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Author(s):
Dubaniowski, Mateusz Iwo; Stojadinovic, Bozidar

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Agent-based framework for assessing systemic risk of interdependent sociotechnical and infrastructure systems

Mateusz Iwo Dubaniowski
Future Resilient Systems at Singapore-ETH Centre (SEC)
ETH Zurich
Singapore, Singapore
iwo.dubaniowski@sec.ethz.ch

Božidar Stojadinović
Future Resilient Systems at Singapore-ETH Centre (SEC) &
Dept. of Civil, Environmental and Geomatic Engineering
ETH Zurich
Zurich, Switzerland

Abstract*—Sociotechnical systems consisting of infrastructures, businesses, and households are constantly expanding and evolving due to, among others, rapidly progressing economic development, urbanization, and globalization. These complex interdependent cybernetic systems become increasingly prone to both natural and man-made disruptions. Such complex systems exhibit emergent effects in response to any disruption which propagates throughout those systems. Consequently, using traditional methods of risk assessment of individual systems is insufficient to predict the emergent systemic impacts of disruptive events of the future. Hence, there is an urgent need to develop models assessing systemic risk of such complex interdependent sociotechnical systems. The aim of the presented study was to (1) present and apply a framework for modeling interdependencies between complex sociotechnical systems at different levels of detail, with a particular focus on urban areas; (2) develop disruption generators and devise the method of assessing impact of disruptions on the systems; and (3) demonstrate how the modeling framework can be applied to assess systemic risks. Our study resulted in the development of a simulation combining socioeconomic agents' models, such as households and businesses, with physical infrastructure systems models to assess systemic risks, reliability and safety associated with interdependencies in such sociotechnical systems. The disruption cost served as a measure of performance of the system used to assess the risk. Our model was shown to capture the emergent behavior of complex sociotechnical systems in response to disruptions. Based on our analysis, the most risk was associated with low-reconfigurability infrastructure systems, particularly disruptions to the water supply system, resulted in largest impacts. We also identified areas for future research that focus on including a wider range of systems, more accurate disruption generators, and on applying the presented modeling framework to other complex networks and sociotechnical systems.

Keywords*— risk assessment, infrastructure modeling, input-output model, complex systems, urban systems, infrastructure reliability, system safety, resilience

I. Introduction

Sociotechnical systems consisting of infrastructures, businesses, and households are constantly expanding and evolving due to, among others, rapidly progressing economic development, urbanization, and globalization [1]. As urban areas are becoming more densely populated, larger in area, and more complex, these complex interdependent systems become more and more prone to disruptions due to both natural and man-made hazards [2]. Such complex systems increasingly exhibit emergent effects in response to any disruption which propagates throughout those systems. The propagation of a disruption between systems contributes heavily to its negative impact, where a relatively mild disruption in one system could result in a massive impact to other systems or to the overall urban area [3].

This poses a challenge: using traditional methods of risk assessment of individual systems, such as risk matrix and analyzing historical data, might be insufficient to anticipate the future impacts of disruptive events on interdependent complex sociotechnical systems [4]. Hence, this study addresses the need to develop models assessing risk and reliability of such complex interdependent systems, with a particular focus on urban areas.

Several models exist that address the issue of risk in various infrastructure systems, such as water supply, traffic, and power grids [5]. However, these approaches analyze individual systems and omit interdependencies between those. A system-of-systems (SoS) methodology has been used to model interdependencies among infrastructure systems by Eusgeld et al. [6]. However, the feasibility of this model was not analyzed, and the model was not applied in the context of system risk assessment. Dubaniowski and Heinimann [3][7] proposed a modeling framework for interdependencies between infrastructure systems, businesses, and households. A similar approach was attempted by Didier et al. [8], who focused on modeling demand and supply for infrastructure resources. However, these studies did not consider physical properties of infrastructure systems and were not adapted to assess systemic risk and safety in urban areas.

The aim of this study is to (1) present and apply a framework [7] for modeling interdependencies between complex sociotechnical systems at different levels of detail, with a particular focus on urban areas; (2) develop disruption generators and devise a method of assessing impact of disruptions on the systems; (3) demonstrate how the modeling framework can be applied to assess systemic risks. In particular, the novelty of this study is to introduce physical models along higher-level socioeconomic models such as multi-input-output agent-based model.

