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MODELING THE BEHAVIOR OF INTERDEPENDENT INFRASTRUCTURE, BUSINESS UNIT AND HOUSEHOLD SYSTEMS UNDER MULTIPLE DISRUPTIONS

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ABSTRACT

Urban systems are growing into a fabric of interdependent systems-of-systems that are increasingly demonstrating the behavior of complex systems, particularly emergence and regime shifts. System-of-systems perspectives pose a new challenge, raising the question how the high degree of within and between system interdependencies affects their behavior under a broad range of disruptions. Though many models are "single system models," "system of system models" demands for a new modeling approach that represents the interaction of systems with different purposes, lifecycles and governance structures. The present study takes up this challenge and aims to develop a proof-of-concept of a distributed simulation model, representing sets of business/household units, the metabolism of which is linked to a set of infrastructure systems, which together are exposed to a broad range of disruptions.

In particular, this study aimed: (1) to develop an agent representing the metabolism of a socioeconomic unit such as a household or a business; (2) to develop a network model of infrastructure lifeline systems and socioeconomic entities, the interdependencies of which are represented by the flows of goods and services, which are facing a broad range of disruptions; (3) to investigate how synchronization of constituent systems of a system-of-systems model should be designed to ensure proper mapping of disruptions between systems; (4) to explore the application of the system-of-systems model of infrastructures, businesses, and households in a real-world use case.

The study resulted in three major findings. First, it developed and verified a proof-of-concept of a distributed simulation model, representing the metabolism of business/household units, important lifeline infrastructure systems, and disruptions that are interacting in an adaptive way. The price mechanism represented the self-adaptive capability of the overall system, where price increases signaled increasing disruption magnitudes. Simulation experiments yielded that disruptions of the water and power network have significantly higher impact than those of the transportation network wherein flows can be reconfigured. They additionally demonstrated that the concurrent disruption of the water and the power network has the highest impact on the system-of-systems, and that the impacts to the systems exhibit emergent behavior.

Second, simulation experiments explored how different time granularities of interacting systems affect the simulation model. The simulation experiments demonstrated that the time granularity of a specific system has to be finer than the expected length of an average resilience cycle. The experiments additionally suggested that if the time granularity is too coarse, then the model does not yield propagation effects appropriately. A recommendation for the time granularity of a system-of-systems simulation of infrastructures is to select time granularity similar in magnitude to the smallest expected recovery time from a major disruption of the constituent systems.

Third, the system-of-systems simulation model was applied to a real-world use case, the Clementi area of Singapore. Because the availability of infrastructure systems data was limited, Moore neighborhood was used to represent the lifeline system based on expert judgment. Simulation experiments demonstrated that disruptions of utility provider systems and networks such as power grid and water supply are costlier than those of transportation systems or other businesses. Furthermore, the model identified geographical areas, which are especially affected by disruptions being introduced into the system, and quantified the impact in areas of Moore neighborhood.

Finally, this study identified several open questions that should be addressed in future research. These include: (1) the study of another area with different infrastructure topologies; (2) the analysis of alternative resource allocation systems; (3) the development and verification of sophisticated disruption generators that allow generation of a wider range of unexpected disruption patterns; (4) the development of novel, clear and comprehensive methods for presentation of simulation results.

ZUSAMMENFASSUNG

Die fortschreitende Urbanisierung führt dazu, dass sich urbane Systeme in Richtung von gekoppelten Supersystemen (Systems of Systems) entwickeln, welche Eigenschaften komplexer Systeme aufweisen, beispielsweise Emergenz oder Regimewechsel. Die Supersystem-Perspektive ergibt neue Herausforderungen, beispielsweise die Frage, inwiefern gegenseitige Abhängigkeiten innerhalb von und zwischen Systemen das Gesamtverhalten unter internen und externen Störeinflüssen prägt. Es ist ein beträchtliches Wissen vorhanden, um Modelle zu entwickeln, die das Verhalten von Einzelsystemen abbilden. Hingegen ist das Wissen noch immer lückenhaft, welches zielführende Ansätze sind, um das Verhalten von Supersystem-Modellen abzubilden, deren Teilsysteme unterschiedliche Zwecke, Lebenszyklen und Kavernen-Strukturen haben. Die vorliegende Studie greift diese Herausforderung auf und verfolgte das Ziel, ein Proof-of-Concept eines verteilten Simulationsmodells zu entwickeln, das eine Menge von Geschäfts- und Haushaltseinheiten abbildet, die mit ihrem Metabolismus (Energie-, Güter-und Dienstleistungsflüsse) mit verschiedenen Infrastruktursystemen gekoppelt und einer ganzen Palette von Störungen ausgesetzt sind.

Die Studie verfolgte folgende Detailziele: (1) einen Software-Agenten zu entwickeln, der den Metabolismus von sozioökonomischen Einheiten (Haushalte, Firmen) repräsentiert; (2) ein verteiltes Netzwerkmodell zu entwickeln, das die gegenseitigen Abhängigkeiten zwischen Infrastrukturnetzwerken, sozioökonomischen Handlungseinheiten und exogenen Störungen abbildet; (3) zu untersuchen, wie die Synchronisation von Teilsystemen zu gestalten ist, damit das Supersystem-Modell die Ausbreitung und Kaskadierung von Störungen genügend genau wiedergibt; (4) das verteilte Supersystem-Simulationsmodell auf einen realen Fall anzuwenden, um sein Verhalten zu verifizieren.

Die Untersuchung resultiert in drei Hauptergebnissen. Erstens entstand ein verteiltes Supersystem-Simulationsmodell, dass die gegenseitigen Abhängigkeiten zwischen Handlungseinheiten, Infrastruktursystemen und Störungsregimes zielgerichtet abbildet. Das verteilte Simulationssystem hat selbst-adaptive Eigenschaften, die mit einem Preismechanismus abgebildet wurden, und die Preisanstiege für die Dienstleistungen ergeben, wenn das System Störungen ausgesetzt ist. Es zeigte sich auch, dass die Störung von Wasser- um Stromnetzwerken einen wesentlich grösseren Effekt

haben als die Störung von Transportsystemen, bei denen sich die Transportflüsse relativ einfach rekonstruieren lassen. Zudem ergab das Modell, dass die gleichzeitige Störung der Wasser- und Energieinfrastruktursysteme den stärksten Einfluss auf das Verhalten des Supersystems hat und dass sich bei massiven Störungen auch emergentes Verhalten beobachten lässt.

Zweitens ergaben Simulationsexperimente, wie verschiedene Zeitgranularitäten von Teilsystemen das Verhalten des Supersystem-Modells beeinflussen. Die Zeitgranularität eines Teilsystems muss bedeutend feiner sein als die erwartete Länge eines Störungszyklus. Falls die Granularität zu grob ist, so bildet das Supermodell die Ausbreitung und Kaskadierung nicht oder nur ungenügend ab. Als Faustregel ergab sich, dass die Granularität etwa gleich gross sein soll, wie die kleinste erwartete Erholungszeit nach einer massiven Störung.

Drittens ergab die Anwendung des Supersystemmodells auf das Clementi-Gebiet Singapurs, dass das Gesamtsystem gegen massive Störungen von Versorgung-Dienstleistern und Elektrizität- und Wassernetzwerken empfindlicher ist als gegen Störungen von Transportsystemen. Zudem erlaubte die räumlich explizite Modellierung, Gebiete zu identifizieren, die von Störungen besonders stark betroffen sind. Da die Verfügbarkeit von Daten limitiert war, wurden die Netzwerke mit einer vereinfachten Moore-Nachbarschaft abgebildet und die wesentlichen Eigenschaften durch Expertenurteile eingeschätzt.

Die Arbeit resultierte auch in offenen Fragen, die im Rahmen zukünftiger Forschung aufgegriffen werden sollten. Dazu gehören insbesondere: (1) die Untersuchung eines weiteren Bereichs von Infrastruktur-Topologien; (2) die Analyse alternativer Systeme für die Ressourcenallokation; (3) die Entwicklung und Verifizierung verfeinerter Störung-Generatoren, die es ermöglichen eine breite Palette auch unerwarteter Störungsmuster zu generieren; (4) Entwicklung von Methoden, um die Simulationsergebnisse verständlich und nachvollziehbar zu präsentieren.

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CONTENTS

ABBREVIATIONS

FREQUENTLY USED SYMBOLS

ABM	agent-based modeling
CapG	capital goods
CG&S	consumer goods and services
DDS	Data-Distribution Service
DIS	Distributed Interactive Simulation
DS	disruption size
FOM	Federation Object Model
HDB	Housing and Development Board
HLA	High-Level Architecture
MoP	measure of performance
OMT	Object Model Template
RT	recovery time
RTI	Real-Time Infrastructure
SOM	Simulation Object Model
SoS	system-of-systems
TG	time granularity
VaR	value at risk

1

INTRODUCTION

Nothing in life is to be feared, it is only to be understood. Now is the time to understand more, so that we may fear less.

— Marie Skłodowska Curie

Cities and urban areas are continuously growing at an unprecedented rate as a result of advancing urbanization processes. Populations tend to gravitate to cities as worldwide economic patterns are changing. The emergence of advanced technologies and conveniences available in urban areas are resulting in the continuing rapid growth of cities, which tend to concentrate human activity. These urbanization processes are only going to increase in scale in the future as more and more dependence on urban ecosystems will emerge. UN estimates that the number of *megacities*, that is cities with populations above 10 million will increase by 32% over the next 14 years [1] .

As cities grow, urban systems consisting of infrastructures, households, and businesses are similarly growing and evolving. The growth of urban systems results in several phenomena [2]. First, the value at risk exposed is increasing due to denser accumulation of assets within cities. This is because disasters of similar magnitudes affect more densely populated areas, and so more people, infrastructures, goods, and services. Singapore is affected by this especially, having one of the highest population densities in the world. Second, urban metabolism and the flow and exchange of goods and services between households and businesses in cities continue to increase significantly. This high urban metabolism needs to be supported by infrastructures that are able to facilitate the complex flows of people and resources within cities. Third, modern cities become increasingly futuristic cybernetic organisms [3], and represent a combination of interdependent and highly advanced infrastructure systems, technological solutions, and social systems. Such cities become more dependent on technology and critical infrastructures to even perform their most basic functions.

An increasing flow of goods, services, information, people, and other resources between socioeconomic units in urban organisms, consisting of intertwined infrastructure and social and economic systems, results in these organisms becoming more complex and interdependent within themselves and with the outside world. This development has brought on several issues. First, the increasing complexity of urban organisms results in an increasing impact of disruptions, as the at-risk values of these urban areas increase. Second, interdependencies between different elements of urban systems mean that propagation of disruptions throughout these constantly expanding systems is likely to happen, and thus the effect of even a small event might be amplified to unpredictably huge proportions due to emergent disruptions and unprecedented failures. Third, climate change is contributing to changes and regime shifts in environmental conditions that underpin the design of many of the current interdependent systems serving urban areas.

Interdependencies are the central concept to understanding how modern infrastructure and sociotechnical systems work [4]. Nowadays, almost all businesses, in order to provide goods or services, require the use of technology. To be able to use technology they are dependent on infrastructure services such as electricity, telecommunication, and transportation. Similarly, all infrastructures need countless other infrastructure services to operate adequately. The importance of their interdependencies and identification is the subject of many major ongoing studies [5]. Also, interdependencies provide links between individual infrastructure systems that show how these systems influence each other. Moreover, these links illustrate how disruptions can propagate between the systems, causing cascading failures, and also how increasing interdependence of systems increases the impact and occurrence of disruptions.

Development aims usually focus on positive outcomes from achieving these aims, resulting in a very limited analysis of the negative and unexpected outcomes of these developments. Expanding cities mean more disruptions and more interdependencies between systems, which in turn mean a larger impact of potential disruptions on the cities. Risk management has been traditionally used since the 1950s to mitigate losses due to potential disruption events. Risk management, however, assumes independent disruption scenarios, thus omitting the effects of interdependencies between systems, which are nowadays increasingly present in high-density urban areas. In a highly interdependent system, a single event can have major implications for various assets that are not necessarily directly impacted by the event. Similarly, events that seem spread out can have a huge impact on a single, specific system. Traditional risk management approaches have been shown to be costly and ineffective for such cascaded, outlier, and large-scale events [6][7]. This is because historical data cannot be used to represent cascaded events that result in emergent impacts. There is a systemic change in analyzing disruption impacts, where the impacts of adverse events can no longer be described with just probability distributions anymore. As a result, the concept of resilience and integrated risk management as more comprehensive and flexible approaches to tackling the issue of assessing and preparing for responding to and recovery from disruptions was proposed.

Resilience, as a concept, originated from materials engineering, subsequently spreading in the 1970s into psychology and ecology. According to Heinimann and Hatfield, the notion of resilience that "stems from system's resistance, and mimics postevent recovery functions of natural systems" consists of resistance to and recovery from disruptive events [2]. Resilience and its importance to various fields have been highlighted by policymakers, researchers, and practitioners, especially in recent years [8]. According to Jackson [9], resilience is defined as "the ability of organizational, hardware, and software systems to mitigate the severity and likelihood of failures or losses, to adapt to changing conditions, and to respond appropriately after the fact." In a similar fashion, Cutter et al. [10] defined resilience as "the ability to prepare and plan for, absorb, recover from, and more successfully adapt to actual or potential adverse events." Both definitions focus on system resistance and system resilience; system resistance is the ability to absorb shocks and withstand any disturbances occurring to the system, while system resilience is the ability to recover from those quickly and learn from these shocks for the future. Resistance comes from the traditional engineering approach to ensuring that systems can survive extreme conditions. Resilience itself comes from the Latin word, *resilire*, which means to spring or rebound. A good example of system resilience is the immune system's ability to learn and adapt to diseases, thus increasing the immunity of the organism to future diseases. From a biophysical standpoint, the system needs to avoid destruction by preserving the most critical functions in times of crisis, and only when the critical danger to the system's survival disappears rebuilding, recovering, and adapting the non-essential functions. Taking the above into account in the context of this study, resilience is understood as "the capability of a sociotechnical system to maintain and reconfigure its essential functions, structures, and feedback loops in the face of acute shocks and chronic strains. This capability consists of biophysical and cognitive functionalities. The biophysical functions include (1) resistance within the acceptable limits of degradation,

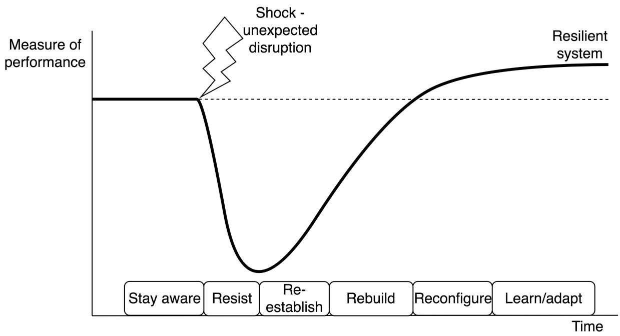


FIGURE 1.1: Resilience cycle. Resilient system recovers from an unexpected, large shock–disruption–and adapts to the shock reoccurring in the future through learning from the disruption. The stages of the resilience cycle include: preparedness - awareness, resistance to disruption, re-establishment of basic functions, reconfiguration to adapt, and learning from the adverse event to improve the system's original performance.

(2) restabilization of critical functions, (3) rebuilding of degraded functions, and (4) reconfiguration of substance, energy, and service flows. The cognitive functions include (1) staying aware, (2) sense-making, (3) response, and (4) updating and adaptation."

A resilience cycle curve is shown in fig. 1.1. It describes the system's ability to prepare for, react to, and mitigate any disruption that is applied to the system, following the disruption to rebuild and adapt in the future.

Resilient systems are needed to survive disruptions that might have significantly larger and more emergent impacts than ever before. As cities grow and are exposed to a wider range of unexpected shocks and disruptions, they must be prepared for these shocks and disruptions [11]. This refers not only to shocks, which can be easily predicted or estimated, where risk management approach could be often sufficient but also to unpredictable disruptions, which cannot be easily foreseen when developing and designing a system. Resilient systems are able to recover or limit their exposure even to unpredictable outlier events that have not occurred in the past. Designing resilient systems is crucial to the future of cities and urbanization because it ensures that cities function properly despite the increasing number of impactful disruptions. To be able to design and develop cities that are resilient, simulations and models of urban systems and their resilience are used.

Assessing resilience of urban systems through modeling and simulation is critical to improving these systems' response to and recovery from disruptions. Hence, there is a need for robust models of resilience of urban systems. To achieve this, it is especially crucial to understand and model the impact of interdependencies between infrastructure systems, businesses, and households on the resilience of these urban systems. This is because interdependencies between systems contribute to propagation and cascading effects of disruptions, and the impact of them on disruptions is understudied. The model of interdependencies could aid in designing more resilient cities. Furthermore, it could be used to better assess the resilience of existing cities in order to better estimate the value-at-risk of these cities, hence allowing to make better-informed decisions about asset management, city development, and urban planning. Similarly, there is little information on how the composition of households and businesses affects resilience, and modeling this relationship would help to make cities more resilient. Currently, there exist some attempts to tackle the problem of modeling resilience of urban areas; however, they are often limited to describing general frameworks. Consequently, we focus not only on developing a framework but also on developing an agnostic workflow for the application of a framework for modeling resilience of urban areas to allow resilience analysis in any geographical area desired.

