Modeling Interdependent Socio-technical Networks via ABM
Smart Grid Case

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Abstract: The objective of this paper is to improve scientific modeling of interdependent socio-technical networks. In these networks the interplay between technical or infrastructural elements on the one hand and social and behavioral aspects on the other hand, is of importance. Examples include electricity networks, financial networks, residential choice networks. We propose an Agent-Based Model approach to simulate interdependent technical and social network behavior, the effects of potential policy measures and the societal impact when disturbances occur, where we focus on a use case concerning the smart grid, an intelligent system for matching supply and demand of electricity.

1 INTRODUCTION

The objective of this paper is to improve scientific modeling of interdependent socio-technical networks. This is important in the field of designing critical infrastructures. Failures in these systems are rare events which may have catastrophic consequences. Society requires resilient infrastructure which can cope with a wide variety of threats. Examples of failures include natural disasters like Hurricane Sandy, and technical failures like cable burnout in the energy network in Germany which has a highly distributed renewable energy production. According to the German Federal Network Agency, at the end of March 2013 the electricity network threatened to collapse: “The security of the network can no longer be guaranteed. [...] We have had to intervene more than forty times to prevent surges in wind and solar power from compromising the entire electricity system. The stress generated by these situations is becoming increasingly difficult to handle.”

Since Holling’s (1973) seminal work on the resilience of systems, engineering scientists have endeavored to design critical infrastructures capable of coping with disturbances (McDaniels et al 2008; Boin & McConnell, 2007). However, social components are often missing in models of critical infrastructure. This is a problem for two reasons. First, human behavior can influence the system, and thus the likelihood of failure. Second, effects of disturbances have human dimensions, whereby strategic decisions can best take account of the disruption that people experience (and the perceived effect thereof) rather than use solely technical parameters. This provides our motivation for this research into interdependent socio-technical modeling.

In this study we propose an Agent-Based Model (ABM) approach to simulate interdependent technical and social network behavior, the effects of potential policy measures and the societal impact when disturbances occur. The use of individual or agent based approaches are common in the study of complex adaptive systems (Holland 1995), especially where the interactions between the agents are complex, nonlinear, discontinuous, or discrete, where the population is heterogeneous and where the topology of the interactions is heterogeneous and complex (Bonabeau 2002). This applies increasingly to networks, whether physical or social. Using ABM, its structure and behavior have potential to resemble reality better than simple mathematical models, especially when the underlying real relationships are complex (Remondino 2004).

In order to obtain our objective, we focus on a specific use case: the smart grid, a future intelligent system that helps to match demand and supply of electricity in a sustainable and secure manner. In such a system, both social and technical aspects play

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an important role. The model we obtain for this use case, and that we will describe in this paper, helps to give insight in certain effects arising from the interplay between these aspects. Furthermore, from it we obtain generic insights into interdependent socio-technical network modeling, contributing to our main objective.

2 RELATED WORK

The topic of simulation models for interdependent socio-technical networks is receiving attention in a wide range of scientific domains. This development is based on the enormous amount of data related to social, economic, technology and biological networks, which is increasingly available for research, as well as readily accessible computing power for carrying out the necessary computations (Kleinberg 2008; Jackson 2008; Reed et al 2009; Khanin & Wit 2006). We briefly address a number of the most relevant streams of literature.

In the field of resilience engineering a main focus is on the effects of natural disasters on a range of infrastructural networks. There is a general recognition that interdependencies between networks are both an important driver of cascading failures and a significant modeling challenge (Reed, Kapur and Christie, 2009). Recent work is including the 'human factor' as one of the interdependent networks, in recognition of the importance of modeling the socio-technical system as a whole, e.g. Johnsen and Veen's (2013) assessment of the key communication infrastructure used in emergency communication in railways in Norway, although this is not yet widespread practice.

