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New Methods for Analysis of Systems-of-Systems and Policy: The Power of Systems Theory, Crowd Sourcing and Data Management

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1. Introduction

Our world is a complex socio-technical system-of-systems (Chappin & Dijkema, 2007; Nikolic, 2009). Embedded within the geological, chemical and biological planetary context, the physical infrastructures, such as power grids or transport networks span the globe with energy and material flows. Social networks in the form of global commerce and the Internet blanket the planet in information flows. While parts of these global social and technical systems have been consciously engineered and managed, the overall system-of-systems (SoS) is emergent: it has no central coordinator or manager. The emergence of this socio-technical SoS has not been without consequences: the human species is currently facing a series of global challenges, such as resource depletion, environmental pollution and climate change. Tackling these issues requires active policy and management of those socio-technical SoS. But how are we to design policies if policy makers and managers have a limited span of control over small parts of the global system of systems?

The aim of this chapter is to discuss the roles novel applications of information technology and agent-based modeling have in understanding our world as a complex system and in designing effective policy. In other words, by bringing together systems theory and recent IT developments we can arrive at a better understanding of, and improved decision making on the operation and development of our complex socio-technical systems. We introduce a method for data-driven agent-based modeling, thus illustrate the power of the combination of systems theory and novel methods in data management, and present and discuss two case studies.

System-of-systems engineering (SoSe) methodologies only recently have been applied to policy analysis and design, even though policy analysis has its roots in systems thinking (Meadows, 2008). In this chapter, we continue on that path by further exploring a new combination of methods: serious games (Duke, 1980; Meadows, 1999), collaborative information management and agent-based modeling (Chappin, 2011; Epstein & Axtell, 1996; Nikolic, 2009).

We argue that this combination is especially useful for developing better understanding of our social and physical environment and its interaction with policy design and analysis. New technologies and methods in data management allow us to build better simulations by making use of real-world data. We create and use novel IT systems to bring together and mine relevant data. Patterns found in such observations are then used to create system abstractions – i.e. simplified and systematic perspectives or views on the system. The system abstractions are then incorporated into agent-based models that explore the dynamics in operation and long-term development. The socio-technical approach adds the social and institutional patterns to the technical view of the system examined. When trying to understand our infrastructures and industrial systems, human aspects cannot be ignored, nor be analyzed separately. The agent-based models allow us to explore the effects of policies on a highly interconnected system of systems.

A hybrid approach results – data plus models. We use this approach to explore the new gas market balancing regime in the Netherlands. A second case study deals with a long-term development of the Dutch power market (extending the work of Chappin, 2011; Chappin & Dijkema, 2010; Chappin et al., 2010). For both case studies models were developed using a new agent-based modeling platform *AgentSpring*[1]. The main feature of AgentSpring is its ability to handle large amounts of data. Models use a large number of data points as assumptions and input; models also produce a complex simulated world that consists out of hundreds of actors, thousands of things and millions of relations between them. AgentSpring incorporates new technologies that help mine the simulated world for patterns in the evolving system behavior.

We conclude by arguing that the new combination adds expression to the modeling effort, allowing to encode the complexity inherent in the system. More importantly, we hope to make models more transparent, duplicable, communicable, and understandable to the decision maker. The more comprehensive understanding of the relationships and patterns in the system modeled is one of the ways to increase the maturity of policy analysis and design.

2. Changing nature and application of SoSe research: more social

Systems thinking and system dynamics ideas were first applied in military research, enabled by breakthroughs in computing and fueled by cold war concerns (MIT, 1953). Similarly, traditional SoSe research has its roots in defense related areas. Three out of six SoSe definitions (Jamshidi, 2005) have their origins in military research. While the systems dynamics deals with the relations between the objects within the system (Forrester, 1961), SoSe goes further to understand and manage the relations between such systems. The primary goals of SoSe research have traditionally been overall SoS optimization, ensuring interoperability, reliability and minimizing human error in their functioning (Pei, 2000).

Just as the pioneer of system dynamics Jay Forrester went on to apply his military systems research insights in economics (Forrester, 1968), the SoS research is being transfered to and applied in social sciences. The SoSe practices and ideas are being extended into domains that deal with understanding and managing complex infrastructure: space exploration, transportation, energy and economics (DeLaurentis & Ayyalasomayajula, 2009). While these

[1] AgentSpring is open-source: `https://github.com/alfredas/AgentSpring`

systems are in many ways similar to defense systems, they have a strong social component that has to be taken into account. Arguably, the introduction of social aspects changes the fundamental qualities of the system and the research methods. When dealing with SoS that have explicit social elements we are faced with:

- deep uncertainty and unpredictability of
  - system boundaries and structure
  - system behavior and dynamics
- non-rational and multi-criteria optimization in decision making
- multiple stakeholders with multiple perspectives and values
- no single point of control

Even the very notion of an optimum becomes problematic – it depends on the stakeholder's point of view and the system boundaries that are porous, prone to change. The role of SoSe of socio-technical systems (STS) needs to change from optimizing system performance to assisting human decision making by identifying relevant data, simulating and replicating SoS operation and studying common patterns.

Such transition also means that the user of SoSe research is the decision maker, either of a large enterprise or, commonly – a policy maker. In the context of the following chapters the SoSe are discussed in the context of supporting policy making and terms SoS and STS are used interchangeably.

3. Policy and SoSe

Global infrastructure systems have always been complex, but it seems that only recently we are becoming aware of the true implications of this when designing policy. A semantic analysis of Journal of Systems Science and Systems Engineering (published in 2003-2010), for example, reveals an interesting trend. The term "policy" has been mentioned only in one abstract of the 33 articles published in 2003 (3%), while the same term has been used in 11 out of 26 articles published in 2010 (42%). An analysis based on a Google News search (from 2000-2010)[2] reveals a relation emerges between the terms "policy" and "system" within the mass media since 2008.

In the context of policy, we conjecture that SoS resarch is about the tools that allow us to grasp the complexity and experience the extent of our policy decisions. Such effects are evident in the complex relations between the 2011 earthquake in Japan and European energy flows in the future (i.e. as a consequence of the nuclear phase out in Germany), or the relations with iPad shipments in California (Los Angeles Times, 2011). As long as our understanding has changed we are conditioned to make decisions in a different way. This change can be illustrated by two stories about the same piece of infrastructure – the Moscow-Saint Petersburg railway.