II. Model Description

A. System-of-systems (SoS)

In this study, we developed and present a model of interdependencies between infrastructure systems,

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businesses, and households to assess systemic risk in urban areas. The model consists of several components (also called federates) that operate as a system-of-systems. The SoS approach allows us for easy differentiation in granularity of the model in terms of both level of detail of the model, its duality with the real-world, as well as spatial granularity. The overall conceptual framework of the model and its components is presented on Figure 1.

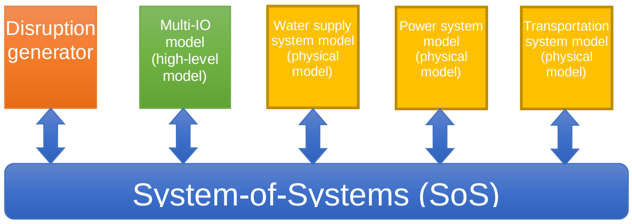

Fig. 1. System-of-systems (SoS) approach to modeling systemic risk of infrastructure systems, businesses, and households. It consists of a high-level multi-IO model, physical models of infrastructure systems, and a disruption generator for introducing disruptions into the SoS simulation.

From Figure 1, we can see that our conceptualization of the system consists of several models, which are integrated together in the system-of-systems (SoS) model of infrastructure systems. SoS approach allows for exchange of important information between constituent simulation models, however, at the same time it keeps each model autonomous in performing detailed simulations of their respective system. To assess systemic risk, we focus on interdependencies between infrastructure systems, households, and businesses. Our SoS model consists of physical models of infrastructure systems. We focus on water, transportation, and power. These three models (yellow boxes on Figure 1) are supplemented by a high-level overarching model, which enables us to easily define interactions between businesses, households, and infrastructure systems, and thus is responsible for capturing interdependencies. We use an agent-based multi-IO model as this high-level model in this study. However, the multi-IO model can be replaced with alternative high-level models, such as e.g. Re-CoDeS [8], representing interactions between infrastructures and socioeconomic agents. We decided to use the multi-IO model as the high-level model because it allows for capture of interactions of infrastructure systems with socioeconomic agents. A particularly useful characteristic of the multi-IO model is that infrastructure systems are represented within the model directly at a higher, more abstract level. In turn, this allows us to abstract away physical properties of the systems and model these in a detailed, specific, purpose-built, low-level model. In the multi-IO model, only the infrastructure system's input-output capabilities with regards to other socioeconomic agents are preserved.

Finally, the above components, i.e. physical models and multi-IO model are supplemented with a disruption generator, which introduces disruptions into the systems. A disruption can affect one system or a combination of systems directly. The generator can be based on predefined scenarios, or it can be a stochastic generator, or a combination of both depending on the needs of the simulation. The generated disruptions can be applied to various points of the model. They can affect the overarching high-level multi-IO model, or individual physical simulations of infrastructures. The details of a particular disruption generator used in each experiment need to be defined by considering the level of detail that the disruption should represent, the overall affected area, whether it affects just one infrastructure system or a set of such systems, and what is the objective of the simulation.

B. *Multi-IO Model*

The multi-IO model represents socioeconomic units, such as businesses and households, as agents, which use an input-output model to represent production and consumption capability of a business or a household. These agents form nodes of a network, in which edges represent infrastructure system links between the agents i.e. resource transfer links between socioeconomic units. Hence, in a multi-IO model we have several input-output models each corresponding to a different socioeconomic unit. The multi-IO model consists of three elements: (1) a set of networks, where each network consists of (a) nodes corresponding to socioeconomic units – agents, and (b) edges corresponding to resource transfer links; (2) agents representing socioeconomic units that perform production following the IO model; and (3) self-organizing mechanism based on cost of resources. [7]. The multi-IO model, which we use and expand upon in this study was developed by Dubaniowski and Heinimann. A detailed description of the model for reference can be found in their works [7][3].

C. *Physical Models*

To complement high-level multi-IO model, physical level models of infrastructure systems are integrated within the SoS model. These allow for a better representation of physical properties of individual infrastructure systems. Such composition allows for a good duality with a real-world on individual system model level, while at the same time allowing for convenient modeling of businesses and households and their responses to various disruptions on a higher level.