A second relevant scientific domain is the sociology of the housing market, where methods are developed for analyzing housing price dynamics (Erlingsson et al, 2013), urban sprawl and individual choices about where to live, and the implications of these choices for residential patterns (Devisch et al, 2009). Individual choices respond to the relative attractiveness of residential areas, but they also change that attractiveness (Bruch and Mare, 2012). ABM have been used to model these choices (Macy and Wilier, 2002; Benenson, 2004) including the interdependencies of different market segments, such as racial residential segregation (Zhang, 2004).

Finally, in direct relation to the case study we address in this paper is the smart electricity grid. Much literature on this topic which implements ABM is focused on multi-agent systems to control distributed smart grid technology, rather than simulate the socio-technical networks including household choices. Studies which do include human behavior include simulating load profiles for households equipped with smart appliances under conditions of real-time variable-price tariffs (Gottwalt et al., 2011), and micro-level models of household capacity adaptation allowing for occupants to vary their achieved comfort by foregoing electricity when the price is too high (Guo et al. 2008). Whether such behavior is realistic in the real world has yet to be demonstrated. ABMs of the smart grid demonstrate herding behavior where many agents independently converge their loads the time intervals they expect to have lower prices, thus leading to undesirable load peaks which can cause network failure (Ramchurn et al., 2011). To prevent such herding behavior developing, simulations have shown that introducing inertia can help, for example by imposing penalties for deviation from past behavior (Voice et al., 2011) or more complex algorithms for spreading load across a number of expected future low-price time intervals (Reddy and Veloso, 2012).

The model we present in this paper builds on the work from these scientific domains, adding particularly to the theoretical grounding of the social model from psychology as a way of improving the combined socio-technical approach.

3 OBJECTIVES

Our aim is to model, in a quantitative manner, interdependent socio-technical networks and the effects that failure cascades can have. Of key importance is the link between infrastructural, (technical) networks and human behavior. In this paper we focus on the smart grid case and in future research we consider other cases and attempt to uncover generic elements one should take into account when modeling socio-technical interdependent networks and their societal impact.

These models need not be highly accurate at this stage, but they should be able to generate the types of network behaviors arising from the interdependency between the social and technical systems based on the characteristics of the different networks and on potential policy interventions.

Our research questions read:

- *How can we model cascading effects between a technical and a social network model, whereby changes and disturbances in a technical network affect human behavior and vice versa?*

- *How can we model the societal impact of these mutually interacting networks, both in hard, financial terms and in a soft, reputational sense?*

In the long term our objectives are twofold. First, to examine to what extent (re)routing / steering / consolidating human behavior is possible when a disturbance in a network occurs. Second, to examine how policy interventions can influence failure cascades between interdependent networks so as to minimize negative societal impact.

4 SOCIO-TECHNICAL SMART GRID MODEL

In this use case we model a future residential-level electricity network, including smart grid elements. A smart grid is an electricity network that intelligently reacts to the behavior of different stakeholders, such as generators, consumers and those that do both, with the aim of efficiently supplying sustainable, economic and secure electricity and coping with disruptions (Clastres 2011). An important element in achieving this is flexible pricing, triggering adaptive consumer behavior.

This use case is relevant in relation to our objectives described in Section 3, because of the strong interdependency between the technical and the human element in this socio-technical system. The behavior of consumers plays a key role in the performance of the future electricity network, since this behavior directly determines electricity demand and decentralized supply, which then affects the pressures placed on the physical electricity network.

We choose to model this human element at the individual level, rather than the aggregated level, so that we can include heterogeneous effects per household, such as the price each pays, the comfort (i.e. the fulfilled demand) and power failures each experiences, as well as the peer influence working via the social network. Therefore, the electricity network at the residential level (low voltage) is relevant to our purposes, although the results can be extrapolated to the neighborhood and regional level.