The Moscow-Saint Petersburg railway, opened in 1851, follows a straight line except for a 17 km bend near the city of Novgorod. The widely believed urban myth states that the bend is a planning artifact. Tsar Nikolaev intended to draw a straight line joining the two cities, but had

[2] The methodology used in the analysis of Systems Science and Systems Engineering and Google News are described elsewhere (Kasmire et al., Submitted)

to draw around the finger holding the ruler to the map. Since then the bend has been know as the "tsar finger", even thought the real reasons for the bend were technical (Wikipedia, 2011a).

The second part to the story deals with the expansion of the railway after 150 years. The planned high speed track was canceled due to environmental protests over the fragile environment of the Valdai Hills.

The two stories (even though the first one is a myth, but a myth widely believed)(Wikipedia, 2011a) exemplify the differences between decision-making. While the Tsar could exercise absolute power and bend the railway, today the complex socio-technical constellation in many a country often requires much more subtle and informed decision making. The role of the decision maker is not only to optimize the technical performance (straight line – optimal) but also to reconcile the different interests and stakes, including the Valdai hills ecosystem preservation.

The role of SoSe is then to provide the methodologies and the tools to support such demanding decision-making process.

4. Proactive study of SoSe

DeLaurentis & Sindiy (2006) recommend a three-phase SoSe approach where a SoS problem is defined, abstracted and simulated. The definition phase consists of identifying and characterizing the SoS problem as it currently exists, seeing the problem in its context. The abstraction phase allows to identify actors, things and relations and gives inputs for the implementation phase. The implementation phase is meant for replicating and simulating the workings of the SoS. This framework is consistent with the role of SoSe for decision support. It also provides a useful skeleton to discuss new tools that are available to the SoSe researcher. Continuous development of these tools can be summarized as proactive study of SoSe.

Proactive study of SoSe focuses on continuous engineering of technical and social components of an information system that maps the complexity of the real-world SoSe. The primary focus of proactive study of SoSe are the new information technologies that can take the SoSe research further.

Proactive study of SoS involves creating an ecosystem of information management tools at researcher's disposal and identifying patterns when to use them and how to combine them to address a research problem. The following sections will identify relevant developments in information technologies, propose a set of useful tools and exemplify their application in the context of SoSe research. The nature of the tools discussed is highly technical but in the scope of this chapter it is the enabling effect of these tools that are important, not the technical implementation. We identify the growing abundance of data and the emergence of the Internet of Things, then we discuss the methods and tools how to use it in the context of SoSe analysis and in combination with models, simulations and games.

4.1 Big data

When Jay Forrester and his colleagues were tasked with creating a military information system half a century ago, one of the main challenges was to manage massive amount of information collected by the various radars (Everett et al., 1957). Later scientists researching ecosystems collected vast amounts of data expecting to mine it for patterns that would allow them to understand and simulate the complex dynamics of biomes (The National Academies, 2011). These scientists spent years observing, recording and documenting the flora and fauna. Data collection and analysis has always been the cornerstone of systems research.

Commoditized hardware, telecommunications equipment and free software have enabled production and collection of massive quantities of data. We are surrounded by various sensors (CCTV cameras, RFID tags, mobile phones, GPS devices) that create a flood of data on auto and marine traffic, weather, performance of computing clusters and industrial facilities (NASA, 2011). Internet applications record information about users' actions and allow to voluntarily contribute data. Applications such as Facebook or Twitter have turned their users into human sensor networks that already span the globe (Sakaki et al., 2010; Zhao et al., 2011).

The phenomenon of *increasing data abundance* has become known by a broad term – *"Big Data"* (Waldrop, 2008).

To give the reader a sense of Big Data, consider that a modern gas-powered power plant produces much more data than the New York stock exchange. The International Open Government Dataset Catalog (Tetherless World Constellation, 2011) currently indexes more than 300'000 publicly available datasets covering data on economy, energy, governance, health and public finance. These are two examples of different dimensions of big data: depth and breadth. Governments and agencies around the world have recently started publishing data covering various aspects of their activities. For example, the European Pollutant Release and Transfer Register (E-PRTR) publishes a database on 28'000 industrial facilities in the EU. At the same time the amount of user contributed data, coming from their mobile phones and on-line activities has exploded. For example, the GoodGuide publishes data on more than 115'000 consumer products (GoodGuide, 2011). While E-PRTR data is managed by an agency, GoodGuide's data is contributed by community or "crowd-sourced". Wikipedia (crowd-sourced itself) defines the term as the act of outsourcing tasks, traditionally performed by an employee or contractor, to an undefined, large group of people or community (a "crowd"), through an open call (Wikipedia, 2011b).

4.2 Semantic Web and crowd sourcing

An important aspect of the Big Data movement is the data format. While many datasets are still maintained in tabular fashion (tables and relational databases), increasingly data is published in semantic format. Semantic Web (SW) is a broad term that defines the ecosystem of next generation of internet technologies (Berners-Lee & Hendler, 2001). While there is still debate on which exact implementation and standard will dominate the future of the web (Marshall & Shipman, 2003), there is no doubt that the Semantic Web is likely to prevail due to two enabling aspects: unique resource identifiers and data interoperability. While the current incarnation of the web is about web pages and the links between them, the SW allows for the "Internet of Things" (IoT). The SW allows assigning unique resource identifiers (URI) to all things in the world and defining relations between them; together these consitute the IoT (Gershenfeld et al., 2004). Another important feature of the SW is the interoperability of the data format. Datasets published by different publishers can be combined and reconciled against each other given that all things in the dataset have been uniquely defined (Lassila & Swick, 2011). While within the traditional data formats the records were uniquely identified only within the scope of a dataset, the semantic data format allows for global unique identity. This essentially simple feature provides a mechanism for Big Data to emerge.

The challenge facing the system scientists (also governments and businesses) is to manage the large amount of data and make use of it in decision making. Arguably the way to make sense out of the Big Data is to create tools that would be semantic and allow for collaborative action. Whether collaboration is among a few scientists working on a dataset of wind patterns in Germany or a "crowd" publishing bird sightings around the world, is not relevant. It is important that the datasets are published in the semantic standards and can be shared. Data analysis made possible by massive cloud computing resources and crowds of collaborating scientists and non-academics will help develop more transparent and objective data-driven representations of the world's problems. Employing big data to analyze SoS is a scientific challenge undertaken by the authors. A number of experiments have been performed aiming to integrate big data into decision-support systems, models and simulations. One of the series of experiments deals with the use wikis to enable collaborative big data management and use of that data within simulations[3].

Remembering the stages of SoSe research prescribed by DeLaurentis, wikis can be used in the problem definition phase. Initial analysis can be performed using a wiki environment to to collect, aggregate, curate data, perform queries and let the data structures emerge.