Physical systems can be included for all infrastructures considered in the simulated urban area. These models can include state-of-the-art models of infrastructure systems, which are currently available, or these can be custom built models developed with unique internal knowledge about the system in question available only to the system operators. The main challenge remaining then is to derive transfer functions between input and output parameters of the multi-IO model and of physical models of individual infrastructure systems so that the relevance and accuracy of the simulation is preserved at both more abstract, high-level, and at the more detailed, low, physical level.

In our study, we limited this inclusion of physical models for simplicity, and so we included two physical system models, which allowed us to improve the representation of the system in the multi-IO model component. Thus, we include the transportation system and water supply system as two physical components of the SoS model. Hence, we use transportation system component to obtain more detailed, physical-level simulation of routing the resources around the transportation networks. The routing derived from the physical transportation system model is then applied to multi-IO model, and the cost associated with the routing configuration can be calculated for all the resources. Similarly, we use water supply system model to obtain physical parameters of water transportation, which then are transferred to cost parameters in the multi-IO model.

The model of transportation system that we used in this study as a physical transportation system model is a User Equilibrium Model described by Sheffi [9] and developed by Zheng Li [10]. The model of water supply system that we used in this study as a physical water supply system model is the Water Network Tool for Resilience (WNTR) model described by Klise et al. [11]. We have used these model implementations as our physical system model components of the SoS model.

D. Model Integration

Having included a simulation of both physical models and a high-level multi-IO model, the crucial aspect is integration of these models at different levels of abstraction. In particular, the output parameters from the physical model need to be transferred to the multi-IO model so that the output parameters of the physical model can be included as input parameters of the multi-IO model. The main output of the physical model is the time for transportation between two nodes of the transportation network and water leak for water supply system. On the other hand, the main input parameter of the multi-IO model would be the cost of transportation of a resource between two nodes. Similarly, the main input parameter to the transportation system and water supply models is the quantity of resources needed to be transferred and the origin and delivery point of resources. This is the data that needs to be exchanged between multi-IO model and physical-level models. The location and quantity of resources is natural and the same both for physical and multi-IO models. However, to convert time and water leaks into monetary cost value, we need to use a conversion factor, where we need to assign a monetary value to a unit of time for transportation and unit of water leak for water supply system. This value differs depending on what is the transported resource. The data exchange between multi-IO model and physical transportation model is presented in Table 1.

TABLE I. PARAMETERS REQUIRED TO MODEL INFRASTRUCTURE NETWORKS IN MULTI-IO MODEL AND IN PHYSICAL MODELS. WE CAN SEE CORRESPONDENCE BETWEEN INPUT TO PHYSICAL MODELS AND OUTPUT OF MULTI-IO MODEL. WE ALSO SEE THE NEED FOR TRANSFER FUNCTION BETWEEN INPUT TO MULTI-IO MODEL (COST) AND OUTPUT OF PHYSICAL MODEL (TIME).

	Transportation model	**Water supply model**	**Multi-IO model**
Input parameter	Origin and destination	Origin and destination	Cost
Output parameter	Time	Water leak quantity	Origin and destination

E. Risk Assessment

To perform systemic risk assessment using the described model, we follow the Monte Carlo approach [12], where simulations are repeated multiple times to estimate the result. We devise a stochastic disruption generator, which follows certain prescribed rules to induce disruptions to components. This approach allows us to derive a distribution of disruption impacts. The process for risk assessment is described below:

1. We devise a disruption generator, which induces a disruption in a single infrastructure system, at random points throughout this system.
2. We execute the simulation with the disruption generator applied and collect the data on the impact of each induced disruption. To simplify this process, we assume that probabilities of disruptions to different points within this infrastructure system are uniformly distributed, which is normally not the case as different components of a single system have different failure probabilities.
3. We repeat Step 2 n times until convergence, e.g. ($n \geq 100$).
4. After collecting the results from Step 3 we obtain a distribution of impacts on the modeled area of a disruption to the single infrastructure system.

The above method allows us to assess risk of the system by estimating the value at risk of the simulated area where we can postulate with a certain confidence what is the largest possible impact of a disruption to the single infrastructure system on the modeled area. Furthermore, we can focus on detecting components of individual infrastructure system whose failures are responsible for substantially large impacts on the modeled area. Such information can be used to prioritize mitigation of disruptions based for example on a risk matrix approach.