There exist models to simulate individual infrastructure systems and groups of these combined together in order to model the response of infrastructures to disruptions. These models, however, fail to incorporate models of businesses and households, as well as interactions with other entities. Similarly, input–output models of geographies and urban areas have been developed. These models analyze inputs to infrastructures and their outputs and aim to recognize interdependencies based on analysis of those. However, such analysis is not dynamic and does not allow for further spatial and socioeconomic factor differentiation, especially under shocks and disruptions. Lastly, there exist distributed modeling approaches that allow combining several infrastructure systems into one simulation. However, there is a lack of analysis on how to perform synchronization of such models so that appropriate data is exchanged within them with an appropriate time granularity.

To tackle the above challenges, our aim was to develop a framework for modeling interdependencies of infrastructure systems, households, and businesses, and their impact on disruptions. First, we aimed to develop an agent representing the metabolism of a socioeconomic unit, such as a business or a household, interacting with infrastructure systems within an urban area. Second, our aim was to develop a model of interdependencies between infrastructure systems, households, and businesses that would allow for the introduction of disruptions to the system, and for dynamic analysis of interdependencies with differentiation for spatial and socioeconomic factors. Third, our aim was to understand how synchronization of such models should be performed in order to better describe disruptions and their propagation. Finally, our aim was to synthesize the ideas presented above in a novel way to develop and apply a comprehensive system-of-systems model of interdependencies between various infrastructure systems, businesses, and households.

2

RESEARCH STREAMS OF MODELING LARGE-SCALE SYSTEMS

It is not enough to be in the right place at the right time. You should also have an open mind at the right time.

— Paul Erdős

In this chapter, we provide a review of founding concepts that form the basis of our work, including key streams of research that we utilized in developing our modeling frameworks. These streams describe different modeling concepts and approaches that are adapted and expanded by us to enable modeling interdependencies of large-scale complex infrastructure systems and their impact on resilience.

2.1 INPUT-OUTPUT MODELING

Input–output modeling is a method of applying an input–output analysis to a certain economic region or unit in order to model their production patterns. Input–output analysis is a framework described by Leontief in the first half of the 20$^{\text{th}}$ century [12][13]. The development of the input–output analysis, also called *interindustry analysis* or simply *Leontief model*, earned its inventor a Nobel Prize in Economics in 1973. One of the main modern works, reviewing input–output analysis advancements and developments since the model's inception, is a book by Miller and Blair [14], which was of immense help in conducting this study. In their book, the model is described, and a wide range of extensions to the model is outlined.

The aim of the input–output analysis is to analyze interdependencies between industries in an economy. The concepts described initially by Leontief are currently utilized in many different types of economic analysis, and it is considered one of the most common modeling methods in economics [15]. Moreover, the model has been applied in various different settings in countries all over the world with different political and economic systems, including the USA, USSR, China, Italy, and the UK. The model is used by the US's Department of Commerce to model economic activity within the US. Similarly, the UN has developed a standard framework of national accounts for developing nations to enable them to use the input–output model for their internal planning [14].

The basic input–output model analysis consists of a set of linear equations described in a matrix notation to form matrix and vectors. These equations describe the distribution of resources throughout the economy. The economy can be understood at different granularities, including micro-level such as individual small companies or households, larger regions or corporations, or even at the regional, national, and international level. Most of the extensions of the original model consider and attempt to apply the model to different spatial and time granularities. Other extensions adapt the model to other fields such as environment or energy consumption. To apply the input–output model, detailed data about the modeled entities is essential. Another set of extensions to the Leontief model address the challenge of accessing or substituting for a lack of such data.

The framework of an input–output model is to use available data for a specific region to create the model. The model is especially suitable to describe industries or economic units that both produce goods and services (resources), as well as consume these from other industries. Such industries take inputs from other units and produce outputs that other industries can use. The number of resources modeled might vary from few to hundreds, and, similarly, the granularity of them might vary. For instance, we can use "consumer goods," or these can be divided into individual groups of consumer goods (e.g., FMCG[1], white goods, etc.) or even individual products (e.g., toothpaste, washing machine, etc.).

The model describes the flow of goods and services between industrial sectors. Each sector is able to produce its output resources with inputs from other sectors and itself. The information needed to develop the Leontief model is contained in a so-called interindustry input–output transactions table. The rows of the table correspond to outputs of resources that can then be used by industries that are producing resources or by final consumers, and the columns correspond to inputs required by the industry to produce a particular resource in the economy. Furthermore, we have columns that define final demand, that is, resources consumed by different entities without producing anything e.g., water consumed by households. There are also rows, which constitute non-industrial inputs to production such as amortization and depreciation, taxes, etc. An example of a simplified input–output transactions table is shown in table 2.1.

1 FMCG – fast moving consumer goods

TABLE 2.1: Simple input–output transactions table.

	Sales to	Producers as consumers (inputs)				Final demand
Buys from		Resource 1	Resource 2	...	Resource n	
Producer of (outputs)	Resource 1	Z_{11}	Z_{12}	...	Z_{1n}	F_1
	Resource 2	Z_{21}	Z_{22}	...	Z_{2n}	F_2
	...	...	...	...	...	
	Resource n	Z_{n1}	Z_{n2}	...	Z_{nn}	F_n
Non-industrial inputs		W_1	W_2	...	W_n	W_D

The input–output model is formed from the analysis of an input–output transactions table, and the data contained within the table is transformed to build the model. It is important to note the difference and relationship between input–output tables and input–output models. The mathematical description of an input–output model consists of a set of n linear equations that correspond to n unknowns; as such, we can use the matrix representation for presenting the notation and calculations in the input–output model. If we model an economy as consisting of n industries producing different resources, we have a set of n equations with the following form eq. (2.1):

$$x_i = z_{i1} + \cdots + z_{in} + f_i \tag{2.1}$$

Where x_i corresponds to the total output of sector i, z_{ij} to the total sales from sector i to sector j, and f_i to the total final demand for sector i. Thus, we have an equation for each of n industry products; hence, we have a total of n such equations. This system of equations can be represented in a matrix linear algebra notation as follows.

$$\mathbf{x} = \mathbf{Zi} + \mathbf{f} \tag{2.2}$$

$$\mathbf{x} = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}, \mathbf{Z} = \begin{pmatrix} z_{11} & \dots & z_{1n} \\ \vdots & \ddots & \vdots \\ z_{n1} & \dots & z_{nn} \end{pmatrix}, \mathbf{f} = \begin{pmatrix} f_1 \\ \vdots \\ f_n \end{pmatrix} \tag{2.3}$$

Where i is the column vector of size n consisting of "1" entries only. Consequently, we arrived with the definition of a matrix of technical coefficients $\mathbf{A}$, eq. (2.4). The matrix of technical coefficients $\mathbf{A}$ describes how many units of each resource are used in producing each column's resource.

$$\mathbf{A} = \mathbf{Z}\hat{\mathbf{x}}^{-1} \tag{2.4}$$

Where $\hat{\mathbf{x}}$ is a diagonal matrix n-by-n with entries of x_i, while $\mathbf{x}$ is the column vector of size n with entries x_i. From this, we can arrive with a matrix expression for the Leontief model eq. (2.5).

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f} \tag{2.5}$$

The above equation comes from the fact that since $\mathbf{A}\hat{\mathbf{x}} = \mathbf{Z}\hat{\mathbf{x}}^{-1}\hat{\mathbf{x}}$, therefore, $\mathbf{A}\hat{\mathbf{x}} = \mathbf{Z}\mathbf{I} = \mathbf{Z}$, and $\mathbf{A}\hat{\mathbf{x}}\mathbf{i} = \mathbf{A}\mathbf{x}$. Then, we have the Leontief model eq. (2.6) and its solution eq. (2.7).

$$(\mathbf{I} - \mathbf{A})\mathbf{x} = \mathbf{f} \tag{2.6}$$

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f} \tag{2.7}$$

Where, $(\mathbf{I} - \mathbf{A})$ is the technology matrix and $\mathbf{f}$ is the total final demand of that resource.

$$\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1} \tag{2.8}$$

The inverse of the technology matrix, $\mathbf{L}$ in eq. (2.8), is often called the *Leontief inverse* or the *total requirements matrix*. The Leontief inverse notation clearly shows the interdependency between the final demand and total output of the system. As such, it is clear that $\frac{\partial \mathbf{x}}{\partial \mathbf{f}} = \mathbf{L}$ is the first derivative of the total output with respect to final demand, which is the Leontief inverse. This important result shows how interdependencies between systems have a significant impact on the total output generated by the systems. The above explanation of the input–output model provides a summary of the model, and a more sophisticated explanation of the input–output model formalism with an example can be accessed in the book by Miller and Blair mentioned [14].

The input–output model has been referenced multiple times by multiple scholars. Initially developed by Leontief to describe interdependencies in the economy of the USA, it has been adapted to other fields and to different regions and granularities. For example, the model has been used to analyze interregional interdependencies and economic growth in a region of Japan [16], to model changes to the manufacturing sector in Germany [17], or to model interregional input–output interdependencies in China

[18]. Moreover, since the model is focused on describing interdependencies, it is frequently applied to fields where interdependencies are studied. This involves fields such as energy analysis [19][20], tourism [21], environmental impacts [22][23][24], ecology [25], and employability [26] to name a few. Similarly, the model has been applied to individual companies where the model was used to model its internal business and production processes [27]. Finally, the model has also been applied to infrastructure modeling and understanding interdependencies in infrastructures. The following authors attempted an analysis of infrastructures with the input–output model. Oliva [28] described an input–output agent-based model to detail the exchange of resources between infrastructures. Haimes et al. [29][30] utilized the input–output model to demonstrate how a dynamic interoperability input–output model can be used to analyze different recovery patterns in attacked infrastructures systems. Similarly, Setola et al. [31] evaluated the input–output model interoperability with a case study by interviewing experts and assigning quantitative values to their opinions. Finally, Jonkeren and Giannopoulos [32] described how resilience can be modeled with the use of an input–output model through introducing some resilience measures, such as inventory status, and applying these to two scenarios.

Although Leontief's model has been used to model infrastructure systems and their interdependencies, this has not been accomplished with the inclusion of households and businesses in the model, and especially so in the context of assessing resilience of urban areas. The model was used to describe and model interdependencies and how different infrastructures interact with each other; however, a dynamic model of these systems interacting with businesses and households and affected by disruptions was not introduced. Therefore, in our study, we intended to include disruptions to infrastructure systems and interactions of infrastructures with other entities such as households and businesses. The analysis of these interdependencies can help to better understand and quantify the resilience of urban areas and to aid in designing these areas to ensure that they are more prepared for disruptions. Moreover, our work aimed to uncover new approaches to the assessment of the value-at-risk of urban areas, and to differentiate the impact of disruptions by social groups in urban societies.

2.2 DISTRIBUTED SIMULATION

Simulations of large complex events or systems require a massive amount of resources and involve an incredible amount of details. The advantages of efficient simulations of complex events have been discussed by Heermann [33] in 1990, where he explained how computer simulations can aid in looking into complex systems and understanding their behavior. For example, to model and simulate air traffic control in the whole of Europe, we would require performing sophisticated analysis of different strategies to arrive with the appropriate solution. Similarly, military situations require significant computing power and time to arrive with an optimal solution to the simulated problem. In such cases, traditional simulations might not be sufficient. The situations mentioned can benefit from a distributed simulation model, where tasks or individual parts of the overall simulation are divided and executed in parallel in a distributed fashion. Formally, as defined by Fujimoto [34] in one of his seminal works on the topic of distributed simulation, distributed simulation technology is a technology that enables simulation program to be executed in parallel over distributed computer systems. Below, we provide a brief review of some concepts relating to distributed simulation, for a more comprehensive review, Fujimoto's book [34] is one of the best resources.

In infrastructure modeling, especially in an urban setting where each system is incredibly complex, has multiple input and output factors, and can get affected by various events, the use of the distributed simulation model is natural. A distributed simulation can help to reduce the execution time when a simulation runs faster as tasks previously executed sequentially can now be executed in parallel. Other advantages in the context of infrastructures are that the distributed simulation approach allows integrating simulations from different providers and that the distributed approach allows the simulation to execute even if some components of the simulation fail. Infrastructures are often modeled by software products provided by different entities from simulations of other infrastructures. In such circumstances being able to combine models from different providers is beneficial, and distributed simulation approach allows it.

There have been several different frameworks for distributed simulation postulated by different authors [35]. An updated comprehensive review of different approaches in this area and future research opportunities was presented by Fujimoto [34][36]. The two main issues in the development of distributed simulation standards were time management, also called synchronization, which allows different simulations to exchange information in a timely manner; and interoperability, which allows for separately developed simulators to cooperate. The latter especially is considered one of the chief advantages of distributed simulation. The research efforts in this field have resulted in widely used distributed simulation standards. These include Distributed Interactive Simulation (DIS) [37], High-Level Architecture (HLA) [38], and Data-Distribution Service (DDS) [39] standards, which are used in many applications where distributed simulation approach is required. Another approach for developing simulations, which we also discuss here, is the agent-based model simulation (ABMS), which shifts the simulation paradigm from a macro view of the system to a micro view of the system simulated [40].

DDS, HLA, and DIS originate from defense applications and were primarily developed by the USA's Department of Defense contractors. Battlefield simulations or flight simulators needed to simulate tremendously complex processes happening in the air, on the ground, and on the water. Thus, the approach of the distributed simulation was devised as perfectly suited to these applications where individual components could be simulated separately and combined together. DDS is a standard that allows the exchange of information between constituent components of a distributed simulation. DDS was developed by the Object Management Group (OMG) and uses the publish–subscribe mechanism to ensure communication between constituent systems [41]; however, it does not provide time synchronization by default, contrary to other solutions such as HLA. Hence, for our application, where time management and synchronization are important, HLA is a better choice.

HLA was developed from DIS with extensions originating from related projects that aimed to improve DIS [42]. HLA specification consists of 3 components:

- HLA Rules–defines rules that simulations must obey in order to be compliant with the standard and other simulations. These rules specify that federations, which are groups of individual simulations (federates), are required to have a Federation Object Model (FOM), in the Object Model Template (OMT) format. During the simulation, all objects are represented by federates, and only one federate can own a given object at any given time. All interactions need to take place through Real-Time Infrastructure (RTI) using HLA interface specification. Federates under HLA rules need to document their public information in Simulation Object Models (SOM) conforming to the

OMT format. Federates can only act based on their SOM when exchanging, updating, transferring, importing, or exporting objects and attributes. Federates need to manage the time accordingly and utilize RTI's time management service to do so.

- HLA Interface Specification–it specifies the services provided to the federates by the RTI, and conversely by federates to the RTI. These include:
  - Federation management–it provides basic functions to create and operate a federation.
  - Declaration management–provides a means for federates to declare what information they will supply and require during the execution of a federation.
  - Object management–provides means to create, identify, delete, and other services related to objects. Information about objects gets transferred to other federates that have interest in that object.
  - Ownership management–supports the transfer of ownership of objects during the execution. This is so that only one federate owns an object at any time.
  - Time management–supports synchronization of data between simulations and provides means to keep track of time in a federation.
  - Data-distribution management–supports the efficient routing of data among federates while the federation is running.
- HLA OMT–these are descriptions of the elements (objects) that are shared by the federation. The OMT is aimed at ensuring that interoperability of simulations is preserved. They are focused on describing the critical aspects of data being exchanged by the simulation. There are two OMT types: FOM and SOM. FOM describes a federation–a collection of individual simulations–and what data in what aspect should be shared in it. On the other hand, SOM describes what data and resources a federate might provide to a federation that it becomes part of in the future. SOM is vital in assessing whether a federate can be joined into and is compatible with a particular federation. HLA specification does not define how SOM and FOM should look like; however, it requires that they conform to the same HLA OMT format standard. The overall OMTs: SOMs and FOMs, depend

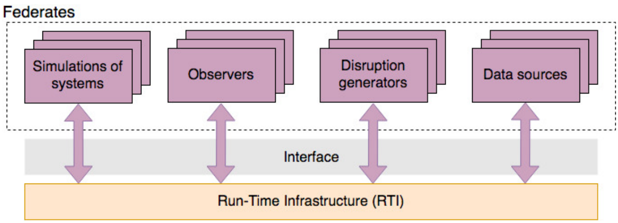


FIGURE 2.1: Sample HLA Federation with constituent federates and RTI.

on the type of simulation we want to execute and on what needs to be simulated.

Accordingly, with the above specification components, HLA consists of federates (individual simulations), which are connected through defined interfaces to RTI. Federates execute individual simulations, while RTI facilitates the exchange of data between federates that conform to the federation's HLA FOM and interface specification. The outline of sample simulations within an HLA framework is shown in fig. 2.1.