4.3 Wikis for collaborative information management

A wiki is defined as "a website that allows the creation and editing of any number of interlinked web pages via a web browser" (Wikipedia, 2011c). The original creator of the first wiki Ward Cunningham had the goal of creating the simplest on-line database that could possibly work. Wikipedia – the on-line encyclopedia that runs a version of a wiki software – currently hosts pages on 4 million different topics. With that in mind the researchers identify two crucial aspects of wiki-type systems. They are simple to use and they are domain agnostic (generic). In the simplest form, wikis allow multiple users to define concepts and link them together. Besides Wikipedia there are hundreds of wikis covering various subjects, from fictional Pokemon world to the very scientific human genome data. These criteria – simplicity and genericness – have helped the wiki software to establish itself as a novel research support system within information driven research areas, such as biology, pharmacy, genetics and engineering. These criteria make wikis a valuable tool for SoSe research too.

A new approach is offered by the next generation of wiki software, combining the simplicity of the wiki approach with modern semantic technologies. Semantic wikis introduce a powerful feature allowing to mix structured and free-from information (text) within wiki pages. The wiki pages are part web-pages and part database entries. While simple wikis allow one to define concepts and link them together, semantic wikis allow us to define things and relations between them. Systems thinking concerns primarily objects and relations between them and semantic wikis are the perfect tool for managing information about systems. An example of a semantic structure is presented in figure 1.

[3] "Enipedia (`http://enipedia.tudelft.nl`) is an active exploration into the applications of wikis and the semantic web for energy and industry issues. Through this we seek to create a collaborative environment for discussion, while also providing the tools that allow for data from different sources to be connected, queried, and visualized from different perspectives"(Enipedia, 2011)

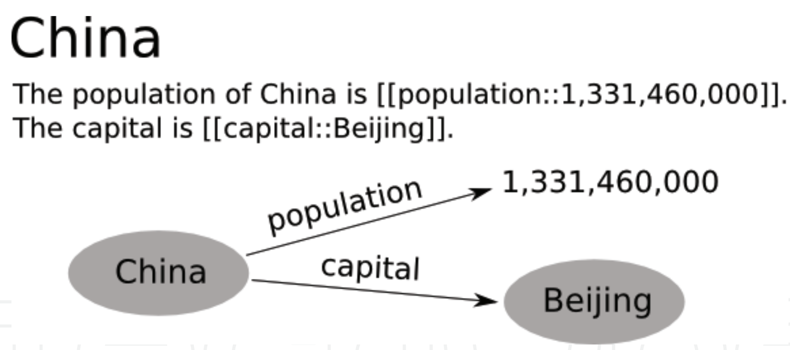

Fig. 1. Semantic wiki – a mix of text and structure

Traditional relational databases have been the dominant decision-support software since the 70s, and have been since then applied in information management across domains. Despite the numerous benefits of relational databases, every database has a unique structure of tables and relations – specific to the domain, environment and problem. Such approach to storing data is called as "structure-first", referring to the fact that tables and relations have to be defined before they can accommodate any data. Moreover, the data structure has to be encoded by professional database developers.

Semantic wiki software offers a different approach, called "data-first". Data can be entered into the system, while simultaneously defining the structure. The fact that the data structure does not have to be fixed beforehand, has tremendous benefits in certain applications. Scientific research, especially interdisciplinary research have embraced the data-first approach. Using data-first approach data structures are part of the continuous research process. In other words the structure of data emerges and evolves as researchers develop better understanding of the problem domain and scope. The evolutionary nature of semantic data structure is especially applicable to managing data in the context of complex, evolving and multi-domain SoSe.

The emergent data structure still allows it to be queried at any point of development. Queries, as in the case of relational databases, are the main method of data analysis. Such functionality allows semantic wikis to assume a new function as domain agnostic (generic) decision-support systems, particularly tailored to interdisciplinary research. The on-line web access, relative ease of use, mix of structured and unstructured data, ability to define and change data structure by the users (not developers) make the wiki approach a valuable tool in ecosystem of the emerging field of big data science.

Another important feature is that any semantic wiki seamlessly ties into the Internet of Things and allows to use and connect to the information entered and maintained by other researchers, agencies, businesses, governments, human volunteers or even machines (Davis et al., 2010). This feature provides semantic wikis with the ability to scale information and knowledge according to the Metcalfe's law (Gilder, 1993), which states that the value of the network is proportional to the number of connected users. Next to this increase of value, Shirky (2008) has talked about the existence of a "cognitive surplus" – the untapped collective mental potential of human society. In other words, it concerns society's spare mental capabilities that go unused in a similar way to computers that are sitting idle. To illustrate his point, he gives a rough calculation that Wikipedia took about 100 million hours of human thought to create. This may seem like an enormous amount of time, but it is roughly the same amount that people in the US spend sitting and watching TV commercials during a single weekend. Finally, Raymond (2001) has observed that "given enough eyeballs, all bugs are shallow". If there is a cognitive surplus, used in a network, we can expect an auto-catalytic increase in quality of networked knowledge and data in semantic wikis.

4.4 Ontologies

One of the challenges often encountered in developing models of complex socio-technical systems stems from the arbitrary boundaries of such systems and the vast number of facts required to conceptualize them. Allenby (2006) argues that the system boundaries are dynamically determined by the query one poses to the system. In other words, the boundaries of the system are determined by the specific research question at hand. For example, studying crime in a city requires different definition of the system than the study of city's water supply.

Using the wikis in the definition phase allows to perform initial analysis of data and create data structures. These data structures can be later translated into system formalisms – ontologies. Ontologies identify things, actors and relationships between them in the system studied. The ontologies already reflect the researchers view of the problem and are part of the abstraction phase withing the SoSe framework.

Mikulecky (2001) emphasizes that complexity manifests itself in the fact that no single system formalization (ontology) can capture all aspects of a complex system. It is a source of much debate how to synchronize or agree on a single ontology of the system. We would argue that such approach is not the most useful. Ontologies are specific to the question at hand and a part of the answer to the research question. Different research questions will require different ontologies but the researcher's tools should allow for flexible mapping of data to ontologies. Semantic wikis allow exactly that.

Ontologies can later be used to create simulations and models of the live system. It is one of the common rules within software development that data structures are more tractable than program logic. Defining simple, clear and transparent ontologies are cornerstone to developing non-trivial agent based models and simulations.