4.1 Description of Model Framework

To model the interaction between a residential-level electricity network and human behavior, we made three separate models. These models interact with each other as shown by Figure 1. The behavioral model is split up into two models:

1. *Short Term Choice Model*: This model covers the short term choices consumers make based on their electricity needs and fluctuating electricity prices. We assume a power-management application adapts demand real-time and that the consumers can choose one of three profiles: maximum comfort (electricity is used irrespective of the price), medium comfort (a price cap is selected but only for a limited time) and minimum comfort (a price cap is selected and usage is halted above that price). Besides this, consumers can choose two other one-off measures: to install a solar panel and to insulate their home. Time steps in this model are intervals of 15 minutes and the model calculates how much electricity each household demands (or supplies) per time step.

2. *Long Term behavioral Model:* This model determines the attitudes and behavioral intentions of the consumers, which in turn influence their behavioral choices in the short term model. We model five attitudes which are influenced by both that household's own experiences and by the attitudes of others in their social network.

The five attitudes are: Attitude about price paid for electricity, attitude about personal comfort (i.e. the willingness to forego electricity), attitude about personal energy efficiency, attitude about renewable energy production, and attitude about confidence in the electricity supply. These attitudes are continuous variables with value between 0 and 1. Time steps in this model are days, weeks, or months (set by an adjustable parameter) and the model calculates the five attitudes per household and what this means for their behavioral intention.

This model is based on the psychological Theory of Reasoned Action (Ajzen and Fishbein, 1980; Bagozzi, 1992; Fishbein and Ajzen, 1975) which states that behavioral intention is driven by attitude and social influence. Social influence is the person's perception that most people who are important to him think he should or should not perform the behavior in question. Later theories of social influence go beyond this normative pressure to include other forms of influence, such as imitation (Langley et al, 2012). As for the link between behavioral intention and actual behavior, in a meta-analysis of 87 studies, Sheppard, Hartwick and Warshaw (1988) report an average correlation between intention and behavior to be 0.53, which means that on average consumers' answers to questions about their intentions account for only 28 percent of the variance in their actual behavior. For low-involvement products, such as electricity, this link may be even weaker (Quester and Lim, 2003). Therefore, we introduce a probability for linking behavioral intention in the long term model to choice behavior in the short term model.

We do not include the extended Theory of Planned Behavior, which includes the role of perceived behavioral control, as the behaviors in our model are well within the behavioral control of the agents (Ajzen, 1991).

Finally we have a technical network model:

3. *Electrical Network Model:* This model computes power flows in a residential-level (low voltage) network, based on demand and supply. It also determines if and where disruptions occur in the electrical network, for example if the supply in a given part of the electricity network exceeds the demand whereby a physical cable burns through. Time steps in this model are intervals of 15 minutes.

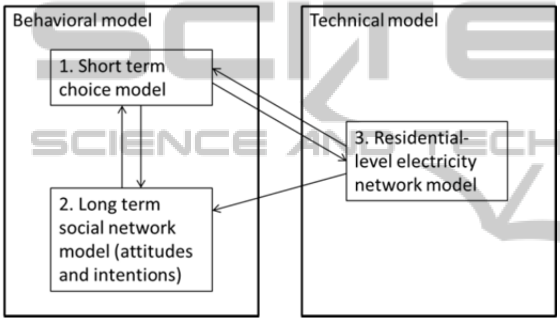

Figure 1: Graphical overview of the relationships between the three models.

These models are connected as follows: Each 15 minute interval, the short term choice model is executed, computing the demand (or supply) of each consumer, based on the price at that moment (which in turn is influenced by total demand and supply), their comfort profile, their devices needing electricity, their insulation level and the production of their solar panel, if applicable. The output is passed to the electrical network model, that determines how the demand is met and if any disruptions in the network occur. This is communicated back to the short term choice model, because disruptions affect the remaining demand of each consumer.

This process continues until one time step of the long term model has been reached. Then the long term behavioral model is executed, taking into account output from both the short term behavioral model as well as the electrical network model over the past time.