Although HLA originated from defense applications, it has been adapted to other situations, where a distributed simulation approach could be beneficial. HLA has been adapted to traffic [43], flight [44], and battlefield [45] simulations. These include situations where many complex individual simulations need to be combined together and exchange certain information. In studies of interdependencies or infrastructure systems, HLA can also be utilized due to its ability to simulate individual infrastructures separately and then combine them into a single distributed simulation. Hence, there have been approaches where HLA was used to model infrastructure systems. These include Eusgeld, Nan, and Dietz's approach to modeling interdependent critical infrastructure systems [46]. These authors considered interdependencies between infrastructure systems and control systems and discussed how HLA might be useful in simulating such systems. However, they did not consider the impact of time management on the outcome of the simulations and did not consider households and businesses in their study. Muller et al. [47] focused on power systems and their interdependencies with information and communication technology systems. They described how the simulation of such systems could be achieved in HLA; however, they did not consider the resilience of these systems and the wider impact on sociotechnical systems.

As described above, distributed simulation technologies, including HLA, have been applied to many fields, which include infrastructure modeling; however, the impact of time management differences and time granularity of constituent simulations on their results have not been analyzed in great detail. Similarly, the impact and interaction of constituent simulations in a distributed infrastructure simulation with sociotechnical systems and socioeconomic units, such as households and businesses, to assess the resilience of urban areas, has not been attempted. In our work, we aim to target these issues primarily by looking at how time granularity affects the propagation of disruptions between systems. Understanding how time granularity affects the propagation of disruptions can help to design better infrastructure systems simulations, and consequently, create real-world systems that are more resilient. Hence, our study contributes to supporting more robust and resilient societies.

Finally, a special case of distributed modeling is agent-based modeling (ABM). In this approach, simulation is divided into individual units, which correspond to single agents of the system simulated. The agents are autonomous and make their own individual decisions based on certain rules or mechanisms [40]. For example, in the case of human systems, the agents would correspond to individuals of different categories with different sets of principles guiding them. ABMs are widely credited with being important in providing additional insights and guidance on issues from fields as diverse as economy [48], health [49], biology [50], and geography [51]. Their advantages include apart from the discussed already advantages of distributed simulation models, flexibility–the ability to use a diverse range of conflicting agents, scalability, and very good correspondence and duality with the natural world [52]. Consequently, ABMs are a modeling technique that is on the rise with various practical applications and following the distributed simulation pattern.

2.3 SYSTEM-OF-SYSTEMS (SOS) MODEL

Real-world systems usually work in combination with other systems, whether these are infrastructure systems, socioeconomic systems, or technical systems. It is very rare for systems to work independently of others. For example, transportation systems depend on energy provision, communication, road network, automation, and control systems. As such, disruptions to any of these systems propagate into others in line with their interdependencies patterns. These systems' interdependencies need to be modeled and simulated to better understand the impact they have on disruptions and their propagation throughout the system. This can be achieved through modeling all the systems as a single large-scale system that combines several systems into one model. However, such an approach would lead to numerous issues such as reduced flexibility, loss of specialization, management, and data collection complexity. This led to a method that corresponds with the natural design of these systems–an SoS model. Under this approach, entities are not modeled as a huge, complex single system model encapsulating all functionalities, but rather, as a collection of individual models that run independently but influence each other. Their influence on other systems is through interdependencies that these systems exhibit with other systems.

Central to the SoS model is the idea of systems-thinking, developed and described by Sterman [53]. In his book, he described the world as a complex system, where everything is connected to everything else. This approach underlines the importance of interdependencies, which are present everywhere, and the need to combine several systems from different domains such as engineering, sociology, economics, infrastructure, biology, and many more. While there exists much interpretation as to how to model these individual systems, there is an agreement that systems-thinking is needed and not utilized enough in analyzing relationships between various fields [54]. To analyze and model relationships between different systems that are themselves self-sufficient and with clear interfaces to the outside world, the concept of SoS was developed.

It is understood that the system is "a collection of entities and their interrelationships gathered together to form a whole greater than the sum of the parts" [55] meaning that systems need to display emergent behavior. According to Jamashidi [56], an SoS is a complex system that has complex characteristics; its constituent systems are able to operate on their own independently and are able to manage their operations independently. The SoS is geographically distributed and exhibits emergent behavior, nonlinearities, and evolutionary development process [57]. SoS comes from the principle of systems engineering that states that the best way to solve a complex issue is to break it down into smaller parts until eventually, we arrive with a part that is small enough to understand it and model it adequately. Subsequently, the overall system is assembled from these small self-contained units to arrive with an SoS model. In an SoS, individual constituent systems are highly interdependent and can have impacts on each other that are difficult to predict and understand at a higher overar-

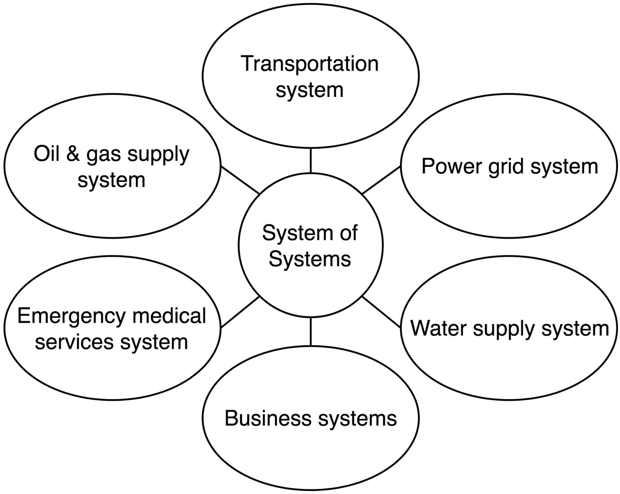


Figure 2.2: An example of a high level view of system-of-systems of infrastructure systems.

ching level. SoS takes a more complex and holistic view of systems including their organization, management, and social and policy aspects. These multidimensional views with special consideration for interdependencies drive SoS methodology's use and popularity. A sample view of an SoS of infrastructure and business systems is shown in fig. 2.2.

SoS methodology has been applied to plenty of fields to model various processes and interdependencies between them. Keating et al. [58] described the concept of SoS modeling in application to engineering management. They presented issues that can be dealt through applying SoS approach, identified what the current developments are in the field, and described the paths for future work, including design and development issues that engineers face. They concluded that the crucial issue to SoS use in engineering is the efficient methods for systems evaluation and evolution. Jackson and Keys [59][60] applied the SoS concept to operational research and outlined other attempts to do so. They focused on presenting different methodologies to solving operational research problems and explained interrelationships between those, thus arriving at the SoS concept application to the operational research field of study. SoS ideas have also been applied to ecology [61], defense and military applications [62][63], energy sustainability [64], and information systems science [65], among others. Moreover, the SoS approach has been applied to model critical infrastructure systems by Eusgeld et al. [46], since infrastructure systems are highly interdependent and can be divided into individual units, which can be modeled separately. In fig. 2.2, an example of a high-level view of how SoS methodology can be used to combine different infrastructure systems to model an SoS of interdependent infrastructure systems is shown.

To develop SoS simulations, distributed simulation frameworks are used due to their natural conformity to SoS models. Distributed simulations consist of smaller simulations that operate independently but are inherently interdependent with one another and combined together to achieve the final result. This situation corresponds to an SoS model, where the full SoS consists of smaller systems that are, however, interdependent. Consequently, HLA and distributed simulation technologies are used to simulate SoS models. Already mentioned, Eusgeld, Nan, and Dietz [46] simulated critical infrastructures using HLA and following SoS framework. Logan and Theodoropoulos [66] applied distributed simulation approach to multiagent SoS simulations of agent-based individual systems. Georg et al. [67] applied HLA framework to model power system control systems, protection systems, and their respective information and communication technology systems.

SoS approaches have been used to study a wide range of subjects, and the model is used to represent various systems. However, the actual implementation of the model and application of the SoS concepts to actual real-world scenarios are still subjects of ongoing research. Furthermore, the SoS model development presents certain limitations. For example, defining the manner of synchronization between individual systems is understudied, especially in regard to infrastructure modeling. This ties with similar concepts and issues in distributed simulation, where synchronization of constituent simulations is a major field of research. Hence, one of our aims was to investigate how the exchange between constituent systems of an SoS model should happen to ensure the most accurate representation of the real world in an SoS model simulation.

As evidenced by the above examples, SoS simulations are often developed with the use of distributed simulation frameworks such as HLA. This has been done also in the context of infrastructure systems simulation, where infrastructure systems are distributed across individual simulations of infrastructures. However, venturing further, the idea of the SoS modeling can be combined with the input–output model to derive a combination of independently distributed input–output models that are interdependent with each other. Such SoS would allow us to utilize and combine the power of distributed modeling, SoS, and input–output modeling ideas. The notion of combining the above concepts to form an SoS of multi-input–output models was at the heart of our study where we implemented and applied such system's simulation and investigated the issues involved in the development of a multi-input–output SoS model.

2.4 SIMULATION EXPERIMENT

To predict the behavior of large-scale complex systems, it is increasingly more prevalent to use simulation modeling, and especially computer simulation models [68]. This approach is especially useful in estimating the impact of random discrete events that affect the systems. Consequently, it becomes crucial to design simulations and develop models that these simulations execute in an adequate way. Otherwise, the usefulness of the results of a simulation might be limited or even insufficient, having considered the expected goals of the simulation experiment [69]. According to Barton [70], designing an appropriate simulation experiment is concerned with both ensuring that an adequate model is developed for the simulation, as well as ensuring that appropriate parameters and data are supplied to the simulation and extracted from the simulation.

Careful planning of a simulation experiment is important to ensure that results of the simulation model are significant and fulfill the goals of the experiment [71]. Simulation and modeling projects are usually constrained by available resources, such as time and budget requirements. The development of model and simulation often takes the majority of these resources with subsequently very limited resources available for applying the model to aid decision-making or to obtain insights about the system under simulation. This can contribute to a mismatch between the kind of information or decision support that can be produced by the simulation and the expectations of what the simulation would be able to produce and achieve. To avoid such scenario, the range of decisions that the simulation model will aid with and the types of results that are produced by the simulation should be defined in advance and continuously updated and verified as the models' development and testing depends on this, and so does the simulation design [72].

The design of a simulation experiment is affected by various factors. These include the type of model used in the simulation, the type of randomness that is introduced into the model, and how and what results to interpret and extract from the model. Taking the above into account, Barton identified the following five steps in the simulation experiment design. These steps correspond to the classical scientific investigation steps of hypothesis definition, planning and conducting the experiment, and testing the hypothesis based on the experiment results. The five steps defined by Barton [69] are listed below:

1. Defining the goals of the simulation experiment.
2. Identification of crucial variables and division of variables into independent and dependent variables.
3. Selecting an appropriate probability model for the simulation model.
4. Choosing an experimental design.
5. Validating the properties of the design chosen.

The first step in the simulation experiment design is to define the goals of the simulation experiment. The goals need to be clear from the beginning of the development process and need to answer the questions of what issue the simulation is helping to solve, and why the simulation experiment is conducted. The goals need to be approved by stakeholders of the experiment, and these goals serve as guidance for the development of the model and simulation throughout the following steps.

In the second step, the variables of the simulation experiment need to be defined. This means defining independent variables–the parameters of the simulation experiment, which can be varied to affect and modify the dependent variables–the results of the simulation experiment. The variables need to be identified before the simulation is executed. The independent variables include factors, which are independent variables that will be knowingly varied throughout the experiment to obtain a range of responses to the simulation experiment. On the other hand, there are fixed independent variables, which will remain unaffected throughout the duration of the experiment. The dependent variables are defined and obtained based on the goals and objectives of the study. These are the values that need to be extracted from the simulation as results for the simulation to fulfill its goals.

In the third step, the probability model for the simulation is selected. The probability model is the hypothesized model of the results of the simulation. The aim here is to estimate the outcome of the simulation in terms of a probabilistic model and compare it with the simulation result in the next step in order to confirm the hypothesized model and extract the parameters of the model. Furthermore, the stochastic elements of the model are devised in this step, and their distributions are defined so that a range of stochastic parameters of the model can be generated for each set of factors.

In the fourth step, the experiment design is created. This involves selecting the number of distinct runs of the simulation, and the values of factors are defined. The experiment designs include random designs, optimal designs, combinatorial designs, and factorial designs. Of these, factorial designs are especially popular, where each factor is tested with every combination of other factors. This design also allows for the estimation of cross-product terms of the simulation model. Factorial designs are the most common type of experiment design; however, their disadvantage is a large number of runs required to complete the factorial design, especially when the number of factors is large and when stochasticity is present in the model.

Finally, in step five, the properties of the design are validated. The simulation experiment is performed, and its response to the change of factors is recorded. Subsequently, the properties of the design of the simulation experiment are validated. This is done by checking whether factors of the simulation have a significant impact on the dependent variables. To perform this process, a statistical test, such as analysis of variance or covariance (ANOVA or ANCOVA) [73], is performed on the results of the experiment. If not, the simulation experiment might need to be redesigned, or the number of runs needs to be increased. It is also possible that independent variables do not have a significant impact on the dependent variables, contrary to what had been expected. Possibly, also, the set of factors that are tested and included in the model needs to be decreased and readjusted.

The above steps are executed to perform a traditional canonical simulation experiment. There are, however, several challenges that we face with the above process. These include especially the SoS simulation models, which are themselves operated as a series of tasks and so are prone to a lot of randomness being introduced into them. Thus, SoS models often operate with stochastic parameters, and as such, the runs need to be repeated with varying parameters to preserve this. In the experiment design step, the stochastic behavior of the model needs to be captured. This is done by identifying points were stochasticity in the SoS simulation model occurs. Their behavior is then described with random value generators following certain distributions. This randomness and its introduction to the experiment is a significant challenge to designing the model, executing it in a simulation experiment, and subsequently to validating and interpreting the results [74]. SoS simulations are especially prone to these challenges since, in SoS simulations, stochasticity is very common.

In the context of this study, the stochasticity of a simulation is crucial. Infrastructure systems, businesses, and households exhibit stochastic behavior and randomness in their utilization of resources. Consequently, these constituent systems have stochasticity introduced to many of its components. This stochasticity leads to different results for each simulation run even when the simulation is run with the same set of factors. Thus, we need to perform the simulation a certain amount of times to obtain the distribution of dependent variables for a given combination of factors considering the stochasticity of the simulation model itself. The main challenge in designing the simulation experiment then becomes to designate the number of runs that are required to obtain the accurate distribution of results. The greater the number of runs, the more accurate the distribution of results we are able to obtain. However, at the same time, there is a trade-off between the number of runs and the time to run the simulation. As each run of the simulation increases the computational burden of the simulation and takes time, the larger the number of runs, the longer the execution of these runs will take.

Depending on what information about the results needs to be extracted, it can take a widely varying number of runs. Obtaining the mean of distribution requires less runs than obtaining its variance, and this requires fewer runs than obtaining the distributions' accurate shape. In the context of resilience and disruption research, we are particularly interested in finding the extreme values and tails of such distributions, which might take an even larger number of runs and is difficult to estimate. Bootstrapping methods [74] are often used to estimate tails of these resulting distributions.

According to Bagdatli et al. [74], the best approach to tackle a scenario in which stochasticity is present in the simulation model, is to run the model a certain limited number of repetitions for each combination of input factors and estimate the required number of repetitions for each input factor combination from this. Their recommended number of repetitions, with random seeds for each run, is 10 to 30. This can then be used using bootstrapping or statistical testing methods to arrive with the required number of repetitions for all input factor combinations. It is also possible that certain subsets of combinations of input factors require a different number of runs than others. This issue of stochasticity present in the model is one of the major challenges in the simulation experiment design of SoS simulations.

Another major challenge in designing simulation experiments involving an SoS model is the analysis of results. Due to stochasticity present in the model itself, the obtained results are themselves distributions. Since the SoS model is non-deterministic, its performance cannot be predicted exactly; only distributions of this performance can be derived. Consequently, contrary to traditional models, in the case of SoS models, we can predict the range of performance and infer trends and relationships regarding the performance, rather than perfectly estimating individual metrics as is the case in traditional physical models. This poses additional challenges. Since we now look at the aggregation of several runs, it is difficult to apply traditional data analysis methods. Another challenge is the huge quantity of data that can be collected about the system, especially if the dynamic behavior and state transitions of the SoS are of interest.

To address these challenges, visual representation and analytics of the data is used. This allows seeing crucial trends and changes in the system due to input factors without necessarily considering the specific values of resulting parameters, which themselves might be of little significance. Visual analytics is concerned with allowing an analysis of and reasoning about big data sets which describe complex behavior [75]. Using interactive visual tools that are linked with each other can be helpful to analyze behavior and to showcase the outcome of a stochastic simulation model. Hence, using ample visualizations is the key to presenting how a stochastic system-of-systems simulation is affected by different input parameters, and what the SoS's response to these is.