III. SIMULATION EXPERIMENT

A. Experiment Design

In this study, we applied the model described in the previous section to a physical area. We focused on multi-IO model as the high-level model for interdependencies between infrastructure systems, businesses, and households. Moreover, we included a physical, low-level model of a transportation system and water supply system. In the study, we consider 5 different types of resources: water, power, business goods, consumer goods and human capital. We assumed that transportation system is based on roads, and these are shared between business goods, consumer goods, and human capital. The model was applied to region of Clementi neighborhood in Singapore and networks were devised based on expert knowledge about the systems in the area and publicly available data about the network of roads and map of the area obtained from OpenStreetMap [13].

The simulation experiment SoS consisted of a multi-IO model; a water supply model; a transportation model covering the transport of 3 resources: business goods, consumer goods, and human capital; and a disruption generator. For the experiment, the disruption generator used was a stochastic disruption generator introducing disruptions randomly to one of the edges of the infrastructure system network. The distribution of disruptions across the edges for each individual infrastructure system was uniform. Thus, it was equally likely that any edge in the infrastructure system would fail. An introduction of a disruption to the edge resulted in a full removal of the edge from the network, thus no resources could be transferred over the disrupted edge.

For each infrastructure system, we executed the simulation for 100 iterations in line with the risk assessment procedure described in the previous section. We executed the simulation for each of the 5 infrastructure systems. Such approach allowed us to compare disruptions to individual systems to see disruptions which have the most negative impact on the system. Such analysis could aid in decision making regarding mitigation measures, as well as in analysis of the systems to identify their most vulnerable components and what interdependencies vbetween the systems contribute to the cascading effects of disruptions the most.

B. *Disruption Metric*

The metric we used to measure impact of disruption on the SoS model is the disruption cost. To find the disruption cost, we find the base cost of satisfying the system in an area without any disruptions, and subsequently, we introduce disruptions following the disruption generator mechanism. After each disruption is introduced, we evaluate the total cost of satisfying the system. The disruption cost is the difference between the cost of satisfying the system with disruption present and the cost of satisfying the system without any disruption present. We collect these values across 100 iterations for each resource.

To assess systemic risk, we can compare profiles of distributions of disruption costs originating in various infrastructure systems. This allows us to see, which system, when disrupted, has the most serious impact on the overall urban area. Similarly, we can assess systemic risk then by looking at 95% or 99% percentile of such distribution of costs, as this might help us to estimate the value at risk (VaR) of the urban area. The comparison of VaR values allows us to notice what is the systemic risk in the area associated with disruptions to each individual infrastructure system. This is a direct measure of systemic risk present in the urban area in question under given simulation parameters. This can be used as a measure of reliability and safety of the urban systems in the area.

C. *Experiment Results*

We have introduced disruptions to 3 infrastructure systems covering 5 types of resources. We present the results for each resource, treating each resource as a separate infrastructure system for the purpose of this study. For each of these infrastructure systems, we run 100 iterations of random disruptions applied to assess systemic risk of the overall SoS model representing the modeled urban area. Depending on the infrastructure system, these resulted in some cases in total collapse of the system if a critical link of the system was targeted by the generated disruption. By collapse here we mean a situation where system could not self-organize to adapt to a disruption to still satisfy the system even at a higher cost. In other words, the system and normal demand could not be satisfied at any cost after such collapse-inducing disruption was introduced.

In our experiment, the above situation happened only to water supply network and power grids, which are less reconfigurable than transportation networks. This is in line with what we had expected from a less reconfigurable system such as water or power supply as compared with road network.

To assess disruptions impacts, we analyze the distribution of disruption costs to the overall system. This is presented on Figure 5, where we can see a percentile graph of disruption costs for disruptions originating in different infrastructure systems. Here transportation system is divided into 3 categories of transported goods: consumer, business, and human capital.