4.2 Model Specifics

Agents with their Social Network

The agents in our model are 208 households in a fictional residential area, divided into 13 streets. Each household has a number of electrical devices that require different amounts of energy and have different time windows within a day in which the demand of the device should be fulfilled.

The agents are linked with each other via a social network ('friends'), which is randomly drawn via the following principles: The number of friends of each household is Poisson distributed with mean λ, and distributed in such a way that two households in the same street ('neighbors') are n times more likely to be friends than two households in different streets. (We chose λ =8 and n=4) This social network will influence the agents' attitudes. We randomly divide the agents into three different types, which fixes initial attitudes of the agents: Comfort (willing to pay for high comfort), Budget (wants to pay as little as possible), Eco (aims towards sustainable energy).

Technical Network

The electricity model consists of a network with 14 nodes, taken from an actual low-voltage network. One of the nodes is the main generator that connects the low-voltage network to the medium-voltage network and thus supplies all demanded electricity which the households do not produce themselves via solar panels. The model computes the power flows over each link needed to fulfill the demands, based on DC power flow methods (Wood and Wollenberg, 1996). Each link is endowed with a maximum capacity which, if crossed, will cause the link to break, leading to rerouted power flows which may cause new failures in turn and possibly derive households of electricity.

The behavioral and technical models connect via the electricity demands of the agents. The demand and supply within a street (16 households per street, 13 streets in total) are aggregated and communicated as input to one of the nodes in the electrical network. In turn, failures in the electrical network influence the behavioral model, by changing attitudes due to unfulfilled electricity demands.

4.3 Implementation and Verification

The two behavioral models were implemented in Repast Simphony 2.0 Beta, a java-based toolkit for agent-based modeling and simulation (North, Tatara, Collier and Ozik 2007). For the technical electricity network model, an existing load balancing low-voltage model is used, which has been implemented in a MATLAB package called MATPOWER (Zimmerman e.a., 2011). The Java package MatlabControl enables the connection between the different models.

In order to verify if the implemented models correspond with our conceptual design and work in the desired way, we follow the verification process proposed by Rand and Rust (2011), which includes documentation, programmatic testing, and test cases. Due to space constraints we do not go into detail in this paper. One issue which we experienced in the verification process is interesting to note: that some of the proposed verification steps are difficult to carry out in the case of modeling interdependent networks. For example, one of the test case approaches these authors recommend is the use of corner cases, whereby extreme values are used as inputs and the behavior of the model is examined for unexpected output (Gilbert, 2008). However, due to the interdependencies incorporated into our model, interpreting the output of corner cases is non-trivial.

4.4 Scenario Analysis

In order to address our research questions we ran a number of scenario's whereby different conditions were assessed. We highlight a number of the most interesting results here.

<u>Crossover Effects</u>

We ran the model in a 'default' setting (Figure 2) and in a setting where network cables are more likely to fail (Figure 3), in order to investigate crossover effects from the technical model into the behavioral model.

The figures show the dynamics in the behavioral model regarding agents choices for the different power-management comfort profiles. We see a clear distinction between these two cases: in the more fragile network setting, the minimum comfort profile is less popular than in the default setting, and there is an increase in the maximum comfort profiles. A reason for this is that disruptions lead to less fulfilled electricity demands than usual, causing more people to wish higher comfort. This in turn may cause even more disruptions in the network, due to increased demand, which shows a crossover effect from the behavioral model back into the social model.

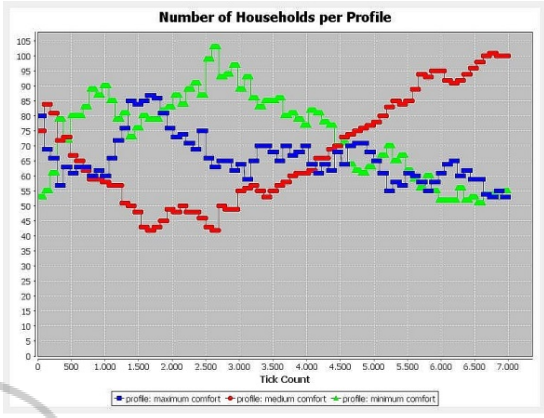

Figure 2: Comfort profiles in the default scenario.