2.5 MAIN CHALLENGES STEMMING FROM THE CRITICAL REVIEW

There exist several challenges in the field of modeling disruptions to and interdependencies between infrastructures, businesses, and households that were outlined in this chapter. These focus around challenges to input–output modeling, distributed simulations, SoS modeling, and simulation experiment modeling. First, input–output modeling has been used to model infrastructure systems successfully in the past. However, the primary challenge remains: how to combine households and businesses with infrastructure systems into a single model. Furthermore, a dynamic model of infrastructures, businesses, and households has not been attempted, nor analysis of the systems under such a model to estimate the system's resilience. Second, distributed simulations have been used to simulate various entities including infrastructure systems. However, the impact of time granularity of exchange of information between constituent simulations has not been studied in depth, especially in the context of simulations of infrastructure systems, businesses, and households. Third, SoS models have been applied to various fields including infrastructure systems. However, the synchronization of constituent systems and combination of input–output modeling and SoS approach in the context of modeling infrastructure systems have not been attempted, and are understudied. Fourth, the simulation experiments on SoS models have been attempted in a wide range of fields including infrastructure modeling. However, there remains still a lot of room for improvement in interpreting and presenting the results of these experiments in a meaningful way. The challenges mentioned here are identified as the crucial aspects of delivering a robust simulation model of interdependencies of infrastructure systems, households, and businesses; and their impact on disruption propagation. It is therefore the aim of this study to tackle these challenges.

2.6 structure of the thesis

This study is taking up the challenges to modeling interdependencies of infrastructure systems, businesses, and households and their impact on disruptions outlined in the preceding paragraph. Chapter 2 provides an in-depth review of key founding ideas and streams of research that we incorporated in our work. It describes: (1) the input–output model that we utilize to model businesses, households, and infrastructure systems; (2) distributed simulation frameworks that we utilize to combine different individual infrastructure system models; (3) SoS approach where various systems are combined together and this approach's challenges of synchronization and interoperability; (4) major challenges in designing simulation experiments especially when SoS simulations are considered. The rest of this thesis is structured in the following way. In chapter 3, a multi-input–output framework for modeling interdependencies between infrastructure systems, households, and businesses, and their impact on resilience is presented. In chapter 4, the issue of time granularity of synchronization of constituent systems of a SoS model is tackled. In chapter 5, an application of the modeling framework to an actual geographical area is described. Also, a workflow for the application of the model is presented, which would allow for the application of the model to any other area. Fi-

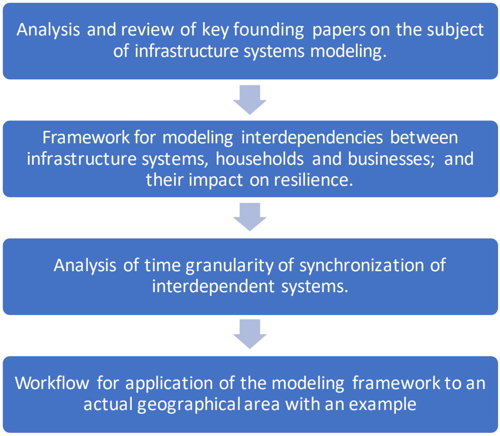


FIGURE 2.3: Outline and the guiding concept of the thesis.

nally, in chapter 6, synthesis, conclusions, and discussion of our study are presented, and some ideas for future research developments are outlined. The outline of this thesis is presented in fig. 2.3 for reference.

3

A FRAMEWORK FOR MODELING INTERDEPENDENCIES AMONG HOUSEHOLDS, BUSINESSES, AND INFRASTRUCTURE SYSTEMS; AND THEIR RESPONSE TO DISRUPTIONS[1]

It is still an unending source of surprise for me how a few scribbles on a blackboard or on a piece of paper can change the course of human affairs.
— Stanisław Ulam

This chapter is based on and includes work submitted for publication in Reliability Engineering & System Safety.

3.1 INTRODUCTION

Urban systems of infrastructure, businesses, and households are constantly expanding and evolving. An increasing amount of human activity is centered around cities, which causes populations to gravitate toward them. Consequently, the number of large cities is growing rapidly [76]. The number of megacities, that is cities with population of over 10 million inhabitants, is expected to increase by 32% over the next 14 years [1]. As urbanization advances, related entities become more prevalent and involved in shaping humans, businesses, infrastructure, and government interactions. This has several implications for urban systems. First, the impact of similar disruptions is heightened because a higher concentration of entities within a city is associated with a greater degree of damage that arises from disruptions of the same magnitude. "Disruption" is defined here as an unexpected, undesirable disturbance that negatively influences a system, or

1 This chapter is based on the following publications:

1. Dubaniowski, M. I. Heinimann, H. R. A framework for modeling interdependencies among households, businesses, and infrastructure systems; and their response to disruptions. *Reliability Engineering & System Safety*, Submitted (2019).
2. Dubaniowski, M. I. Heinimann, H. R. *A framework modeling flows of goods and services between businesses, households, and infrastructure systems* in *Resilience The 2nd International Workshop on Modelling of Physical, Economic and Social Systems for Resilience Assessment : 14-16 December 2017, Ispra* **I** (Publications Office of the European Union, 2017), 182.

any, or several of its components. Second, the flow of goods and services between businesses and households is continuously increasing. These entities require access to various goods, services, and infrastructure systems if they are to survive and perform even the most basic functions. Third, recent approaches in cybernetics refer to cities as organisms that combine businesses, households, and infrastructure, all of which are becoming more involved and interdependent [77][3] due to technological advancements and the greater complexity of production processes [4] [2].

This rapid urbanization and increasing dependence on urban systems present issues that are vital to inhabitants of cities. For example, the extent of the damage caused by similarly sized, simultaneous, disruptions can be larger for cities with higher densities. Furthermore, the flow of goods and services depends upon the unique profiles of households and businesses. These profiles can become more flexible and change frequently in response to factors that then lead to dynamic changes for urban metabolism. Realizing and modeling the behavior of socio-economic units within the context of infrastructure is a major challenge for societies, businesses, and governments. Therefore, it is crucial that we gain more knowledge about these interdependencies, their fluctuations, and their impact on such systems.

The objective of our study was to address the need for understanding the interdependencies among businesses, households, and infrastructure systems; as well as how they affect reactions to various disruptions. Our aims were to (1) develop an agent that represents a business or a household by mimicking the process of transforming a set of supplied goods and services into a set of output goods and services, (2) devise a network of these agents that is dynamically self-organizing under a disruption based on varying costs of resources throughout the network, and (3) to introduce disruptions to these systems and then investigate how that might influence performance. Follow-up experiments allowed us to evaluate the feasibility of our model for assessing disruption-related changes in performance by networks. Our ultimate goal was to improve the ability of planners and managers to prepare for system failures by recognizing which types of disruptions are most threatening and could have the most severe impact on a system of interest.

The resilience of infrastructure and economic communities is quickly becoming a vital feature of urban systems. Historically, risk management was the primary approach taken for predicting and dealing with disruptions in such settings. However, new scenarios have arisen for which the concept of risk management is less feasible. For increasingly interdependent systems, we cannot predict disruptions and their impacts as accurately as was done previously. Conventional approaches to risk management often overlook unexpected, system-wide threats and are not concerned as much with system recovery. In fact, employing risk-based protocols can be costly and ineffective against sudden disruption-generating events [7][6][78]. Such disruptions can take various forms, from carefully planned attacks to natural disasters. In highly interconnected societies, even a small disruption to one part of one system can propagate and generate extremely negative consequences for other systems [79]. As a result, shocks to a system become more frequent and more detrimental to households and businesses [80]. Hence, the concept of resilience, originating in a system's resistance to and recovery from severe or unexpected disruptions, is now the defining characteristic of urban systems and is also being introduced and applied to other fields of research [2].

Contingency plans and response scenarios can make systems more resilient. However, having a better understanding of a disrupted system can aid in estimating disruption related costs. The process of recovering can also be modeled and illuminated by examining how a system might adapt. To model these unexpected disruptions, one must consider the following factors: (1) behavior of businesses and households that mimics their interactions with infrastructure systems, and (2) dynamically variable interdependencies among those interacting components.

Several streams of research have described the recovery and response of infrastructure to disruptions [81]. Those efforts include a focus on modeling individual systems for electrical power [82][83], water supplies [84], or transportation [85]. Another stream [86][87] is devoted to simulating various interdependencies, including agent-based models [88][89][90] and system-of-systems (SoS) approaches [46]. Although input–output models can be used to describe interdependencies among infrastructure systems [91][30][31][92], none of these streams accounts for the interactions of infrastructure with business and household agents, which would help provide insight into differences in vulnerabilities between population groups, an opportunity overlooked in regional models [93]. These include variations in the impact of and response to disruptions based on income level, health status, or type of business. For example, households that contain disabled and low-income members respond differently to disruptions when compared with households made up of fully healthy persons or those with high incomes. Similarly, retail stores are affected differently to a restaurant when a power outage occurs.

Interdependent networks of infrastructure as well as individual infrastructure systems have been analyzed within the context of graph theory. The connectiveness of such graphs and other topological properties of these graphs also have been analyzed. These measures can be used to understand vulnerabilities within infrastructure system networks such as electric grids [94][95] or urban street networks [96]. However, these mathematical methods do not consider the costs of producing resources, or any interactions among various interdependent infrastructure networks, businesses, and households during that production phase, as well as the dynamic nature of disruptions.

In looking at the internal workings of businesses and households, the input–output model developed by Leontief [97] has long been used to illustrate their behavior [27][14]. However, that type of model has not been applied to simulate such interactions within an SoS setting. Instead, other models of household and business behavior have incorporated more insight into their internal social organizations, rather than relying upon the effects of external production, as would be the case in the input–output model [98][99]. In modeling disruptions to systems, researchers have examined the impact on supply-chain networks and developed useful frameworks [100][101][102]. Disruptions to the infrastructure have been analyzed with water supplies [103] and healthcare services [104].

3.2 MODEL SPECIFICATION

We developed an agent-based network that formed an SoS for the flow of goods and services among all of those agents. This flow was meant to represent the relationships and interdependencies among different actors within a society. The system-of-systems reflects the multitude of different independent infrastructure systems included in one simulation that involves businesses and households, i.e., socio-economic systems. Examples of an infrastructure system would be power grids, water or gas supplies, transportation, or telecommunications.

Our specifications called for a conceptual model that could simulate the flows of resources throughout a network of socio-economic agents and infrastructure systems. The new framework and its components consisted of agents and internal working mechanisms of the network. It also included means by which one could generate network disruptions and identify the factors possibly responsible. Furthermore, the framework featured a coordination system that managed resource flows among the various network agents.

In our model all resources including infrastructure, production, business and household resources are introduced or produced by agents, with agents being joined together to form networks. Agents are linked together under this model with infrastructure links that provide means for transfer of resources between the agents. This results in interdependencies in the system being represented in two ways: (1) through infrastructure links; (2) through matrices of technical coefficients within agents.

The comparison of our proposed approach with an existing model is shown in fig. 3.1. For our model, interdependencies among infrastructure systems were manifested through households and businesses, with the latter also providing infrastructure. Thus, infrastructure is represented by both the infrastructure network and the business agents that ensure production of the resource delivered through the infrastructure network. In the existing approach, interdependencies were defined between each pair of infrastructure systems, which themselves operated independently. In our model, the dependencies among socio-economic units included combinations of resources from various infrastructure systems that would then be used to produce other resources.

For example, to provide water, the supply company represented by an agent required electrical energy, petrol, gas, transportation and maintenance equipment (capital goods), and consumer goods that their employees might consume at work. The producer distributed the water through a supply network connected to that company agent. If, due to some adverse conditions, the energy supply to that company became more expensive, the cost to provide water would increase. This effect was then propagated throughout the entire water network connected to the supplier company agent, thereby influencing all of the following agents that were dependent on the water supply from this source. These included the agent for the power company, which needed water to generate electricity. Increasing the cost of water sent to the power supply agent increased the price of electricity even further, again leading to a propagation of that effect through the network to other household and business agents. Therefore, we observed a feedback loop representing the interdependency of these two systems. Moreover, the increasing costs seen by both households and other businesses that received those essential sources resulted in higher prices for the resources produced or consumed by those household and business agents.

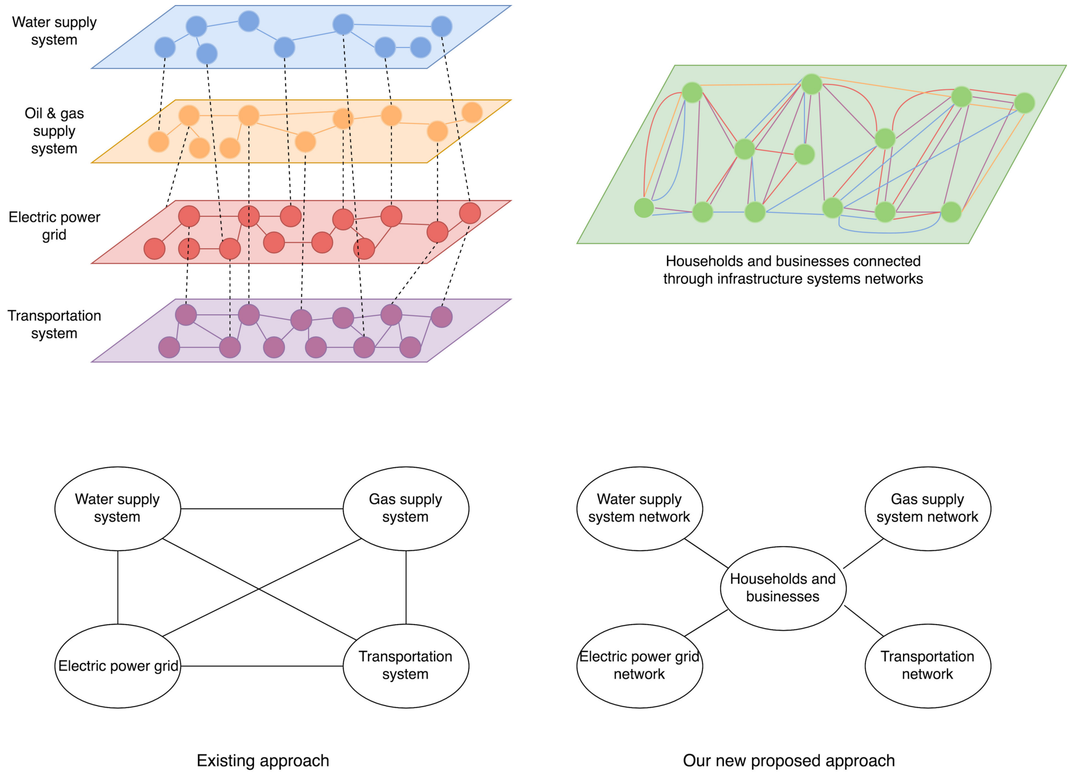


FIGURE 3.1: Comparison of existing approach for modeling infrastructure systems and their resilience versus new approach. In latter, households and businesses are included to indicate interdependencies between systems. Infrastructures are represented through network links and their corresponding infrastructure business agents.

3.2.1 *Conceptual framework*

Our network of agents corresponded to households or businesses that exchanged goods and services through infrastructure links that represented flows through an infrastructure system. Those agents could produce as well as consume the resources. This production process entailed a set of inputs being transformed into a set of outputs. The steps that could be performed were defined uniquely for each agent, who then took inputs from the network and converted them into outputs that would satisfy the demand for goods and services by another agent. This transfer and exchange from one agent to the next was accomplished over a network of infrastructure systems that corresponded to physical and sociotechnical links between agents. They included roads, telecommunication lines, pipelines, power grids, and similar components. The infrastructure links corresponded to the edges of the agent network. Each edge was associated with a cost vector that specified transportation costs per unit for each resource over that edge.

The disruptions introduced here were stochastically modeled as discrete events. We used different methods depending upon whether we wanted to simulate a disruption to a production process, an infrastructure system, or the external demand of the entire system. Agents were connected through infrastructure links that coordinated the flow of goods and services with a pricing mechanism that governed how and where resources moved, and, effectively, where production occurred. The aim was to minimize the overall costs of satisfying total demand from the system. Simulation of the model was dynamic and ran in discrete timesteps that constantly adjusted to any possible disruptions introduced to the system.

The conceptual framework is shown in fig. 3.2. Agents exchanged goods and services through edges that were responsible for resource flow between agents, based on a pricing mechanism to minimize costs. Those edges corresponded to network components, e.g., power grids, transportation, water supply, and telecommunications connections. Disruptions were generated and introduced at various points within the SoS. Emergent behavior was observed under various disruptions, during which agents could perform different functions based on their unique advantages relative to other agents post-disruption. Together, the network of agents, coordination mechanism, and disruption generator formed a system that dynamically reorganized and coordinated the network under a disruption. The SoS was

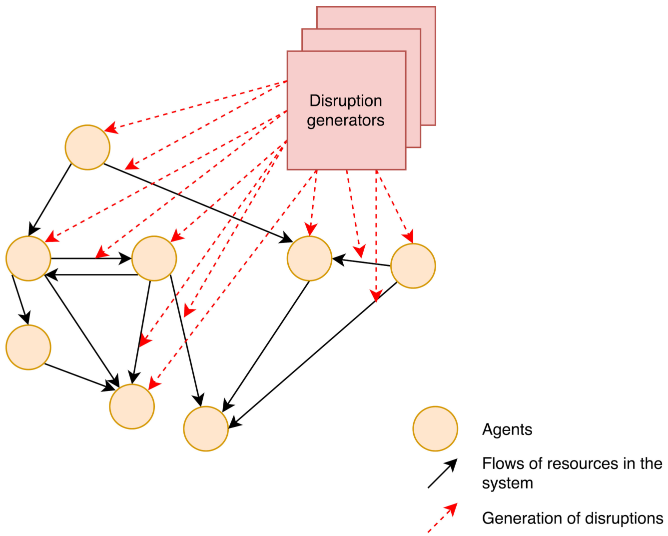


FIGURE 3.2: Conceptual framework of business/household agents interacting with infrastructure systems while facing disruptions. Network of agents exchange goods and services through links. Both agents and links could be interrupted by disruption generators.

able to model interdependent responses to disruptions that individual systems, if simulated separately, might have failed to capture.