4.5 Agent Based Modeling

Agent Based Modeling (ABM), used in DeLaurentis implementation stage, is a holistic approach, as it provides a perspective on a system from the smallest individual elements to the highest level of system aggregation. While it considers systems in its entirety, it is also reductionist in a sense that it reduces systems to smaller elements if they are fully interrelated with other elements (Bar-Yam, 2003). It is generativist, as it understands systems as a result of continuous process of emergence across multiple levels, starting at the lowest level elements (Epstein, 1999).

In the words of Borshchev & Filippov (2004), the Agent Based approach "is more general and powerful [4] because it enables capturing of more complex structures and dynamics. The other important advantage is that it provides for construction of models in the absence of the knowledge about the global interdependencies: you may know nothing or very little about

[4] than System Dynamics, Dynamic Systems or Discrete Event Simulation

how things affect each other at the aggregate level, or what the global sequence of operations is, etc., but if you have some perception of how the individual participants of the process behave, you can construct the AB model and then obtain the global behavior."

Agent-based models take agents (components) and their interactions as central modeling focus points. Stuart Kauffman has been quoted to say that "an agent is a thing which does things to things" (Shalizi, 2006). Furthermore, Shalizi (2006) states that " An agent is a persistent thing which has some state we find worth representing, and which interacts with other agents, mutually modifying each other's states. The components of an agent-based model are a collection of agents and their states, the rules governing the interactions of the agents and the environment within which they live."

From these interactions, using simple rules and ontologies derived from real data, ABM generate patterns of complex behavior, and serve as a *in silico* experimental device. It should again be noted that ABM are not used to predict the future or identify optima. Their generative nature does allow of to explore *possible futures* through asking what-if type questions.

4.6 Serious games

Karl Jung argued that one of the functions of dreams is to allow the dreamer to practice complex situations and difficult decisions before they happen (Jung & Jaffé, 1989). In that aspect serious games are similar to dreams. They allow the player to practice making decisions in the virtual world. In addition to that they are effective tool for studying, teaching and understanding complex socio-technical systems.

From the systems scientist's perspective serious games are a way to involve humans in simulations. Games have a special power to motivate and instruct (Meadows, 1999). Other advantages are that they can present complex environments, are repeatable, produce high levels of immersion, and are fun (Garris et al., 2002). Serious games provide a basis for organized communication about a complex topic (Duke, 1974; 1980; Kelly et al., 2007), often developed for learning within organizations. Serious gaming has a long history of military purposes and has broadened to a variety of applications, such as business and management science, economics, and inter-cultural communication (Mayer, 2009; Raybourn, 2007). Games are used for education and for the exploration of strategies and policies (Gosen & Washbush, 2004) and, compared to other simulation techniques, games result in a high involvement of the users.

The use of serious games on itself is not sufficient to provide a comprehensive set of insights (Bekebrede, 2010; Bekebrede et al., 2005), therefore, it should not be adopted in isolation. So far, in the literature the combination of serious games and simulation is only adopted as what is now referred to as *simulation games*: serious games with embedded aspects of simulation models. The main disadvantage of games is that there are strong limitations to the complicatedness and length of a game. Even stronger, a conceptually complex game needs to be relatively simple in mechanical terms in order to be effective (Meadows, 1999). Meadows refers to game design, which involves the art and craft of constructing games (Rollings & Adams, 2003). Although there is an elaborate literature on game design for non-educational purposes (cf. Fullerton et al., 2008; Rollings & Morris, 2004; Salen & Zimmerman, 2004; Schell, 2008), there is less literature on serious game design. Several approaches exist, though (cf.

Aldrich, 2004; De Freitas & Oliver, 2006; Frank, 2007; Hall, 2009; Winn, 2009). Essentially, the challenge is to design a game with a good game-*play*, an interesting model of *reality*, and the correct underlying *meaning* (Harteveld, 2011). The opportunity for games to be used together with simulation models is large (Chappin, 2011).

In terms of the DeLaurentis framework, games are another means of implementation, that serves to reconstruct the system analyzed and generate complex phenomena from relatively simple rules.

5. Case studies

Together the Internet of things, semantic information management systems, ABM and games create an ecosystem of data, processes and tools that allow to look at the systems of systems with higher precision and make it easier to find relevant patterns. The primary use of this ecosystem is to advance our understanding of the complex environments and the maturity of our decision making within those environments. The ideas mentioned are not sufficient to change the way we see the world. It also requires commitment from the implied users of these relatively complicated techniques. But recent experience has shown that there are real world interest and applications. Some of this experience is presented further in a form of case studies.

The following case studies demonstrate the use of the tool ecosystem to analyze energy systems.

The first case study concerns the new balancing regime of the natural gas market in the Netherlands and uses the wiki to describe the system and assumptions, later to be used in a simulation. The second case study to analyze the possible future outcomes of the long term development of the European electricity sector, both with an Agent-Based Model and a serious game. Again the wiki [5] is used to gather and define data on thousands of power plants that are later simulated within a complex power market. AgentSpring is the novel ABM simulation framework developed to support the approach already discussed in this chapter and used is in both case studies.

5.0.1 AgentSpring

Before discussing the case studies, it is useful to introduce the modeling framework used in those case studies. Knowing the approach of the framework is helpful in explaining the structure of the models and the terms used.

There are around 60 ABM frameworks in existence, some more popular than others. The motivation for creating another framework was two-fold. Firstly, the framework had to seamlessly integrate the semantic data. Secondly, the framework had to be suited for "super-social" simulations, where behavior of agents is elaborate and diverse. In other words, the framework has to help build models that are data driven and support extensive behavior algorithms.

Surely, these two requirements could be fulfilled by the existing frameworks, provided some modifications were made. But there was also the opportunity to build a framework that would

[5] `http://enipedia.tudelft.nl/`

leverage off the new and powerful open source libraries and changing software development paradigms. AgentSpring gets its name from and makes use of Spring Framework – a popular software development framework, that promotes the use of object oriented software patterns (Johnson et al., 2009). One such pattern calls for separation of data, logic and user interface (Krasner & Pope, 1988). Most modeling frameworks mix the three, which it is a reasonable choice when creating smaller models. However, the separation of concerns (Hursch & Lopes, 1995) and other patterns are especially helpful guidelines for creating models and applications that are sophisticated but transparent.

Another component that AgentSpring brings to modeling is a powerful graph database. A graph database is a database that uses graph structures with nodes, edges, and properties to represent and store information (Eifrem, 2009). The world modeled is created from the ontology that is essentially a graph of objects and their relationships. AgentSpring allows the graph to scale to hundreds of agents, millions of things and relations between them, as represented in figure 2. Such graph databases already power the social networking and other Internet services. The application of graph databases in ABM is new but promising as it allows for more straightforward representation of the system modeled. The graph database makes maintenance of the graph easy and allows to find things and observe patterns by performing pattern matching queries.