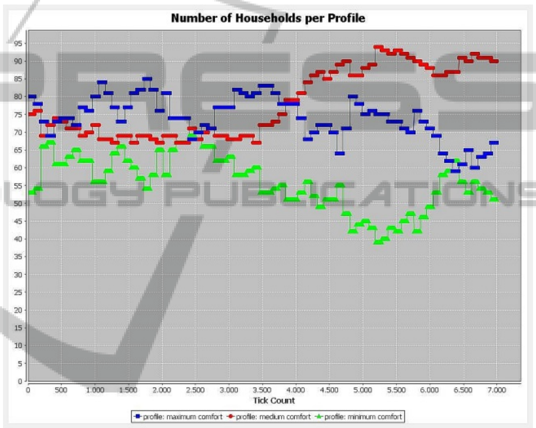

Figure 3: Comfort profiles in the scenario with a more fragile electricity network.

<u>Policy interventions</u>

We can use the smart grid model to investigate the effects of policy interventions. For instance, by increasing solar panel subsidies, assuming this influences people to buy more solar panels, we see that more people will opt to go for the medium comfort profile compared to the default scenario (see Figure 4).

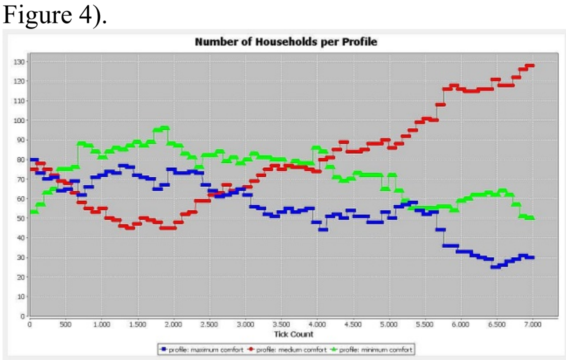

Figure 4: Comfort profiles when solar panel subsidies are high.

This happens because their energy needs are more easily fulfilled via their solar panels (so their comfort is sufficient enough), and energy prices for them will drop also due to solar panels (so the price is cheap enough).

However, there is also an unwanted effect on the electrical network: more disruptions occur in the network compared to the default scenario (where hardly any disruptions occur), throughout the timeline. This can be explained by the fact that the solar panels will create synchronized supply (on sunny periods), which may disrupt the technical network. This effect increases if the number of solar panels people buy will be increased.

<u>Societal Effects</u>

Another crucial aspect in the smart grid case is the impact that disruptions have on society, in 'hard' financial terms as well as a 'soft' reputational sense, like trust. There are several ways to look at financial impact. In (Baarsma, Berkhout and Kop, 2004) several formulas are derived for financial impact for individual households and companies based on both frequency and duration of disruptions. Both of these may differ per agent in our model, so applying the formulas give insight in e.g. the variability of financial impact in a residential area, which turns out to be quite high in a scenario with many disruptions.

Trust (in the electricity system) is more difficult to measure in real life. Surveys can help to give an estimation for trust. In our model, we use the variable attitude about confidence in the electricity supply as a measure for trust. We use this to assess the relationship between fraction of disturbances and trust levels, in particular the impact trust has on the operation of the network. The nature of the model will reflect a level of distrust in the network when there are more failures due to the behavioral aspects built into the modeling. Therefore the impact looks at the relationship between the two in terms of what happens to the fraction of disruptions as distrust increases and how do agents adapt to this.