Our new model assumed that socio-economic agents and infrastructure system links behaved linearly at each timestep in the simulation. This served as a fair approximation of the real world where, in the absence of any major disruptions, infrastructure systems and businesses would operate similarly at any given time. Even though our model was linear in the way that socio-economic agents, infrastructure systems, and a coordination mechanism were based on pricing, the disruption generators were intended to be non-deterministic and to reflect the non-linearity of the entire SoS under a disruption or due to passage of time. Those generators represented dynamic changes to both infrastructure system links and the internal workings of the socio-economic agents. Their disruptions were non-deterministic, periodic, or one-time events; recoverable or not; and could have negative or even positive impacts on the components of the system that they disrupted. Despite the linearity of socio-economic agents and the coordination mechanism itself, the overall model was non-linear due to the introduction of random and non-deterministic disruptions.

The linearity within short timeframes is a fair assumption. Approximating production with a linear model is adequate since the demands and production of a society in a short time window to a large extent exhibits linear behavior and can be described with a linear model. Throughout the day there are several periods, which are characterized by a particular linear relationship such as in the morning, where commuters travel to work, and companies do not operate yet, and throughout the day where most businesses operate at full capacity. These periods can be approximated with a linear model each. At the time granularity, where the time window we propose to be 15 minutes, the linearity assumption is valid. The production processes within such time window can be approximated and characterized by a linear model. The time granularity can be adjusted accordingly depending on the proposed disruption generation patterns. For shorter disruptions, the time granularity would need to be decreased adequately, strengthening the linearity approximation of the model even further. There exists also a tradeoff between time granularity and speed of the simulation, which needs to be considered when applying the model. The combination of linear and non-linear model is a natural consequence of the immense complexity inherent in modeling infrastructure systems, businesses, and households; and the need to introduce non-linear events such as disruptions into these models. The interdependencies between infrastructure systems and businesses in a given instance can be approximated with linear models, while introduction of disruptions, which are non-linear, is achieved through altering these linear models between subsequent timesteps. This overall set up presents a good approximation of the real world, where linear relationships are good approximations at certain low time granularities. These are, however, disturbed by random, non-linear stochastic processes, which need to be registered by the simulation model.

3.2.2 *Agent specification*

We defined a socio-economic agent as a single unit – business or household – that manifested economic activity in terms of goods and services produced or consumed by that agent. As such, it was the smallest unit in the SoS model.

Reflecting real-world conditions, an agent took in a set of inputs (external supply) and produced a set of outputs (external demand) through a prescribed process. The agent's behavior was primarily defined by that external demand together with the final consumer-demand vector. The production process was modeled by a technology matrix [97][21] to determine what quantities of which resources were needed to produce a single unit of another resource. Thus, it served as the "brain" of an agent. This process, as well as the agent, could also supply resources to itself (fig. 3.3). For example, an intermediate step might require a resource produced by the agent that was then used in the final step by the same agent. Some agents also had the capacity to introduce raw materials through a provider component. The costs associated with supplying each resource could differ among agents according to different price levels. Finally, the agent was connected to a final consumer-demand vector that represented the sink, or ultimate consuming capacity, of the system. This vector was used to show which resources an agent consumed without producing anything in return. Such consumer agents simulated the overall, aggregate external demand of the entire SoS. The difference between external demand and final demand from the agent's point of view was irrelevant; both were combined to form the total demand from the agent. However, in terms of the entire network, their purposes differed. Similarly, the provider of raw materials and the external supply were uniform from the agent's perspective. However, from the network's perspective, they corresponded to different functions and properties, as clearly demonstrated in fig. 3.3.

3.2.2.1 *Production process*

The production process was represented according to the technology matrix originally suggested by Leontief [97] and elaborated upon by Lin and Polenske [27] and Albino, Izzo, and Kühtz [105]. This matrix described the quantities of each resource needed to produce a single unit of another resource. Those inputs were transformed into outputs based on the matrix entries (example shown in table 3.1). An agent could perform a production process by utilizing its technology matrix, or conduct other tasks to satisfy

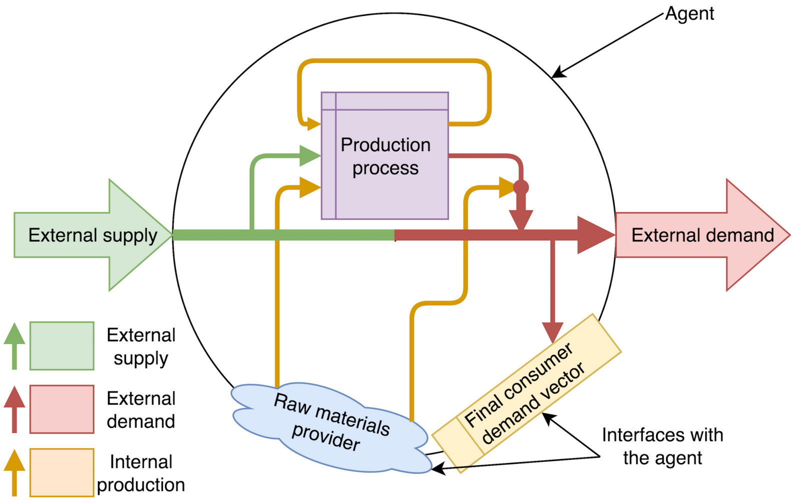


FIGURE 3.3: Functionality of household/business agent (signified by circle on diagram) that receives input resources from preceding agents (external supply) and performs production processes on these resources to satisfy demand by next agents (external demand). Agent can also introduce raw materials and be final consumer through interfaces with provider and demand vector, or can also serve as through-transportation link, conveying resources to subsequent agents without performing production processes.

its external demand. The following formulae were used with this matrix to determine the cost and amount of each necessary resource:

$$\mathbf{X} = \mathbf{A}\mathbf{X} + \mathbf{D} \tag{3.1}$$

$$(\mathbf{I} - \mathbf{A})\mathbf{X} = \mathbf{D} \tag{3.2}$$

$$\mathbf{X} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{D} \tag{3.3}$$

$$\mathbf{S} = \mathbf{X} - \mathbf{D} \tag{3.4}$$

Where, $\mathbf{S}$ represents the supply (all inputs) to a production process, $\mathbf{X}$ is the production vector (i.e., the sum of all inputs and external outputs), $\mathbf{A}$ is the matrix of technical coefficients, $(\mathbf{I} - \mathbf{A})$ is the technology matrix [21], $(\mathbf{I} - \mathbf{A})^{-1}$ is calculated as Leontief's inverse technology matrix [21], and $\mathbf{D}$ represents the external demand (outputs) of the process. More elaborate explanation of Leontief's model is presented in chapter 2.

Solving these equations for the process used by each agent, as well as the specified level of external demand for each agent, allowed us to identify which inputs and resources must be supplied to each agent to satisfy production demands at the lowest cost. For agents not connected to the final consumer-demand vector, the technology matrix was the most important component for an individual agent because it could be manipulated or replaced throughout the simulation either to show dynamic changes in production processes or demonstrate processes undergoing periodic variations or disruptions.

3.2.3 *Disruptions to the system*

The model described in this paper was designed to help predict the effects of disruptions on a system, as well as to predict its recovery afterward. As such, disruption generation was integral to the model. Recovery and response differed according to how and where a disruption occurred, such as when introduced to production processes or infrastructure system links. Moreover, demands from the system could change drastically, thus initiating a disruption. Real-world disruptions translate into corresponding disruption representations in our model (fig. 3.4).

A disruption in our model was designed to be non-deterministic and random, thereby influencing the workings of the system. In particular, it could affect the production process(es) of an agent(s), the infrastructure system network, demand from the system, or any combination of these. It was generated according to certain governing criteria. In the real world, disruptions correspond to natural or man-made hazards that occur within a

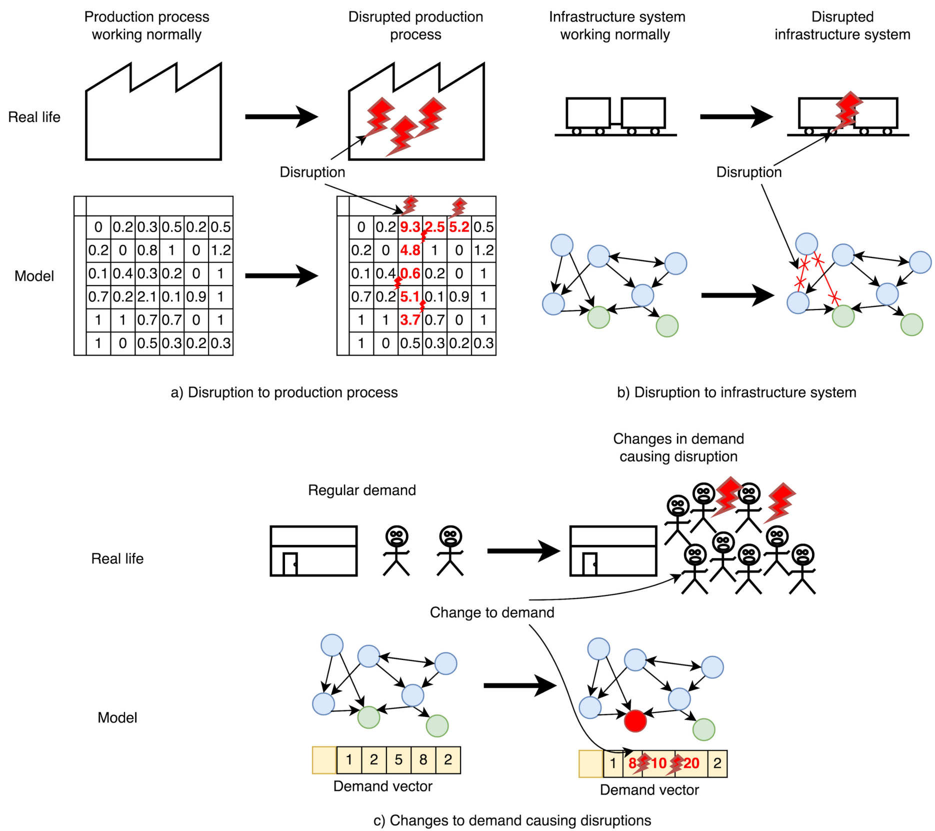


FIGURE 3.4: Three types of disruptions with their correspondence in real world: a) disruption to production process, b) disruption to infrastructure network links, c) disruption due to change in demand.

system. They can include earthquakes, hurricanes, terrorist attacks, or cascading equipment malfunctions. Here, such disruptions followed a stochastic process and were introduced as a discrete event that might then either progress or retract, depending upon the intended nature of the disruption. The system responded to the onset of a disruption by adjusting its internal workings, thus resisting the challenge. Resources were then redirected in accordance with the coordination mechanism due to changes in production, transportation, or demand caused by the disruption. A resilient system was considered one that could sustain a wide range of disruptions at a reasonable cost. In contrast, a system lacking resilience would crash or incur high costs. One purpose for our model was to assess this degree of resilience. Systems with high resilience would incur small increases of supply curve for a wide range of disruptions, while less resilience would suffer higher increase. This process would allow us to compare two or more systems in terms of their resilience. The ones with the highest increase of supply on average being the least resilient.

As illustrated in fig. 3.4 and fig. 3.5, disruptions due to failures in production processes could include broken machinery (business or manufacturer) or a faulty water faucet (household). This required changes in the relevant fields of the technology matrix. Consequently, the need might increase for some resources that were necessary to produce another resource (here depicted as a change in a column of the technology matrix). Alternatively, this could mean an enhanced demand for the same resource regardless of what was being produced (i.e., a change in a row of the matrix).

Introducing a disruption that would vary the production process's technology matrix required a thorough knowledge of that process itself. For example, a particular type of disruption might develop or certain fields within the matrix for each agent might be coupled and then be involved in the same kind of disruption.

Disruptions could also affect various aspects of infrastructure, e.g., a transportation system that experienced cuts to power lines, or failures in telecommunications links or in the process of delivering resources. These possibilities were represented in our system by removing or decreasing the capacity of links between agents, or by increasing the cost of transporting certain resources over a particular link. Such failures could induce a rise in the cost of resource distribution or, in extreme cases, a complete failure to deliver goods and services demanded by an agent. In particular, any failure introduced to edges, i.e., links between agents, could result in higher costs

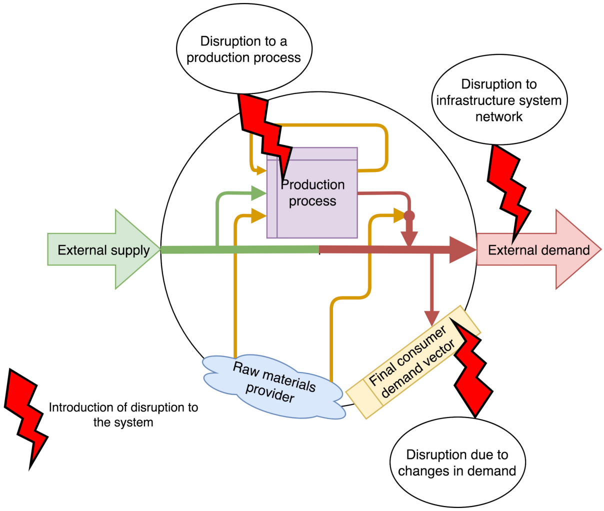


FIGURE 3.5: Types of disruptions: agent within production process (1), infrastructure links between agents (2), or unexpected (extreme) changes in final consumer demand (3).

or a total inability to deliver specific goods unless that link had not been utilized prior to the disruption.

Dynamic changes in agent demands, or the sudden need for a large quantity of one resource type, could also disrupt a system, thereby increasing the cost of that resource or even causing a system failure. Before applying the generator for any of these types of disruptions, the modeler had to understand how those infrastructure systems were linked together, which of those links were likely to fail simultaneously, how patterns of demand were shaped, and which resources an end-user might want to consume, and are the most critical.

Disruptions in the model were introduced through a random generator that followed specific principles depending upon the type of event it was mimicking. Various generators could model different events and affect different components of the system. Those generators were non-deterministic and followed processes meant to add randomness and non-linearity to the model. They could also include any possible description of the recovery process, which then alleviated the impact of that disruption based on prescribed principles that followed a stochastic process.

3.2.4 *Coordination mechanism based on pricing*

The coordination and allocation of resources between agents was based on resource prices, which were computed according to the costs to produce (C_P) and transport (C_T) both intermediary and raw materials that were inserted by providers into the system through agent interfaces. Each transportation link within an infrastructure system had a cost associated with each resource that could be moved via that link. For our model, the agent selected individual suppliers in a way that reduced the cost of producing each resource. This then minimized the overall cost of satisfying the final consumption demands of the system, and helped us calculate the costs incurred for various quantities of resources by different agents, as shown below, eq. (3.5):

$$Productioncost = C_P + C_T \tag{3.5}$$

When implemented, the model derived the distribution of production costs among agents, which could then be aggregated and averaged across all of the resources produced to render a supply curve for the entire system. "Demand" represented the willingness of a consumer to pay for a given resource. A demand curve was obtained for the entire system by aggregating the willingness-to-pay data across all consumers and all resources, which then indicated the overall distribution of consumers' willingness. By overlaying these two curves (fig. 3.6), we can identify the point of equilibrium for producing resources in terms of quantity and price. Our proposed model then allowed us to shape the supply curve by varying the final consumer demands in the simulation. By manipulating the quantity of final resources produced by each consumer agent we shaped the distribution of production costs across different final consumers, thus obtaining the supply curve for the system. However, our model did not enable the derivation of the demand curve.

3.2.5 *Implementation of the system*

The simulation was developed in Python 3.5.0, and was run and evaluated under Anaconda 2.4.0 Python distribution [106] on the Mac OS Yosemite 10.10.5 operating system. This network simulation and implementation was supported by the *igraph* library, version 0.7.1 [107]. Linear algebra operations were performed using the *numpy* library, version 1.10.1 [108]. The networks were stored in the Graph Modelling Language format. Results

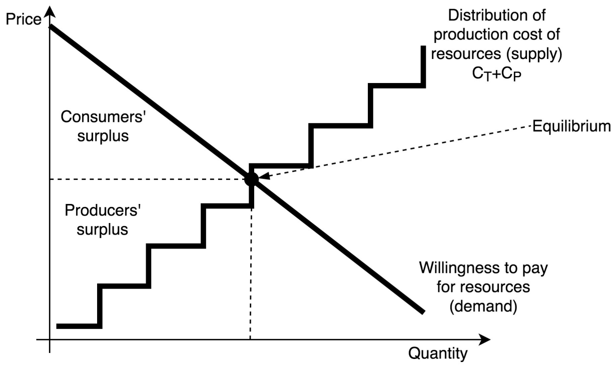


FIGURE 3.6: Demand curve represents distribution of willingness by consumers to pay for resources. Supply curve represents assignment of production costs across consumer agents. Production costs correspond to transportation cost for intermediate resources (C_T) + cost to obtain intermediate resources (C_P). In proposed model, supply curve can be derived, and overlaid with demand curve to identify equilibrium of system in terms of quantity and price of resources.

were displayed with an interfacing web page developed in JavaScript and HTML, using the *CanvasJS* library [109] to visualize the flows of goods and services and changes in costs in the form of dynamic bar charts.