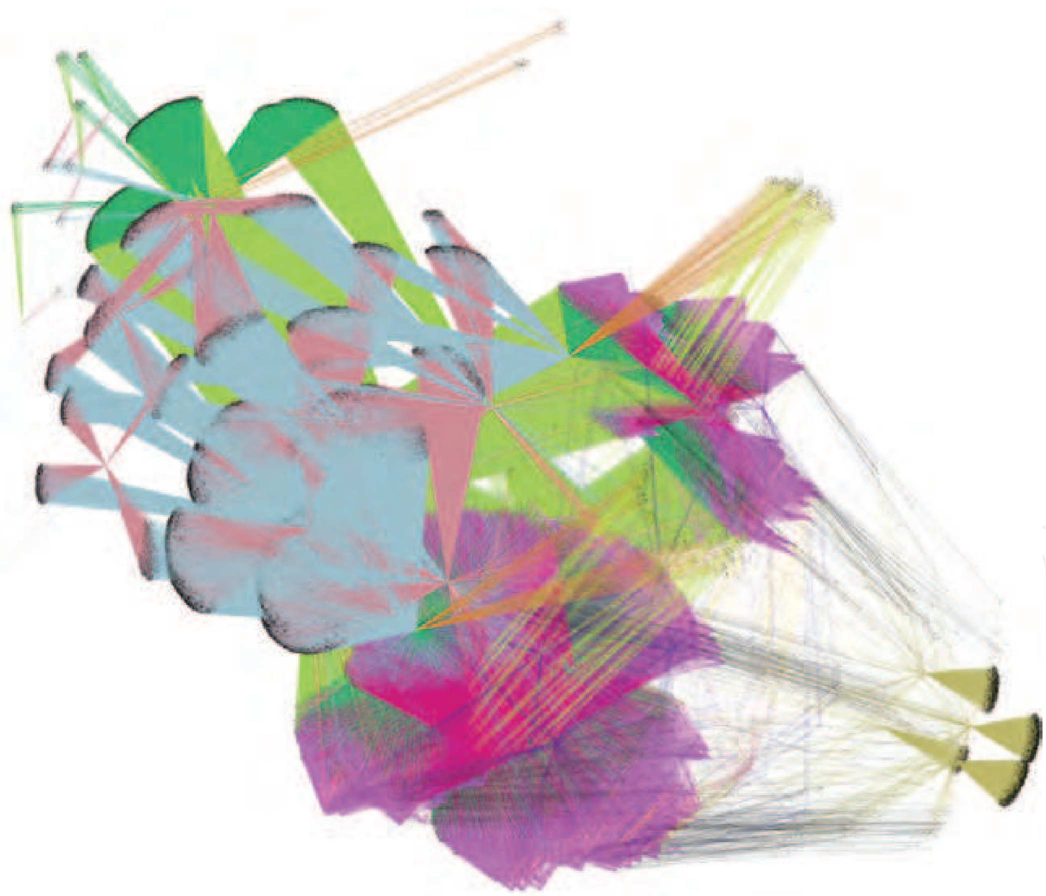

Fig. 2. Simulated world: 170’000 agents and things; 650’000 relations between them. Different colors represent different types of relations.

On the conceptual level AgentSpring is inspired by the artificial intelligence classic “Scripts, Plans, Goals, and Understanding: An Inquiry Into Human Knowledge Structures” by Roger C. Schank and Robert P. Abelson. The book suggests that human behavior and understanding of the world is compartmentalized as scripts that are used to execute bigger plans and higher goals (Schank & Abelson, 1977). When executing a plan to go to a restaurant, a person would invoke a script to make reservation in advance, call a cab, perhaps dress up and so on. AgentSpring makes use of the scripts concept to encode agent behavior in a modular way. Agents play their roles in the simulation by executing various scripts. Models are made by combining agents and scripts that define their behavior in the context of social situations. This makes AgentSpring particularly suited to modeling complex socio-technical systems.

AgentSpring decouples agents, their behaviors and their environments making the pieces reusable, composable and easy to manage. Experience has shown that modular and reusable models are the only kind of models that can accommodate changing scope and new research questions.

5.1 Case I: Balancing the natural gas network in the Netherlands

5.1.1 Introduction

As the indigenous natural gas resources near depletion, the goals of the Dutch gas policy have shifted from maximizing state revenues towards energy security and sustainability. It is the intent of government’s agenda for the Netherlands to become the gas marketplace of Northwest Europe Ministry of Economic Affairs (2009). In addition to having affordable gas supply the Dutch government hopes to create a liquid gas market and a profitable gas services sector. The new gas balancing regime is another step towards a liberalized gas market in the Netherlands.

In a nutshell, the new balancing regime encourages the market participants to collectively maintain balance of the gas network. The system balance means that the aggregate gas volume entering the system should be equal to the amount of gas leaving the system at any point in time. The system load is determined in the day ahead market, where the market participants submit their gas feed-in and take-off schedules. The individual imbalances are not important as long as the system is in balance as a whole. A power plant operator can consume more gas than scheduled as long as there is someone willing to consume less or supply more at that point in time. If the system goes off balance there are financial penalties introduced to the causers of the imbalance. At the same time the traders contributing to balancing the system are rewarded. Such relatively simple rules could generate interesting aggregate system behavior and complex phenomena might emerge (Bucura et al., 2011).

5.1.2 Model description

An agent based model is constructed to explore the possible effects of the new rules. The operation of the system is simulated to determine the total imbalance, the market participants’ cash flows and the natural gas price emerging in the balancing market. Calculating the progression of these variables allows for an ex-ante assessment of the efficiency of the incentive scheme proposed by the new balancing regime and its social cost. Through such modeling and simulation a better understanding of the consequences of the new balancing regime can be obtained.

To arrive at this model the system is decomposed into agents, things and scripts. In the balancing market model initially we distingush between only two types of agents: the system operator overseeing the operation of the gas network, and the gas market participants. Market participants could be traders, gas shippers, power producers, other utility companies. In the context of this initial modeling exercise they are not differentiated. Things represent the physical reality: contracts, capacities, technologies used by the agents. Agents and things are defined in the wiki using the Internet of Things methodology. Every thing or an agent is assigned a unique wiki-page, where the properties and its relations to other things and agents are defined. Figure 3 presents the structure of the model.

