computational structure for determining the impacts of certain types of extreme weather events on the performance of the infrastructure. We are in the process of linking these components with an R-based interface (item 4), which will allow decision makers to run the model under different parameter conditions and view results in a readily-understandable format. We also plan to link this model with weather datasets (item 5) based on the results of climate models, allowing for the capture of uncertainties associated with the trajectory of climate change. A challenge here will be the different timescales involved – the weather-infrastructure interactions model operates on a timescale of hours, while climate projections are based on models with a timescale of decades.

Further discussions with experts and decision makers revealed the importance of also capturing decade-spanning changes in the topology and technological composition of the electricity network. This incited

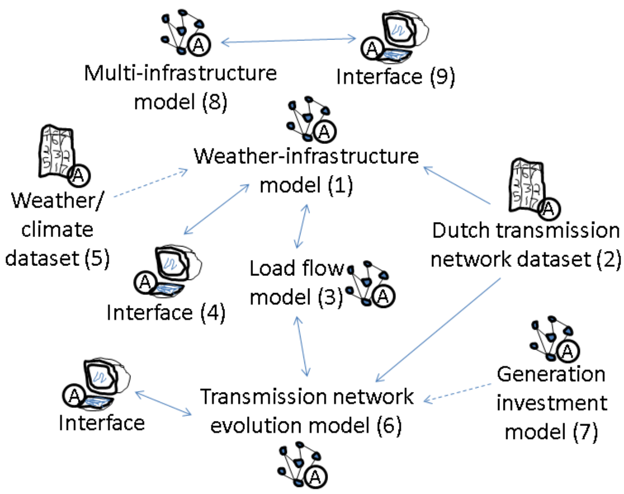

Figure 2: Schematic of the multi-model ecology in development. Solid arrows indicate implemented links between components. Dashed arrows indicate links in planning. Decision makers are excluded from this schematic.

the development of an agent-based *transmission network evolution model* (item 6), in which the growth and evolution of an electricity transmission network is captured as the consequence of repeated decisions and interactions of a transmission system operator and power producers. The initial phase of model development was quite exploratory, driven by the developer and domain experts and based largely on theory. Later phases of model development, however, have been more participatory, involving decision makers in conceptualizing the system and delineating assumptions.

This model is currently implemented in the agent-based modeling platform Netlogo (Wilensky 2012). However, in order to accurately represent the decision making process of the transmission system operator – who needs to calculate projected power flows through his network – it became necessary to establish a runtime link with a power flow model. For this we use the same power flow model employed above (item 3). However, in addition to translating the semantic base, implementation in this case necessitated the development of a software link between Netlogo and GNU Octave (the numerical simulation software used to run the power flow model).

The current version of the transmission network evolution model includes a vastly simplified representation of power producer investment decisions which is unable to capture several of the main drivers of such investments. Based on discussions with decision makers and experts, it was determined that this representation was insufficient. To remedy this, we are planning to implement a static link with an existing Java-based model (item 7) that captures these investment decisions at a higher resolution (Chappin et al. 2012).

Partway through the development of the above models, discussions with experts and decision makers highlighted a new and important sub-problem – the dynamic consequences of links between the electricity infrastructure and other infrastructures such as road, rail and gas. To address this issue, an exploratory model was initiated with the aim of investigating the consequences of random failures in multi-infrastructure networks at an abstract level (item 8). Like the transmission network evolution model introduced above, this model is implemented in Netlogo, and uses the platform's native interface (item 9). The model has not yet been linked to any datasets, nor is it yet clear how or whether the model may link with other models or datasets in the ecology.

Key challenges

The development of this ecology has highlighted several important challenges in realizing multi-model ecologies. Chief amongst these is the semantic gap that exists between models – and between models and databases – developed in different contexts. For instance, a *power substation* in the transmission network evolution model is similar to the notion of a *bus* in the power flow model, but there are also important differences in the use of these concepts that affect the validity of results under certain circumstances. Systematically identifying and tracking these differences is an important challenge with which we are still struggling. In our experience thus far, translation between the ontologies employed by different entities in an ecology is often feasible, but can be time consuming and can engender new assumptions. Moreover, imprecise translations can invalidate results. These challenges can serve as barriers to the use of pre-existing models and datasets, and highlight the importance of systematic documentation with clear delineation of assumptions.

As has been emphasized in the preceding paragraphs, the components of the multi-model ecology described here are not static – new needs may arise in the course of interacting with stakeholders, and insights from one model may lead to new pertinent questions. As such, models, datasets and interfaces need to be developed with an expectation that they will change over time, and that they exist as units in a flexible and ever-changing ecology. We seek as much as possible to use tools that are amenable to this – that are open source, well documented and capable of interaction with other software. An example of this is Enipedia – the database we have used for cultivating infrastructure data – which enables the extraction and export of targeted data for different uses.

A potential advantage of a multi-model ecology approach lies in enabling the use of models in multiple contexts – a single model can be linked with other models, datasets and interfaces to address multiple research questions. However, it is not always possible to anticipate the future demands that may be placed on a model, which makes it difficult to design them to accommodate this. Our experience with this ecology suggests that the use of a model in multiple contexts within an ecology is sometimes feasible. However, manual modifications are often necessary to enable compatibility, both from a software perspective and an ontological perspective.

CONCLUSIONS AND FUTURE WORK

This paper has introduced and demonstrated the application of a *multi-model ecology* approach to addressing MMCU problems – an approach based around an interacting and constantly evolving system of models, datasets, interfaces and humans. This approach leverages several existing M&S techniques, including microworlds, multi-perspective/resolution/aspect modeling and exploratory modeling and analysis. In the last section, we have described an implementation of this approach currently in progress, focused on the case of electricity infrastructure adaptation to climate change.

This pilot implementation of the multi-model ecology approach has highlighted several important areas for future research. First, the multi-model approach establishes tooling criteria, but does not prescribe specific tools to be used. We believe that these tooling decisions should be context dependent, but see the need for the development or adaptation of additional tools that better match the needs of the multi-model ecology approach. An example here is tools that can aid in the explicit tracking of assumptions across multiple models, datasets and interfaces, and can enhance the ability of decision makers to readily comprehend their consequences.

Additionally, further research is necessary into methods for effectively engendering learning on the part of decision makers dealing with highly complex problems. The microworlds approach offers some hints here, but analyses of its capacity to enhance the mental models of decision makers have demonstrated mixed results (Langley and Morecroft 1996; Stouten et al. 2012). A particular challenge has to do with the capacity of the human mind to comprehend uncertainty – Kahneman (2011) suggests that our subconscious minds are not geared for dealing with multiple incompatible interpretations of the world. How can we train the intuitive mechanisms of decision makers to deal with MMCU problems when their brains may not be wired to comprehend a key aspect of these problems?

From sustainability to climate change adaptation, MMCU problems pose an enormous challenge to a society ill-equipped to deal with them. We believe that M&S can contribute meaningfully to addressing such problems, but only with careful consideration of the limitations of M&S techniques and of the realities of decision making. We offer a small step in this direction.

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