System development followed the complementary modules presented above. For example, the pricing mechanism selected incoming edges with the lowest costs for resource delivery while the production process was solved using linear algebra libraries to define the required inputs to the agent based on required outputs and costs associated with resource production. Those costs were then dispersed to the outgoing edges. For an individual agent, interfaces were arranged between the providers of raw materials and the final consumer-demand vector, all of which could be easily adjusted. Disruption generators followed a stochastic process that changed technology matrices, edge parameters, and final consumer demands accordingly to simulate those interruptions.

This system was evaluated under different network topologies and various agent parameters with several disruption simulators. It was initially tested with an extremely small network size of only three nodes that exchanged only three types of resources and ignored the capacity of the links. This sample system is shown on fig. 3.7 with clearly marked matrices of technical coefficients, transport cost vectors, a provider of raw materials,

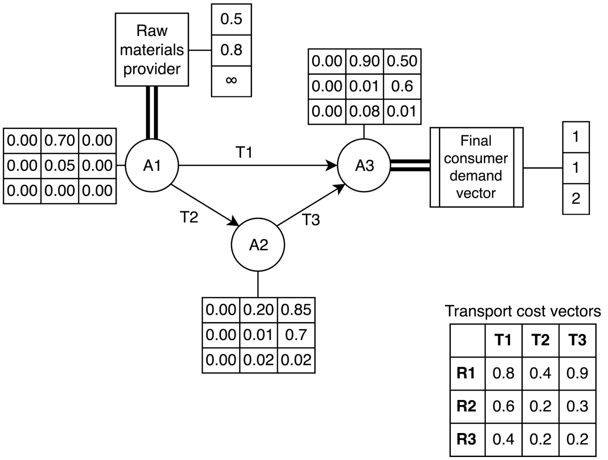


FIGURE 3.7: Initial validation of model. Sample system consists of 3 nodes connected with 3 links transferring 3 types of resources. Transportation cost vectors are shown in small tables on the figure. Matrices of technical coefficients appear next to nodes. One agent is connected to final consumer demand; another, to provider of raw materials.

and a final consumer demand vector. Under such a scenario, the system distributed resources as expected, i.e., in line with the price mechanism. There, resource $R3$ was to be produced by agent $A3$, and $R2$ by $A2$. This was exactly how the system did perform. Resource $R1$ was introduced as raw material to $A1$. Similarly, resource $R2$ could have been introduced as raw material to $A1$, but it was more efficiently produced by $A2$. Because the system reflected this as expected, it passed this simple validation. The response to basic disruptions by such a small system was also analyzed after introducing a disruption scenario (full break within link $T2$ and an increase in matrix values for $A1$ in fig. 3.7). It also involved randomly generated disruptions. The system again performed as expected, decreasing in performance when disruptions were introduced correspondingly to the perceived severity of disruption, and recovering when disruptions were subsequently removed. Moreover, the system could be easily integrated with various disruption generators. Likewise, the providers of external raw materials and models of final consumer demand were easily integrated into the system with a clear interface.

For slightly larger systems, such as the system under investigation, the outcome could not always be so easily identified analytically. Consequently, we conducted a limited validation that tested whether the allocation of resources and the path that these resources followed throughout the network was indeed optimal. For this, the system passed the validation. However, for larger systems and random, non-deterministic components and disruptions, it would have been impossible to perform conclusive testing because, except for extreme cases (e.g., intentional breakdown of the system) where SoS-wide expectations and measures of performance would be clear, we could only broadly define the expected outcome here. The difficulty of validating and testing an SoS might be attributable to trouble associated with assessing expectations, and the metrics of those expectations, for the system. Even when they can be defined, such testing can be difficult in a conventional sense [110]. Likewise, in this case, the theoretical outcome of disruptions was not known beforehand because the very purpose of the simulation was to assess that outcome. If that result had been easy to obtain prior to the disruption, then the SoS simulation would have been redundant. Hence, validating the system under larger test-case scenarios was performed qualitatively, based on whether a more-complex system would respond to disruptions in a similar fashion to the very small scenarios of just three nodes.

3.3 simulation experiment

We designed and ran a 3x3 factorial simulation experiment to explore the validity of our model. The consequences of predefined disruptions were assessed using cost as the main measure of performance.

3.3.1 *System under investigation*

As proof of concept, we developed a small-scale simulation of this proposed model applied to an abstract geographic area that represented a single block of streets in an urban setting (fig. 3.8). This area incorporated a network of household and business agents connected by links through infrastructure systems. Those links supported the transportation of resources between agents that then performed production processes. By assigning parameters to each component of the system, we defined a technology matrix corresponding to a production process for each agent. This network also included transportation cost vectors for each link. After establishing the raw-material providers and final consumer-demand vectors, we generated disruption scenarios to simulate how system performance might change under such circumstances.

The network comprised 14 agents, i.e., eight for households and six for businesses, that might be found within one block in a certain urban neighborhood (fig. 3.9). The role of each agent was to represent particular type or types of businesses or household in the particular location. The business agents either were individual companies or else they aggregated several, multi-functional businesses in the same location, the latter type serving as a single simulation agent. For each location the household agents represented units with unique population characteristics, differentiated by income level. Agents exchanged resources with each other through 16 edges that stood for the infrastructure links between those households and businesses. The system simulated the exchange, transportation, and production of six different resources: electrical power, water, gas, petrol, capital goods, and consumer goods/services. These resources were selected as the most important to urban areas and covering as many infrastructures a possible to ensure the widest coverage of interdependencies between infrastructures and socioeconomic units. Electrical power is vital to almost all production processes and to survival of households that need electricity to operate technology and to perform all tasks. Water is likewise crucial to survival of cities, where cities cannot last longer than few days when water supply is restricted. Similarly, gas and petrol are crucial to transportation and many business processes, as well as heating of households. Consumer and capital goods represent the products of businesses that are consumed primarily by households or businesses respectively. Consumer and capital goods are at the heart of modeling interdependencies of businesses, households and infrastructure systems.

In the network, two agents were attached to the providers of raw materials, thus allowing us to introduce new resources without undergoing another production process. Those resources were capital goods and petrol (agent $A0$); and water, gas, and electrical power (agent $A1$). Nine agents ($A5$-$A13$) were connected to the final consumer-demand vectors. They included eight for households and one for a business (i.e., company). All 13 agents were also permitted to produce certain resources as necessary. The rules for generating output resources, based on input resources, are listed in table 3.1, as they applied to a single agent ($A2$), while the various specifications of roles for these agents are displayed in table 3.2. Table 3.1 is just an example, full specification of all matrices of technical coefficients is presented in appendix A. These specifications are based on agents' roles as

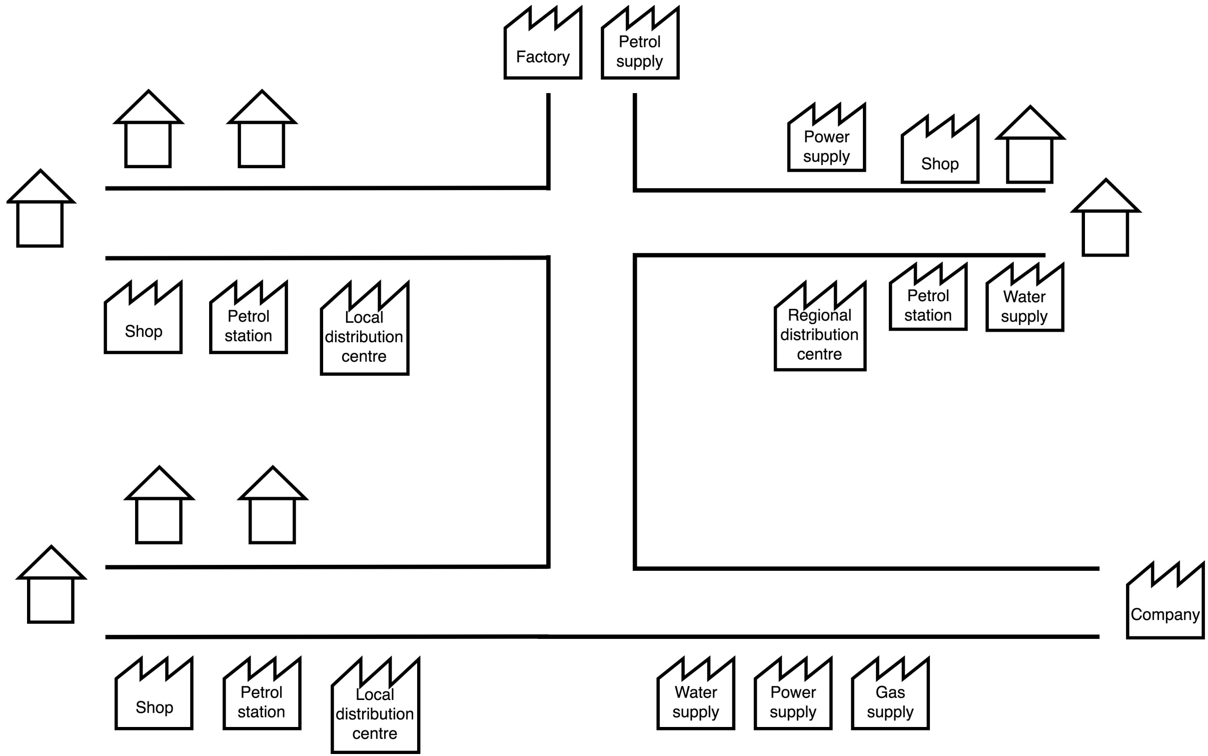


FIGURE 3.8: Case study for simulation experiments involving single test block within urban geographical area comprising interconnected households, businesses, road network, and suppliers of electrical power, water, gas, and petrol.

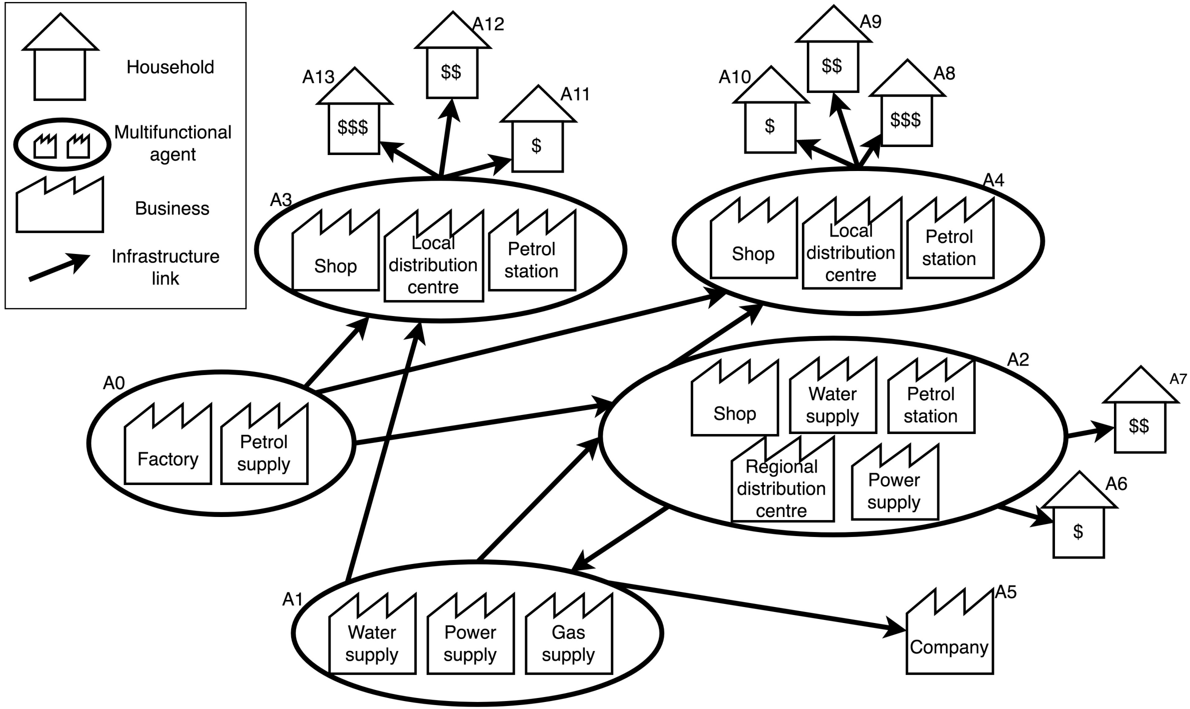


FIGURE 3.9: Case study of simulated system covering 6 types of resources (capital goods, consumer goods/services, water, power, gas, and petrol) transported over 16 infrastructure system links (roads, gas pipes, power lines, and water pipes) between 14 business and household agents. Different businesses at same location are grouped into aggregate multifunctional agents. Households are differentiated according to distinct demographic properties, here marked by $ signs signifying income levels.

can be seen from fig. 3.9. Consequently, matrices of technical coefficients differed among agents. These matrices were devised to reflect a real-world concept that the production of most resources involves a relatively large quantity of one resource and smaller quantities of other resources (cf., table 3.1). The actual numerical values are secondary to the outcome of this study, the relative magnitude of values is important and the change of these values, when a disruption is introduced. The matrices reflect production of resources as per fig. 3.9, where certain agents produce goods utilizing other goods, and certain agents just consume them. These follow the principle that most production utilizes primarily one resource with some additional inputs from other resources. Example of a matrix of technical coefficients constructed from fig. 3.9 following these principles is shown in table 3.1. Some households were also able to produce certain goods as is normal due to domestic workers or household production. Each link in the system was assigned a vector to define its associated transportation cost and capacity. This was also done with the principle that commercial links have cheaper operating cost per unit than consumer links. Similarly, the actual numerical values are secondary for the purpose of this study, as their intention is to show relationships between agents and infrastructure links, and the relative impact of disruptions. In all, agents could use up to six resources in their production processes and could produce up to six types of resources.

In choosing this particular topology as a prototype case study of our model, we were guided by principles meant to mimic a small system representative of a real-life geographical block in an urban area. As stipulated above (cf., fig. 3.9), only agents $A0$ and $A1$ were allowed to introduce raw materials into the system, while three business agents – $A2$ through $A4$ – performed the task of producing resources without the ultimate consumption of any goods. The largest group of agents ($A5$-$A13$) served as the final consumers, corresponding primarily to households or end-user businesses. The producing agents were connected with infrastructure system links to form a loop between them and to provide them with a choice of suppliers. This demonstrated the main functionalities and situations that the model might face in real-life scenarios, e.g., a wide selection of suppliers or the co-dependency found among businesses.

The system is physically reasonable and aims to mimic adequately the outline of socioeconomic units presented in the case study shown on fig. 3.9. The values of matrices of technical coefficients, such as the one presented in table 3.1, for each agent represent the amounts of individual resources

TABLE 3.1: Example matrix of technical coefficients of producing agent A2. Columns show amounts of resources needed to produce one unit of corresponding resource. In this case the agent is capable of producing power, water, and consumer goods and services. All matrices are presented in appendix A.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0.18	0.90	0	0	0	0.20
	Water	0.30	0.10	0	0	0	0.30
	Gas	0.76	0.10	0	0	0	0.40
	Petrol	0.30	0.08	0	0	0	0.30
	CapG	0.14	0.05	0	0	0	0.20
	CG&S	0.10	0.05	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

required for a production of each resource by each agent's production unit. The choice of numerical values for the matrices was done based on needs of production processes that were to take place within each agent. The relative values were selected based on expert opinion inputs from infrastructure engineers and economists. These values were selected to ensure that close correspondence with the case study was maintained, particularly in terms of relative importance of resources for specific production processes. Since the key relations between the systems were of primary interest in this work, the exact numerical values used and represented in the table were secondary to the study. Consequently, we focused on adequately representing the key relationships between production processes. An assessment of physical reasonableness of the system is presented in appendix A. The relations of numerical values of matrices of technical coefficients in the base case system correspond to respective relations in real-world production processes undertaken by the agents and shown on fig. 3.9. The justification and motivation for the use of particular numerical values for each of the agents are explained in more detail in appendix A alongside tables corresponding to each agent's matrix of technical coefficients. The system is shown and justified to be physically reasonable for the base case scenario.

TABLE 3.2: Specifications of system flows: S, supply of raw materials; I, input for production process; O, output from production process; and C, final consumer demand.