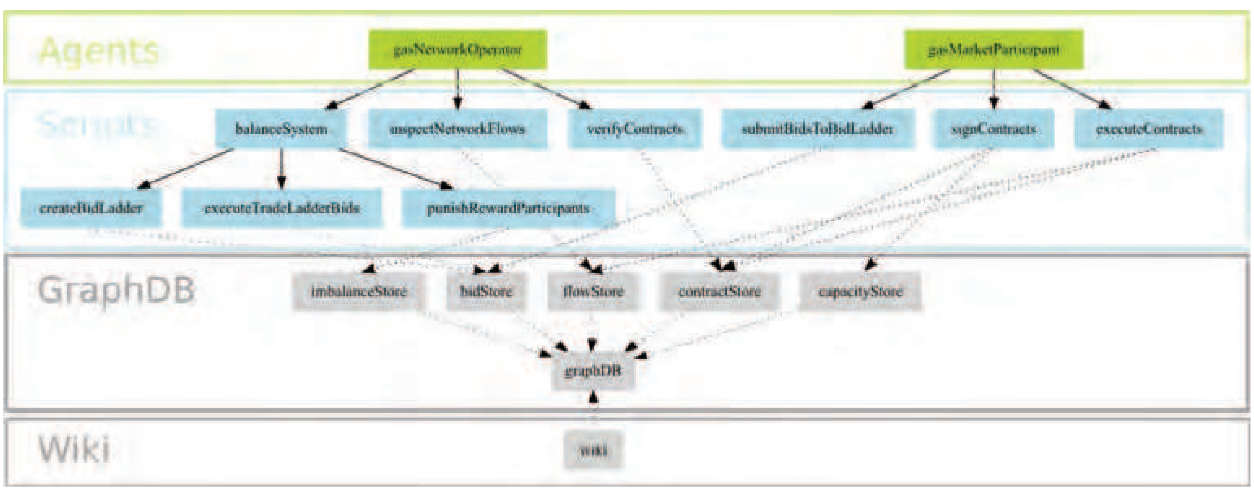

Fig. 3. Model structure

The simulation logic is then decomposed into scripts as discussed previously. The system operator has to make sure the system is in balance during every hour of its operation. The system balancing script is made up three more scripts: *createBidLadder*, *executeBidLadder* and *punishRewardParticipants*. This shows how the scripts can be composed from other scripts and made modular – easier to understand, communicate and maintain. The names of the scripts almost tell the whole story. If the system is out of balance the system operator initiates a secondary market called "bid ladder" (*createBidLadder*), where the imbalance amount is traded in an auction (*executeBidLadder*), balance is restore and the participants are either punished or rewarded (*punishRewardParticipants*). The scope of each script is debatable – one could mold the whole simulation into one big script. But it is most useful when the script contains one piece of simulation logic that is performed by one type of agent and can be well understood and debugged by the modeler.

During the execution of the simulation the agents and things are loaded into a graph database. Scripts are executed within a predefined order: contracts are signed, bid are actioned, gas quantities are delivered – and a complex graph of agents, things and their interactions emerges. The agents acquire knowledge of their environment by querying that graph. They find the cheapest suppliers of gas, the available capacity of the gas transmission network and so forth. The researcher queries the same graph to find patterns in the aggregate system behavior.

5.1.3 Model results

Using the agent based model simulation to explore the operational pathways of the new gas balancing mechanism brought interesting insights. Without going into much detail – which would otherwise require a more dedicated effort and detail explanation of the real system – the results indicate certain pathways of the operation that could lead to increased volatility of the system, higher redistribution of profits and higher social costs of gas network balancing. The research is still in progress and the initial model is being extended to, for example, include heterogeneous behavior of the natural gas traders and different types of contracts.

5.2 Case II: De-carbonization of the power sector

5.2.1 Introduction

Electric power production is largely based on fossil-based combustion, except in environments with abundant hydro-power (IEA, 2008). Fossil fuels have become the lifeblood of developed economies: reducing or replacing their consumption is difficult and expensive. This technology inevitably leads to the emission of carbon dioxide (CO_2), as carbon capture and storage and renewable energy sources are not yet feasible or available on a large scale.Global climate change caused by CO_2 and other greenhouse gases (IPCC, 2007) can be considered a *tragedy of the commons* (Hardin, 1968) for which no effective global coordination, regulation and enforcement has yet been developed. While the cost of abatement is high, doing nothing will eventually be much more expensive (cf. Stern, 2007).

The growing consensus that CO_2 emissions need to be stabilized and then reduced in the course of this century has led to much interest in achieving cost-efficient emission reduction through incentive-based 'carbon policy' instruments – using market signals to influence decision-making and behavior (Egenhofer, 2003) – rather than command-and-control regulation. They need to affect the long term carbon efficiency of the system through investment in new power generation capacity and replacing the old, creating incentives for the "right" investment.

In order to explore the possible effects of the carbon policies we have simulated the complex power generation system of systems (Chappin, 2011; Chappin et al., 2010). The SoS is composed from social systems (power and commodity markets), technical systems (power grids, generation technologies), and the web of relations between the them as illustrated in figure 4.

5.2.2 Model and serious game description

In order to explore the impacts of the policies on the CO_2 emissions of the power generation sector, both a serious game (de Vries & Chappin, 2010)[6] and an agent-based model (Chappin et al., 2010) were developed. In both the model and the game the technical and the social

[6] The serious game is called "Electricity Market Game", and is played online: `http://emg.tudelft.nl`