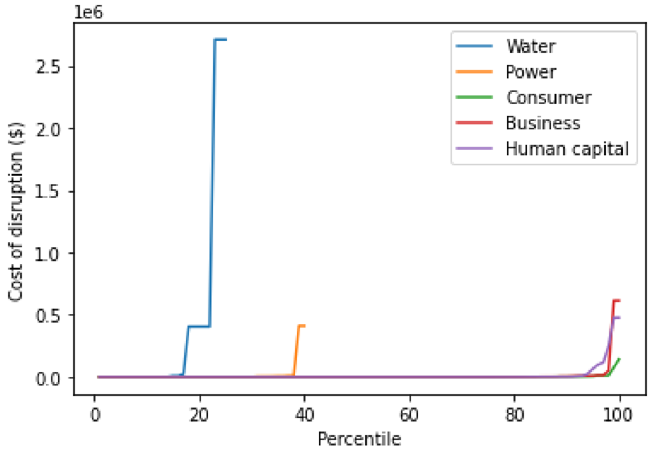

Fig. 2. Percentile graph of disruption costs by originating infrastructure system. The lines cut off for water and power systems, where disruptions start causing collapse of the overall SoS system i.e. the cost reaches infinity from that point as the system cannot be satisfied at any cost. For transportation larger impact begins only from 90th percentile.

From Figure 5, we can see that the disruption to water supply system results in the most impactful disruptions. The lines for power and water systems cut off where the cost reaches infinity, this is when the collapse happens and the overall system cannot be satisfied anymore. From the diagram, we can see that the water supply is the most impactful if disrupted. This is closely followed by the power system, which also causes costly disruptions and results in a collapse of the overall system quickly. This is because power grid and water supply networks have low reconfigurability and cannot be adjusted easily in response to disruptions. On the other hand, the transportation system is highly reconfigurable, and can respond to any disruptions by rerouting goods that are transported over the transportation system. There are many redundancies and opportunities for reconfigurability. As a result, the transportation system never collapses, and results in lower costs of its disruptions, when only one link is disrupted. Similarly, we can see that business and human capital transportation causes more impact than disruptions to consumer goods transportation. This is in line with our expectations, as consumer goods are not as critical compared to business goods and human capital in production processes. Furthermore, the demand for consumer goods is more limited and more disbursed around the area, so a single impact to the network is not as impactful as it is the case with business goods or human capital transportation.

Another interesting point stemming from the analysis of the graph is that the distribution of disruptions seems to follow power law, where most disruptions do not result in a very large impact or do not have impact at all, while very limited number of infrequent disruptions results in massive impacts. This is especially true for the transportation system in our study, where the lines grow sharply beyond the 95th percentile. The probability distribution of costs of the impacts of disruption might have a separate distribution for its tail, where infrequent events result in large impacts.

IV. CONCLUSIONS

The modeling framework was extended to include components with various level of detail and adapted to an urban area. A method for risk assessment was described, presented, and applied. We have applied a high-level multi-IO model together with a low-level physical level models of transportation system and water supply system to an urban area and considered flow of 5 resources throughout the area: water, power, consumer goods, business goods, and human capital. This is novel in this study. A Monte Carlo simulation approach was described and performed to assess systemic risk assessing reliability and safety of the urban system due to interdependencies between infrastructure systems, households, and businesses.

The study resulted in the following findings:

- Low reconfigurability infrastructure systems, such as water or power supply, exhibit greater risk than higher reconfigurability systems, such as transportation system.
- Water and power systems can instigate critical disruptions that cause collapse of the urban system, where the system cannot be satisfied at any cost.
- Transportation system can self-adjust well to maintain level of performance required. Disruptions to transportation system never caused the urban system collapse under our experiment for all types of transportation resources: consumer goods, business goods, and human capital.
- Disruption impact distributions follow power law, where the small amount on infrequent disruptions results in a disproportionately large cost of these disruptions.

The findings are consistent with our expectations and previous studies, where disruptions to lower reconfigurability systems exhibit larger impacts due to more difficulties with recovering and readjusting these systems [14]. Similarly, the power law features of disruption impacts are consistent with literature on the distribution of disruption impacts on infrastructure systems [15]. The method allows to estimate VaR of the urban area in terms of infrastructure systems in general, as well as with regards to disruptions originating in each individual system and propagating to other systems. The model allows to assess reliability and safety of the systems in urban areas.

Future work on this topic can involve conducting the study for a more diverse range of areas, resources, and with more low-level infrastructure system models. Disruptions originating in several systems at the same time can be attempted, which was outside of the scope of this study. Integrating the presented model with financial and economic models to represent the costs of production more accurately, as well as with AI approaches, which could be used to better characterize constituent systems of the SoS model and disruptions can be attempted.

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