		Resource					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
Agent	**A0**				S	S	
	A1	SIO	SI	SI	I	I	I
	A2	IO	IO	I	I	I	IO
	A3	I	I	I	I	I	O
	A4	I	I	I	I	I	IO
	A5	IC	IC	IC	IC	IC	OC
	A6	IC	IC	IC	IC	IC	OC
	A7	IC	IC	IC	IC	IC	OC
	A8	IC	IC	IC	IC	IC	OC
	A9	IC	IC	IC	IC	IC	OC
	A10	IC	IC	IC	IC	IC	OC
	A11	IC	IC	IC	IC	IC	OC
	A12	IC	IC	IC	IC	IC	OC
	A13	IC	IC	IC	IC	IC	OC

a CapG - Capital goods
b CG&S - Consumer goods and services

A system supply curve was derived by first setting the aggregate total demand and then measuring production costs aggregated across all resources for each consumer agent. This allowed us to shape the curve and determine the distribution of production costs across the final consumer agents for each scenario.

The above mechanism was implemented for various disruption scenarios to monitor possible changes in the supply curve and system performance. This was quantified with a metric to examine the cost of satisfying the system in response to a disruption. For purposes of comparison, we initially ran the system at normal operating capacity, without any disruptions. Final consumer demands were fixed and data were collected to estimate the cost of producing resources across all agents. After obtaining this default supply curve, we introduced eight different types of disruption, repeating the above process each time to acquire new supply curves for individual scenarios.

3.3.2 *Layout of the simulation experiment*

The 3-by-3 factorial layout is shown in table 3.3. For each scenario, the distribution of production costs served as our metric of performance. In developing our model, we predicted that the cost of producing the same quantity of resources would rise due to the increasingly negative impact of a disruption on the system. This layout was the smallest that could be applied for testing the features of our model prototype, i.e., confirming the effect of a disruption and revealing the emergent behavior of the system when multiple scenarios were combined. Its size was sufficient to understand the model and provide a convincing example of how it could be used by the scientific community and practitioners.

3.3.2.1 *Disruption scenarios affecting infrastructure links*

In Scenarios 1 and 4, we destroyed certain key connections between agents to simulate a disruption to infrastructure system links that would not inhibit the production processes themselves. These situations corresponded to, for example, a hurricane or a blizzard. In Scenario 1 (medium intensity), we introduced disruptions to two infrastructure system links between the agents (i.e., from $A0$ to $A3$, and from $A0$ to $A4$). This was done by setting the cost of transfer to infinity and the capacity to 0 for all resources. Hence, no resources could be moved through those links. This simulated a breakdown in infrastructure systems that prevented the passing of goods and

TABLE 3.3: 3x3-factorial layout for eight experimental scenarios of varying impacts compared with base conditions (normal operations). Scenarios 1 and 4: disruption to infrastructure system but not to production processes; Scenarios 2 and 6: disruption to production processes but not to infrastructure system; Scenarios 3, 5, 7, and 8: disruptions to both infrastructure and production processes.

		Production process disruption		
		None	**Medium**	**Heavy**
Infrastructure systems disruption	**None**	Base scenario	Scenario 2	Scenario 6
	Medium	Scenario 1	Scenario 3	Scenario 7
	Heavy	Scenario 4	Scenario 5	Scenario 8

services between households and businesses over a certain route that otherwise would be available. In Scenario 4 (heavy disruption), we additionally increased the costs for transporting all resources over an infrastructure link (from agent $A2$ to $A1$). This simulated a disruption in which only transfer costs were higher over a certain link.

3.3.2.2 *Disruption scenarios affecting production*

In Scenarios 2 (medium disruption) and 6 (heavy disruption), we introduced system-wide changes that would only alter the amount of resources needed by the agents to produce other resources. Those disruptions were achieved by modifying the matrices of technical coefficients for agents $A1$ through $A5$. The scenarios corresponded to situations in which a household or business suffered a malfunction, such as a labor strike or equipment failure. Hence, the demands for inputs by the affected agents changed, along with the inputs into the system overall. Consequently, the agents' inputs increased because their processes required more resources to produce the same quantities of resources as before. Because its disruption was greater, Scenario 6 incurred larger changes in its matrices of technical coefficients.

3.3.2.3 *Disruption scenarios affecting infrastructure links and production*

Scenarios 3, 5, 7, and 8 featured all combinations of concurrent disruptions to both the infrastructure system links and the agents. The matrices were modified for the agents while cutting the links so that production processes malfunctioned simultaneous to the breakdown of infrastructure systems. This mimicked a real-life, direct interruption that might affect the transportation network as well as some households and businesses, causing the movement of resources to be re-routed, such as due to an earthquake or a terrorist attack. Under such conditions, agent demands would likely also increase because production processes would have required more input resources to produce the same amount of output.

3.3.3 *Simulation results*

We set the aggregate quantity of resources produced, represented by the aggregate final consumer-demand vectors (table 3.4), to be the same for each scenario. Those selected vectors corresponded to consumers with different demand requirements. We wanted to achieve a situation where each final agent consumed at least a portion of each resource (some in large amounts, others in small quantities), thereby depicting a wide range of consumption patterns. Our primary goal was to exhibit a range of final consumer agents with different characteristics. Fixing the aggregate quantity of resources produced allowed us to obtain the cost distribution for supplying resources across agents in response to each type of disruption. Those costs shaped the supply curve of the system under each disruption scenario. However, the distribution of types of resources produced still varied among agents. The actual numerical values corresponding to demands are secondary to their relative differences and changes due to disruptions being introduced. We were primarily concerned with analyzing impacts of disruptions relative to other disruptions, and the response of the system to these.

The aggregated demand selected was reasonable and representative of a small community. As we are primarily interested in the relations between the systems and agents, the specific numerical values are secondary to the study. The relationships between different agents corresponded to a real-world, small community. When deriving the exact numerical values, we followed principles which were agreed with experts on particular infrastructure systems and economists. The numerical values were derived with the following principles in mind, which were devised to ensure adequate representation of a small community in our model. The agents consume amounts of resources in similar amounts and there is no large order of scale differences. Less wealthy households consume less resources than the wealthier households. Business agent consumes the most resources. The

TABLE 3.4: Final consumer-demand vectors used in simulation experiments to derive supply curves for each scenario. Columns: vectors corresponding to agents (A) with final consumer demands; Rows: amounts demanded for respective resources.

	A5	A6	A7	A8	A9	A10	A11	A12	A13
Power	21.75	7.75	9.75	12.75	9.75	8.75	7.75	9.75	14.75
Water	15.75	6.75	8.75	10.75	9.75	7.75	8.75	10.75	12.75
Gas	14.75	4.75	6.75	9.75	8.75	5.75	5.75	9.75	10.75
Petrol	18.75	9.75	10.75	12.75	9.75	8.75	9.75	11.75	13.75
CapG[a]	18.75	3.75	4.75	9.75	7.75	4.75	3.75	5.75	7.75
CG&S[b]	20.75	10.75	15.75	17.75	12.75	9.75	10.75	13.75	14.75

a CapG - Capital goods
b CG&S - Consumer goods and services

consumption of water and power is the greatest by households alongside consumer goods and services. For a business consumption of gas, petrol, and power is the greatest alongside capital goods. The above principles are reflected in the consumer demand vectors, shown in table 3.4, which were derived for use, and subsequently used in the simulation experiment.

The aggregated demand distribution reasonably represented a small community and its constituent units. Agents corresponding to socioeconomic units had varied demand patterns, however, their magnitudes were similar within each socioeconomic category. This represented a small community accurately because in such small communities, we also see similar magnitudes of demands, however, with slightly different demand profiles. These 9 agents allowed us to explore different profiles of demands for consumers and accurately represent a small community consisting of 8 households and a final consumer business.

Under all scenarios, the supply curve shifted upward, and its shape changed (fig. 3.10). This reflected the increased costs of producing the same level of resources when compared with normal operations. Whereas we had expected this upward shift in response to a disruption, we could not predict how the curve shape changed under our test scenarios. For example, the curve associated with normal operations was relatively flat but became steep as the production quantity rose. In contrast, the curve under Scenarios 1 and 4 (disruption only to infrastructure links) was flat and initially overlapped with the no-disruption-scenario curve. It then showed

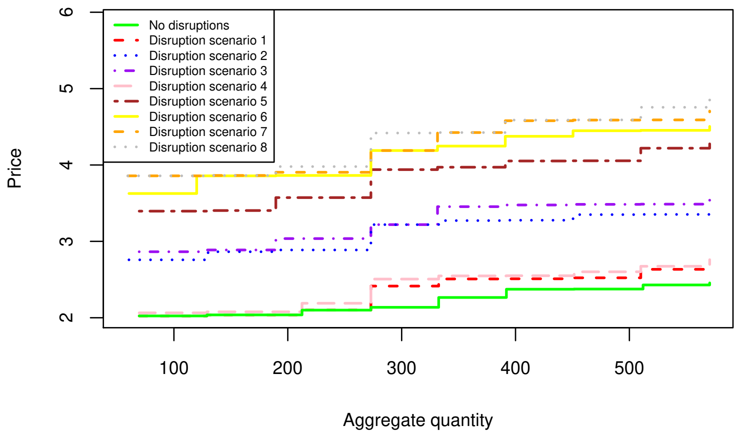


FIGURE 3.10: Cost of providing additional units of resources in response to system disruptions. Curves indicate prices based on given aggregate quantity of goods and services produced under various scenarios. Upward shifts in curves demonstrate higher costs associated with introduction of disruption.

a larger increase before flattening out as the aggregate quantity increased. For Scenario 2 (medium disruption, only to production processes), the supply curve again shifted upward, signifying the rising cost to produce the same quantity of resources as under normal conditions. This shift was significantly larger than that revealed by Scenarios 1 and 4 but was still smaller than that found under other scenarios. The shape of the curve also changed drastically, being flat for low quantities but becoming steeper in the middle and again flattening toward the end. Similarly, in Scenario 6, the shift was significantly larger than in Scenario 2. This signified the strong impact that malfunctions had on production processes.

The most dramatic change was associated with the introductions of Scenarios 7 and 8, in which both infrastructure and production processes were severely affected. When compared with normal operations, the significant upward shift in the supply curve corresponded to a major disruption in multiple parts of the system. This movement clearly indicated the severe impact these disruptions had on the system, which led to a rise in costs.

TABLE 3.5: Total costs to satisfy aggregated final consumer demand from system – normal conditions versus various disruption scenarios – for two demand configurations.

	Total cost under disruption scenario no.:								
Aggregated final consumer demand from the system	**None**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
44	98.6	100.3	148.9	150.0	104.6	179.9	186.8	188.0	199.2
570.5	1277	1348	1798	1866	1383	2213	2378	2446	2491

The consequences of Scenarios 3, 5, 7, and 8 differed from those detected when only single impacts were combined. These findings demonstrated the significance of emergent behavior in our model, where failure to both infrastructure links and socio-economic units resulted in a disruption that was larger than the sum of disruptions to those components individually. The variations among curves in our model helped elucidate how an administrator might limit the quantity of a critical resource distributed to the population suffering a disruption so that one would not exceed the maximum cost that could be borne by the society. Those variations also could be used to assist in managing demand to ensure the delivery of a critical resource to the population.

We also applied other measures of performance in these experiments, assessing the total cost of satisfying the demand from the system based on a given configuration of final consumer demand from each particular node. The total cost of satisfying the system is the sum of costs across all agents. This entailed recording how a system would respond to a third type of disruption, that is, one that altered patterns of consumption. Table 3.5 presents the results when this metric was used for two different configurations under the eight disruption scenarios as well as during normal operations. The total cost of disruption was a sum of all the final demand vectors multiplied by the cost per unit of resource at the final consumer agent aggregated across all the agents and all the resources i.e. it was an aggregation of the final production cost of all resources across all agents.

Finally, performance was assessed as a percentage (fraction) of the demand that a system could provide under a particular disruption as compared with demand provided by an unstressed system at a given price. This represented the degradation of system performance from the basic scenario due to an introduced disruption. According to this metric, a price of 3.8 units was associated with 100% performance (i.e., 100% of demand satisfied) under normal, non-stressed conditions and also in Scenarios 1 through 4, versus only 33% performance under Scenario 5, 11% performance under Scenario 6, and 0% performance under Scenarios 7 and 8. This meant that, at a price of 3.8 units under Scenarios 7 and 8, the network completely ceased to function because it could not satisfy any of its demand at that price. Such a metric would appear to be useful in situations where the demand for resources is elastic and can be managed while supply is the main market force. Other available metrics might include calculating the percentage of the original price that the consumers would have to pay for the same quantity of resources after a disruption.

Analysis of fig. 3.10 revealed differently shaped supply curves for each scenario, an indication that those disruptions affected the system and agents in contrasting ways. We found this interesting because it suggested that the model could present not only general shifts in the curves but also changes in their shapes in response to system disruptions. This variability among curves was also closely related to the topology of the system. Hence, one limitation of our experiment was that it was performed under a single, defined topology. Although in scenarios where infrastructure links were disrupted, this topology was transformed into another by removing the edges, the base topology remained unchanged. Modifying the network topology and then performing the experiment with a completely different topology would likely have a significant impact on the shape and placement of those supply curves.

A simulation's runtime performance is affected by the size of the network and the number of resources included in the system. The problem is scalable because computation of each node is independent and can be distributed. Similarly, after each such computation, information is exchanged through network links. For larger networks, however, that exchange, or system synchronization, can require a significant amount of time. To accommodate that challenge due to size, households and businesses can be aggregated for a certain area or sector based on criteria of similarities or orthogonality between these units, e.g., location, income, health, or age (for households and locations), or the type of business (for company agents).

Those aggregated, multifunctional agents are then worked into the network. Thus, scalability of the simulation is preserved at minimal expense to accuracy of the simulation under certain assumptions.

3.4 CONCLUSIONS

The purpose of this study was to (1) develop an agent that mimicked the metabolism of a business or a household obtaining supplies from and providing output to infrastructure systems; (2) implement a network of agents that exchanged goods and services, as coordinated by a price mechanism; and (3) test the response of this prototype system to disruptions.

We achieved three main outcomes. First, we developed an agent that applied Leontief's input–output model to describe metabolism of business and household units. Under the model, production was represented as the transformation of supplied goods and services into output goods and services. The former included those supplied by infrastructure systems and by the production processes of other business and household units. In our simulation model, the agent also interfaced with providers of raw materials and with final consumer demands.

Second, in developing our proof-of-concept simulation model, we set up a network of agents that utilized a price mechanism to coordinate the allocation of goods and services in an adaptive way when the self-organizing system was disrupted. The network edges constituted lifeline infrastructure systems joining agents together to represent interdependencies as flows of critical resources. The resources were dynamically assigned to agents based on production and transportation costs in an attempt to satisfy agents' demands. In our model, price increases signaled increased disruption magnitudes. This scalable distributed model could be used with a varying number of resources and agents.

Third, we conducted simulation experiments to assess the feasibility of the model under normal operating conditions and also after introducing disruption scenarios that affected infrastructure system links, production processes within agents, or several combinations of the two. This allowed us to test our theoretical model under a simple abstract prototype application that corresponded to an urban setting. In order of impact, the situation in which both components (infrastructure system links and socio-economic agents) were influenced was the most damaging, followed by the scenario that interrupted only production processes. The experiment yielded that concurrent disruption to water and power providers and their supply network was the most severe. Moreover, the experiment emphasized the emergent nature of disruption impacts.

In our new approach, we utilized Leontief's input–output model to represent a network of individual agents, and monitored their interactions when combined into a system-of-systems. Previous researchers tended to focus on modeling individual infrastructure systems and their resilience [111][112][113]. Others, such as Rinaldi et al. [4], described the interdependencies among infrastructure systems and showed how they could be thought of as flows. In contrast, Furuta et al. [114] portrayed those interdependencies that exhibited within a network of infrastructure systems as an SoS model. However, none of those studies included models of interactions between socio-economic units and infrastructure systems. Therefore, our proposed strategy is unique in that it combined a model of household and business agents with a model for a self-organizing distribution network of goods and services, i.e., infrastructure system, between those agents. In doing so, our model could differentiate between population groups and types of businesses, a feature omitted in regional-level models.

Our self-organizing adaptation of the model to disruptions, as presented here, is novel. Cascading failures that are propagated through several infrastructure systems and their components have already been examined [79]. Kotzanikolaou, Theoharidou, and Gritzalis [115] have analyzed the interdependencies among infrastructure systems to measure the impact that such cascading failures might have. Likewise, Rinaldi and colleagues [4][86] have investigated interdependent infrastructures in an effort to improve their understanding about model failure and its influence on those systems. These topics are of great concern to governments, businesses, and the public [116] and we have now expanded upon the results from those earlier studies to develop a self-organizing mechanism for adaptations to disruptions.

Since its first mention by Leontief [12], the input–output model has been applied to describe the production of resources by geographical area in economies [117]. It has also been utilized to investigate the inoperability of interdependent economic sectors due to infrastructure disruptions [30][118]. In the field of supply-chain management, this model has been used to determine different production processes within a business [27][105][95]. By implementing it with agents to simulate those processes by a business or a household, we have confirmed that Leontief's model is effective when extended to the interfaces that an agent might have with suppliers of raw materials, final consumer demands, and even other agents.