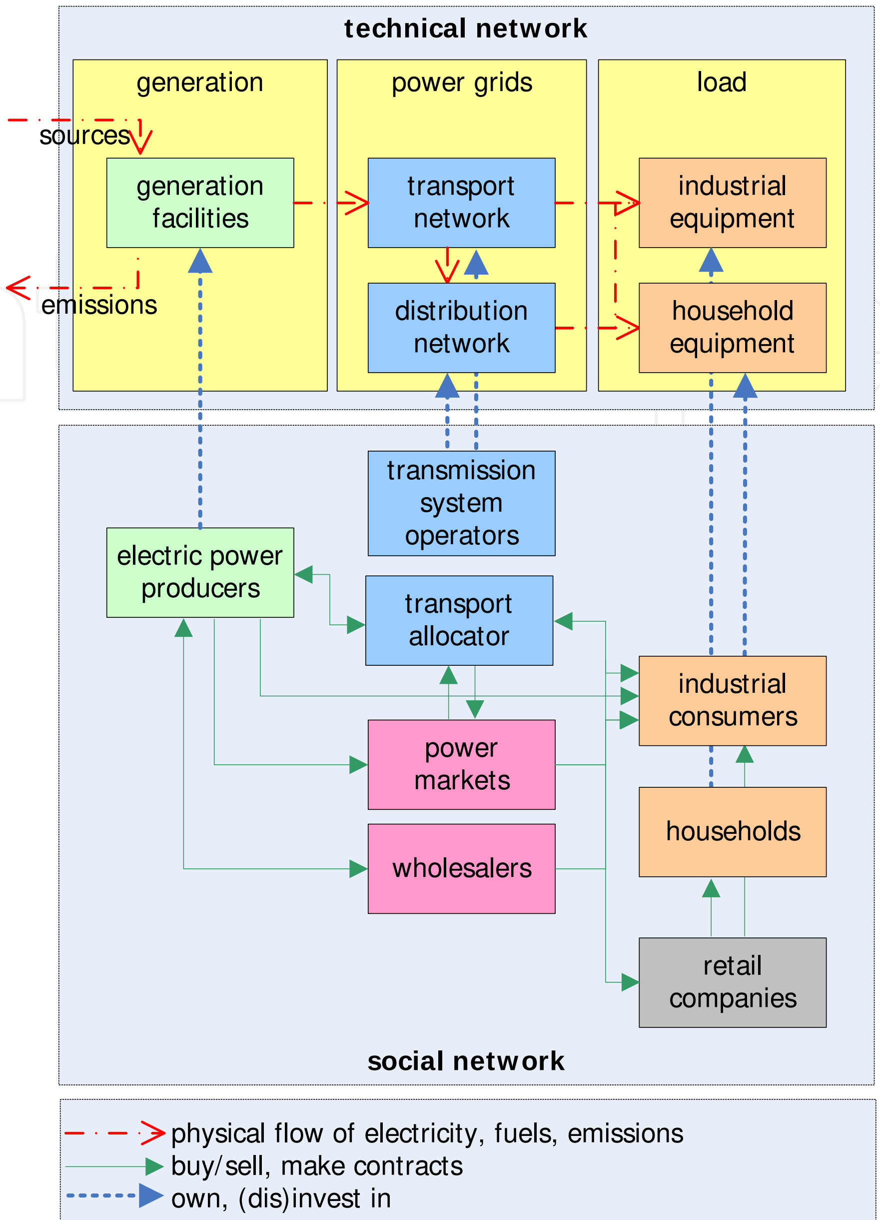

Fig. 4. Socio-technical system-of-systems of electricity production (adapted from (Chappin, 2011))

components of the power system are contained. In the game, people play the roles of the energy producers, which are in the model represented as the agents. Other agents in the model are commodity traders, banks, governments and energy consumers. The game players and the modelled agents interact through markets. A simplified ontology of the system presented in the the model is depicted in figure 5 – a similar ontology is present in the serious game. The model defines multiple commodity markets for coal, natural gas, uranium and biomass, two electricity spot markets, a CO_2 auction, a secondary CO_2 market and a market for power generation technologies. Markets provide a unified mechanism to introduce feedback loops into the model. For example, if many players or agents decide to invest in wind generation technology, the price of the technology in the market may increase, depending on the decision making process of the technology supplier.

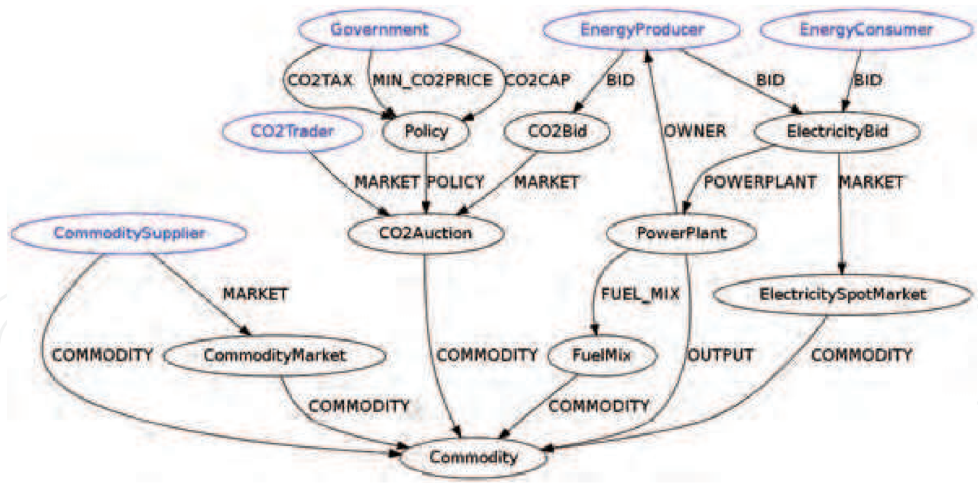

Fig. 5. Simplified model ontology

The decisions and actions of the agents are decomposed using the AgentSpring methodology – into scripts. The diagram in figure 6 lists the scripts executed by the energy producer. Energy producers have the most versatile behavior in the model, they have to operate their generation portfolio, purchase fuels on the commodity markets, sell electricity on the power market, arrange for loans, invest in new power plants and trade on the CO_2 markets. Modular scripts allow to compartmentalize complex agent behavior and allow to develop it piece by piece. Each script concerns only one aspect of agent logic in the context of one function. For example, when trading in the commodity markets the electricity producers are buyers, when trading in the power market they act as sellers, similarly to the commodity traders in the commodity markets. The scripts allow the behavior logic to be reused in different contexts. They allow for more generic and simple algorithms that are easier to understand, maintain and communicate.