For this analysis a conditional probability was used focusing on the probability of failure given that there is high distrust in the network, $P(F|D>0.5)$, compared to the overall probability of failure, $P(F)$. Looking at a run with many failures we found that the probability of failure is higher when there are high levels of distrust in the network, as would be expected. However, this also suggests something on the behavioral impact of these failures: When there is lower trust in the network agents are more likely to demand energy whenever they have access to it, as if there were a sense of urgency to use the energy before it goes out again as opposed to behaving in an energy efficient way to safeguard their energy levels (for instance by adapting a maximum comfort profile). The relationship between trust and behavior in this model implies a more irrational actor when trust is lost, increasing the probability of a network failure which would only perpetuate the cycle as represented in the figure below.

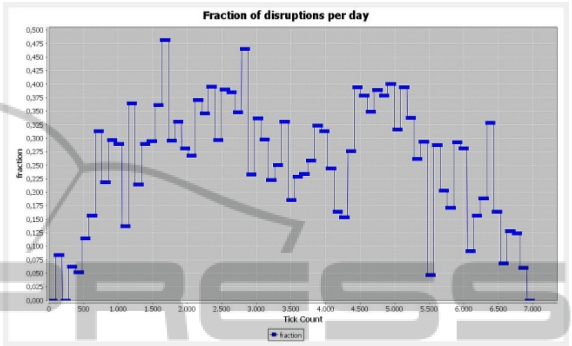

Figure 5: Fraction of disruptions per day in extreme case with many disruptions.

However, we also encounter other scenarios where a loss of trust in the network occurs at a certain point in time, but where the system was able to overcome that to provide stable energy supply. These types of scenarios are interesting to model in terms of exploring alternative scenarios to restore or redirect trust.

Overall, the societal impact of the smart grid can be modeled to show how disruptions affect agents under various scenarios, and, in turn, to see how this influences the behavior of agents. This provides a foundation for further exploration into these interactions.

5 CONCLUSIONS AND FUTURE RESEARCH

Some observations can be made in the smart grid setting:

- A consumer's individual actions, e.g. to compensate for a fragile network, may cause a worsening effect on system level, in the end causing more damage for the individual.
- Policies with good intentions (e.g. subsidizing increased solar production) may lead to unwanted effects (disruptions in the network).
- Possibly, other pricing strategies might enable policy makers to better obtain the effect they want (e.g., a stable network).

Sensitivity analysis can be applied to gain more insight in the effects of (combinations of) parameters on the outcome.

The ABM approach seems suitable to investigate interdependency between social and technical networks. It allows to observe unforeseen (possibly unwanted) effects arising from this interdependency and certain policy interventions. It also allows to investigate impact on society. The java-based toolkit Repast Simphony is flexible for this purpose, and allows for connections with other programming languages, which is useful for embedding a specific technical model into a social/behavioral ABM.

Our case highlights the need for a multi-disciplinary approach to using ABM for socio-technical networks. Each research domain has its own ontology which typically does not readily combine with that from other domains (van Dam, Nikolic, and Lukszo, 2012). For example, the concepts and entities generally included in system models of technical electricity grids are incompatible with social psychological models of human behavior. And yet we attempt to combine both ontologies in a single ABM.

An essential next step to take is validation of a socio-technical network. Because we need to make many simplifications (compared to reality) in both the social and the technical network model, the question is whether the combined model actually fits reality reasonably well. If unforeseen events arise from the socio-technical model, one would like to know if these events are plausible in reality or come from an oversimplification or wrong specification of the model. It should be stressed that our aim is not to create perfect accurate predictive models at this phase; instead we would like to use our models to generate the types of network behaviors arising from the interdependency between the social and technical systems based on the characteristics of the different networks and on potential policy interventions. In the smart grid case, the setting is futuristic, therefore we had to use fictional data and could not directly validate the complete system, though we need to take further steps in this direction.

Another relevant research direction is balancing the level of required detail or complexity in both the social and the technical network models, in order to make them fit together best.

For both themes our future research focuses on obtaining guidelines that are as generic as possible, i.e. that should be applicable also to other socio-technical networks. We aim to obtain these goals through the study of different use cases, like residential choice models and financial networks.

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