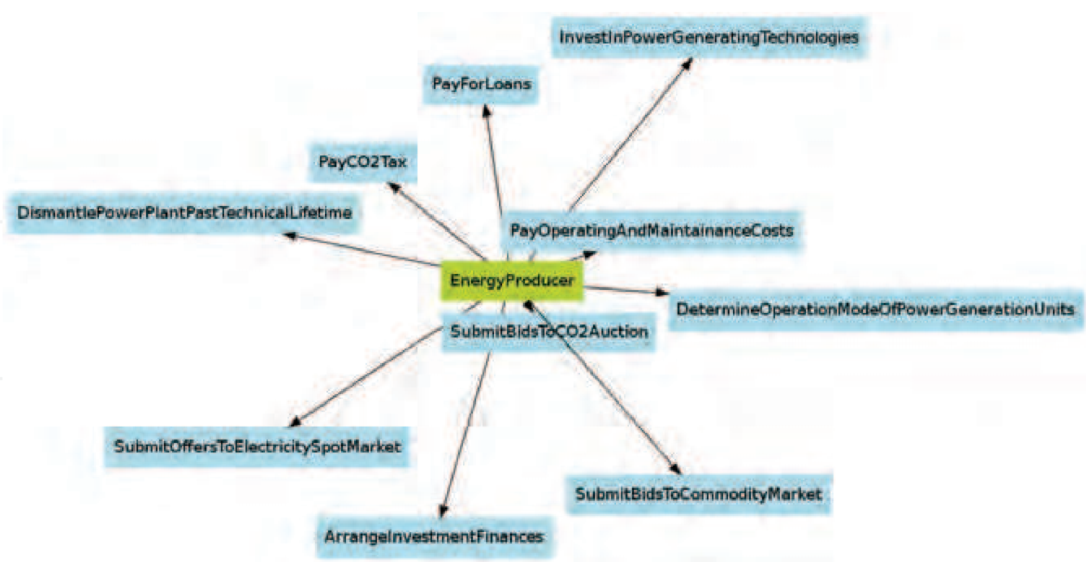

Fig. 6. Energy producer's behavior decomposed into scripts

In the serious game, the players act out their roles, as they have the objective to optimize the value of their company in the long run. Players have to define a strategy to do so and translate their strategy to timely investment and dismantling, and appropriate bidding on markets (de Vries & Chappin, 2010). They are uncertain about future prices and policy instruments.

Crucial for their performance is how players react on such uncertainties and on each other's actions.

This modeling exercise is interesting in the fact that it already uses the Internet of Things to power the model assumptions and scenarios, see figure 7. The power plant data is aggregated from multiple sources (agencies, company data) and includes detailed information on current power generation portfolios of all European countries. The assumptions about technologies, their physical properties are also extracted from EU state of the art specifications. The hour level electricity demand data is also taken from the European Network of Transmission System Operators for Electricity (ENTSOE) databases, converted into a semantic format and used within the model scenario. The wiki in this case is used to aggregate, align and validate the data and re-purpose it for the model.

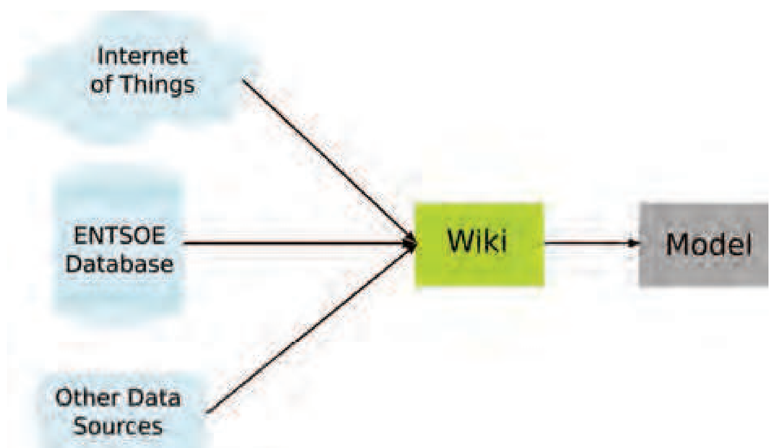

Fig. 7. Using distributed data sources for the simulation

5.2.3 Model results

A key result of the agent-based simulation is that given a certain CO_2 cost – whether through a tax or the price of CO_2 emission rights – carbon taxation leads to lower electricity prices than emissions trading (Chappin et al., 2010). The main reason for this is the difference in investment risk: a tax is more predictable than the market driven CO_2 prices. The uncertainty is factored into the investment decisions via higher discount rates and lead to higher required profitability of the investment. Also the market-based CO_2 prices tend to create investment cycles that induce volatility in the power producer's portfolio. Predictability is a key advantage of taxation, which allows investors to minimize cost over a longer time horizon. In the serious game, similar results have been monitored: if players have the feeling that strict CO_2 policies are in the pipeline they tend to overreact. By playing the game, players tend to be more open to the notion of complex systems and can understand the model faster and deeper (Chappin, 2011). The ecosystem of tools together help in understanding of the evolution – and possibilities of policy design – of the complex system of systems that constitute our electricity infrastructure.

6. Conclusions

The tool and methodology ecosystem described in this chapter are an initial exploration into using big data, collaborative information management to build detailed agent based models of socio-technical systems of systems. It is an iterative process, set in motion by a number of ongoing and planned research projects, with a goal to gain better insights into human behavior and its interaction with the technical and natural environment.

A common misconception about such a research endeavor is that it aims to predict future and will therefore necessarily fail. Instead, the goal of such research is to augment our understanding of reality and make our decision making *less bad*. People will always try to create models of reality and possibly live by them or in them. Heuristics and scripts are useful when we need to make decision with imperfect information. The hope is that with more data, smarter tools and collaborative effort we can reconcile our individual irrationalities into a more objective data-driven understanding of our environment and improve the way we make decisions.

There are number of issues to solve before we are able to enjoy the benefits of this grand vision of data and model augmented decision making. The data is still dispersed in different formats and behind the closed doors of diverse institutions. The different models build by the scientific community are often built in isolation and do not interconnect. Arguably, it is the culture not the technology that is the bottle-neck in progressing systems science. Together with systems engineering we have to do social engineering, in connecting researchers with tools and relevant data, allowing for collaboration and communities to emerge. In order to be effective in analyzing socio-technical systems we have to continuously engineer adequate informational socio-technical systems of systems. This is at the core of the *proactive study of SoSe* proposal.

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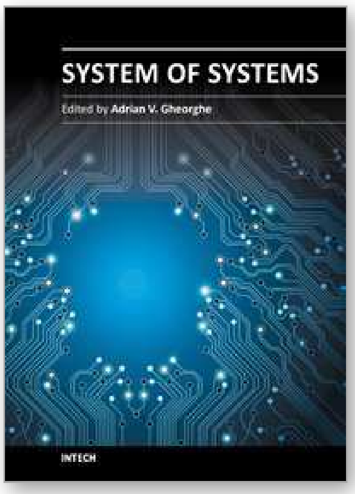

System of Systems

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The present book proposes and fosters discussion on the current applications in the field of system of systems, with emphasis on the implications of the fact that new developments and area of technical and non-technical applications are merging. The book aims to establish an effective platform for communication among various types of practitioners and theory developers involved in using the system thinking and systems engineering approaches at the scale of increased complexity and advancing computational solutions to such systems.