The results of our work have several implications for scientists, policy-makers, infrastructure designers, and businesses. For scientific endeavors, the model presents a scalable approach to evaluating infrastructure systems, their interactions with households and businesses, and the impact(s) that disruptions have on systems at a household/business level of granularity. Members of the scientific community could use the model to determine how different demographics are affected by those disruptions. Policy-makers can employ this as a support tool to aid in making crucial decisions about infrastructure development, real-time assessment of the impact of disruptions, or the creation of contingency plans against future disruptions. Including households and businesses in the analysis allows planners to understand the population groups that are most affected by different types of disruptions because our model can illustrate the impact that disruptions have on the most vulnerable groups within a society. Decision-makers will also gain a greater understanding of how disruptions affect a company, based on regional characteristics as well as on its specific type of business.

For practitioners, this tool can be applied for stress-testing and assessing their systems, or for designers who can compare topologies and different components within a system. The model can assist in examining different topologies, introducing redundancy or more capacity/lower price to various components of the network, and then estimating the impact of these under disruptions. This in turn can help in making decisions as to where a system needs reinforcement or available infrastructure investment resources should be allocated. The costliest vulnerabilities to a system can be identified according to established criteria, based on data collected from an analysis of that system when challenged with a wide range of randomly generated disruptions. Performing such experiments enables planners to predict the value at risk for the system as well as the potential costs associated with the most devastating vulnerabilities. Ultimately, the results of a simulation implementing our model might be used in determining, for example, where to build a bridge or how to expand a power grid.

The importance of demand management has been noted in the literature [119][120]. Our model can help users understand the response of a system to disruptions under different demand conditions and detect the impact that managing demand has on the cost of satisfying the system. The model can help to manage demand to ensure the delivery of critical resources and services under disruption, when resources are limited.

Finally, this model can be applied to studying the effects of business discontinuities, such as those that arise due to shortages or an increase in the price of resources. Those findings can then be incorporated into business contingency-planning.

The primary limitation of our experiment was the use of only one topology for testing, which may have influenced model performance. Different infrastructure systems have different topologies that vary with each other, hence duality with the real world was not necessarily fully preserved. Furthermore, disruptions in real-life scenarios can vary widely, and our selection of only eight scenarios and disruption logic could not cover all possible cases of system failures, which can vary and be domain-specific. In addition, resource allocation might not always follow the lowest cost source. Our experiments did not consider regulatory frameworks or other social factors that can affect the delivery of resources. However, the theoretical model could take these factors into account through different cost functions. In real-world settings, production can, of course, be more complex and involve non-linear factors that cannot be easily described with an input–output model. However, linear models presented in this study present sufficient approximations of production processes. The transportation and supply of raw materials, as well as final consumer demands, can also be non-linear, making them more complex than the linear models and scalars that we employed when evaluating our prototype. However, the approximations presented in the small-scale prototype are appropriate for such models.

Several challenges were identified here that require further examination. Proposed projects might involve extending experiments to evaluate the model under additional topologies to investigate the impact of network topology on the systems, or expand upon the mechanism for resource allocation. In particular, for emergency scenarios, mechanisms other than cost are often employed for such allocations. Future research could also consider a wider range of disruption logic and scenarios that provide better coverage of actual situations. More mechanisms could be included for defining raw material inputs and final consumer demands in the system. This would also correspond more closely to real-world challenges.

4

TIME GRANULARITY IMPACT ON PROPAGATION OF DISRUPTIONS IN A SYSTEM-OF-SYSTEMS SIMULATION OF INFRASTRUCTURE AND BUSINESS NETWORKS[1]

The true logic of this world is in the calculus of probabilities.

— James C. Maxwell

This chapter is based on and includes work submitted for publication in Sustainable and Resilient Infrastructure.

4.1 INTRODUCTION

Development of new technologies results in infrastructure systems becoming more interdependent thus introducing additional complexities. These systems require and produce inputs and outputs not only for internal use by the systems themselves, but also for other infrastructure systems and businesses. Often, those businesses also provide infrastructure resources that are then delivered over a systems network. Along with these heightened interdependencies, systems disruptions are increasing in both magnitude and frequency. This is especially visible within the context of urban settings, where various interdependent systems are vital to the survival and normal operation of a society [2]. As a result, the design and development of infrastructure systems must be done in a way that ensures they are resilient and can sustain a large variety of disruptions. While a major concern of designers is the proper response to disruptions, planners and

1 This chapter is based on the following publications:

1. Dubaniowski, M. I. Heinimann, H. R. Time granularity impact on propagation of disruptions in a system-of-systems simulation of infrastructure and business networks. *Sustainable and Resilient Infrastructure*, 1st Revision (2019).
2. Dubaniowski, M. I. Heinimann, H. R. *Time Granularity in System-of-Systems Simulation of Infrastructure Networks* in *Complex Networks and Their Applications VII - Volume 1 Proceedings The 7th International Conference on Complex Networks and Their Applications COMPLEX NETWORKS 2018, Cambridge, UK, December 11-13, 2018.* (eds Aiello, L. M., Cherifi, C., Cherifi, H., Lambiotte, R., Lió, P. Rocha, L. M.) (Springer, 2019), 482.

policymakers must recognize how disruptions emerging in one system can affect other systems, and how disruptions propagate from one system to another.

Currently, however, there is insufficient understanding about how such propagation of disruptions between systems occur. To understand this, simulations and models of infrastructure systems are often run to predict how systems behave under a disruption. Although the effect of a propagated disruption on a simulation is affected by many factors, the extent to which modeled environments are influenced has not been adequately studied. For example, while time granularity of a simulation is one crucial factor, no comprehensive research has been conducted on how it might affect a propagation of disruptions between infrastructure systems and businesses within a system-of-systems (SoS) framework. Therefore, the practical value of such simulations is diminished, as well as their correspondence to real-world scenarios. Consequently, understanding the impact of time granularity on propagation of disruptions is vital if we are to determine how such disruptions affect societies.

Although models have been designed to examine interdependencies among infrastructure systems [82][4][121], they have not considered the issue of time granularity and how it influences the propagation of disruptions between systems under an SoS simulation. Current investigations include separate analyses of individual systems, e.g., traffic simulation [43], water supplies [84], or power grids [111]. However, only single systems have been involved there, thus constraining those analyses that might address simultaneous disruptions to several infrastructure systems. Another stream of research, utilizing SoS simulations of infrastructures [46][79][91], does not focus on modeling disruptions or ensure the accurate capture of their propagation. In contrast, Dubaniowski and Heinimann [122] have examined the impact of time granularity on infrastructure systems. However, their study has not considered businesses or the impacts of disruption size and recovery time on the propagation of disruptions. Furthermore, an SoS model of infrastructure systems within an urban ecosystem, where disruptions are introduced [91], has limited applicability because it does not account for the propagation of those disruptions, and does not provide for many variations based on time granularity of the simulation and different types of disruptions.

The objectives of our study described here were to develop a distributed system-of-systems model of infrastructure systems and businesses to: (1) study the effects of different disruption characteristics on propagation of disruptions between constituent systems; (2) investigate how time granularity of distributed model can affect propagation of disruptions in the model; and (3) develop a model for selecting the most appropriate time granularity of an SoS distributed model based on expected disruption parameters. In particular, our goal was to investigate how time granularity of a simulation, as well as the size and recovery time of a disruption to a theoretical constituent network – water supply – might propagate and affect the outcome for businesses that are networked within the simulation. Our expectation was that time granularity would have the most significant impact on the propagation of disruptions. For this study, we did not consider a variety of networks or how their topology might affect the propagation of disruptions. The cause of the initial disruption was also outside the scope of this study.

4.2 MODEL SPECIFICATION

4.2.1 *Conceptual framework – system-of-systems of infrastructure systems*

Frameworks and methodologies have been established to model individual infrastructure systems and businesses, e.g., power or water supplies, transportation, emergency services, or financial systems. Those models correspond only to individual infrastructure systems, and are independent and autonomous in the way they represent each separate system. However, in reality, these systems are interconnected due to various interdependencies among infrastructure systems and the businesses to which they deliver. For example, water supply systems are heavily dependent on a power supply to operate their pumps, and emergency services rely upon both power and water to run hospitals that treat sick people. Those people must also be moved to and from hospital over transportation networks.

The interdependencies between infrastructure systems and businesses can be modeled in an overarching framework. The SoS approach models individual systems as being autonomous in their internal operations, but at the same time connected with and affected by other systems [46][123][91]. Therefore, that approach considers both inter- and intra-system interdependencies. In such a framework, infrastructure systems and businesses are standalone models, while the interdependencies between them are simulated as lifeline connections (fig. 4.1). Those lifelines provide vital infrastructures and businesses with access to network systems, thereby mimicking their interdependencies.

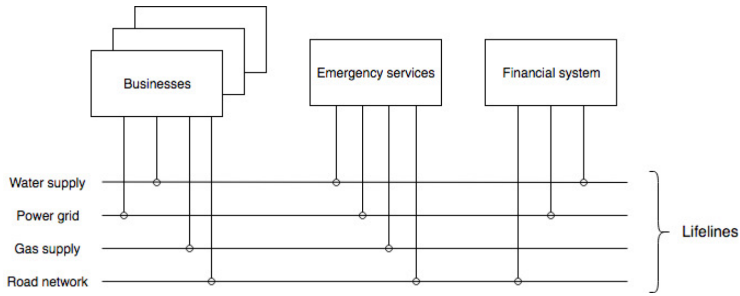


FIGURE 4.1: Conceptual model of infrastructure system-of-systems, where complexity is two-fold, i.e., within and between specific systems. The interdependencies are exhibited through lifeline infrastructure connections between various constituent systems.

The conceptual model shown on fig. 4.1 represents good duality under real-life conditions, with individual systems also linked through roads, power lines, water and gas pipes, and similar infrastructure networks. Services are delivered to provide access to and distribution of actual infrastructure systems and the resources produced by businesses.

The concept of time granularity is of great importance in a simulated SoS setting [122] because the impact and propagation of disruptions between constituent systems can vary significantly depending on the time granularity of that simulation. Therefore, we developed SoS simulation experiments of infrastructure systems and business networks combined with a disruption generator. These experiments allowed us to understand how time granularity affects propagation of disruptions in the SoS. Time granularity within individual constituent system also has a relationship with resilience cycle.

4.2.2 *Experimental layout*

We designed an experimental model system to examine the change in disruption patterns for constituent systems as a function of time granularity. Our analysis comprised three networks corresponding to water supply, power grid, and businesses (fig. 4.2). When combined with a disruption generator, we could introduce system disruptions in accordance with prescribed patterns. Our observer module was then used to visualize results in real time as the simulation progressed so that we could determine how the impact of the disruption was propagated within the system over time.

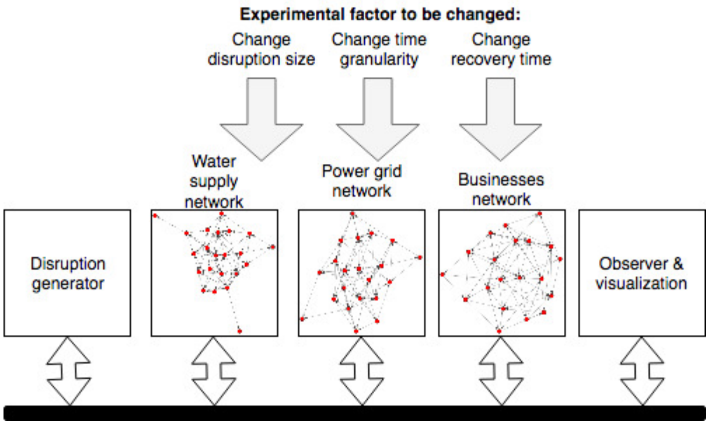


FIGURE 4.2: Experimental model system setup for 3 networks and disruption generator. Disruptions are introduced to water supply network. Responses were measured in businesses network according to alterations in disruption size, time granularity, and recovery time.

The three networks were abstractly generated based on their unique characteristics, as well as on their interdependencies and corresponding connections to each other. The exchange of information among networks was performed via implementation of HLA real-time infrastructure (RTI) software. This enabled us to control timing to ensure that synchronization occurred at a predetermined frequency, i.e., federates performed simulations internally in timesteps without any wait times between subsequent timesteps. However, at the synchronization points, the federates had to halt and wait for all other federates to catch up so that their data could be exchanged. Here, time granularity was defined as the frequency of performing this synchronization, expressed as a number of timesteps between two consecutive synchronizations of all federates.

After disruptions were introduced into the water supply network, their propagation through the SoS was assessed according to the impact they had on the business network. As shown in fig. 4.2, three experimental factors were varied: disruption size, time granularity, and recovery time after the disruption. For our purposes, the disruption generator followed Poisson processes. The two parameters used in our description included (1) actual disruption size, i.e., the number of affected nodes; and (2) actual recovery time, which indicated how long the disruption remained effective in the water supply network. Our evaluation of disruption propagation was conducted in real time and visualized in our model through the observer federate. This allowed us to shape the disruption curve and compare the size of a disruption and its propagation and recovery pattern depending on different simulation parameters and experimental factors' values.

We also determined how time granularity might affect simulation speed. Because synchronization of the system required time, increasing the frequency of synchronizations, i.e., decreasing time granularity, would decrease the speed of simulation. Our goal was to understand the trade-off between accuracy and speed so that we could choose the most appropriate time granularity parameter for the SoS simulation and, hence, estimate the runtime of the simulation under such granularity.

4.2.2.1 *Factorial layout*

We applied a full-factorial experimental layout to study the impact of time granularity (TG), disruption size (DS), and actual recovery time (RT) on simulation results (table 4.1). Those three factors were assigned values based on Latin Hypercube Sampling (LHS) [124]. Because the overall water supply network size was 22 nodes, sampling for disruption size was performed in the space between 7 and 21 nodes disrupted. Time granularity and recovery time were both assessed on the space of between 1 and 30 to provide us with a good overview of real-life simulations. The full factorial experimental layout consisted of 125 parameter configurations. This allowed us to identify solid conclusions by which we could determine the impact of individual factors on the accuracy and outcome of the simulation.

4.2.2.2 *Specification of topologies for infrastructure systems*

Networks used in this simulation experiment were abstract, and were randomly generated via the Erdős-Renyi model [125][126]. They represented water supply, power grid, and businesses. For illustration, they were represented as graphs in which direction signified the way in which interactions would occur between subsequent nodes, such as those associated with normal transportation of a resource over various links. Disruptions were introduced at nodes, which were then removed from the network and their connection links abandoned. Recovery was simulated by returning those nodes to the network and re-establishing their connections with subsequent and preceding nodes.

Table 4.1: 5 x 5 x 5 hypercube full-factorial layout achieved via LHS. Experimental factors included time granularity (TG), recovery time (RT), and disruption size (DS).

		Disruption size (DS)																
		8					12					14	18	21				
Recovery time (RT)	2	**Time granularity (TG)**					**Time granularity (TG)**					…	…	**Time granularity (TG)**				
		2	12	14	21	27	2	12	14	21	27			2	12	14	21	27
	9	**Time granularity (TG)**					**Time granularity (TG)**					…	…	**Time granularity (TG)**				
		2	12	14	21	27	2	12	14	21	27			2	12	14	21	27
	13	**Time granularity (TG)**					**Time granularity (TG)**					…	…	**Time granularity (TG)**				
		2	12	14	21	27	2	12	14	21	27			2	12	14	21	27
	17	**Time granularity (TG)**					**Time granularity (TG)**					…	…	**Time granularity (TG)**				
		2	12	14	21	27	2	12	14	21	27			2	12	14	21	27
	22	**Time granularity (TG)**					**Time granularity (TG)**					…	…	**Time granularity (TG)**				
		2	12	14	21	27	2	12	14	21	27			2	12	14	21	27

In each network, nodes corresponded to units that performed operations and interacted with other nodes in the same network as well as with corresponding nodes in other federates. Edges corresponded to transfer links between operational units within each network. Although the mechanics of each network were similar, they were also distinct and abstract. Each node had its own intrinsic, internal performance, but also took inputs from the incoming edges of its network and from its corresponding nodes in the other two networks. These internal and external performances were then combined and transformed to determine the total performance of that particular node. Performance was then propagated to the following nodes through the outgoing edges. Similarly, performance was propagated through inter-network connections and a synchronization mechanism to the corresponding nodes of the other two networks. In doing so, we designed a working process for each constituent federate to simulate an individual infrastructure system or business network within the SoS simulation environment. Each network had similar but slightly different mechanics for calculating the performance of its own nodes.

The network topologies are shown in fig. 4.3. Each consisted of a certain number of nodes with a certain number of edges between them. The nodes also had corresponding interdependent nodes in other networks of the SoS simulation with which they communicated at a given frequency by exchanging information at synchronization points. We set the following specifications: 22 nodes and 77 edges for the water supply network, 21 nodes/77 edges for the power grid network, and 20 nodes/75 edges for the business network.

4.2.3 *Performance metrics*

We collected data that described how a disruption to the water supply might influence performance of the business network. Our aim was to derive a framework for choosing time granularity for an SoS simulation that would result in the most accurate simulation while simultaneously preserving the efficiency of that simulation. We used a Measure of Performance (MoP) to compare the results from experimental configurations, based on sum of all individual performances of nodes in a network.

As depicted in fig. 4.4, the simulated propagated recovery time (t_{rec}) enabled us to calculate the length of time needed for a system to recover after a disruption was propagated and, subsequently, retracted. Recovery was determined to be the point at which that system had returned to within

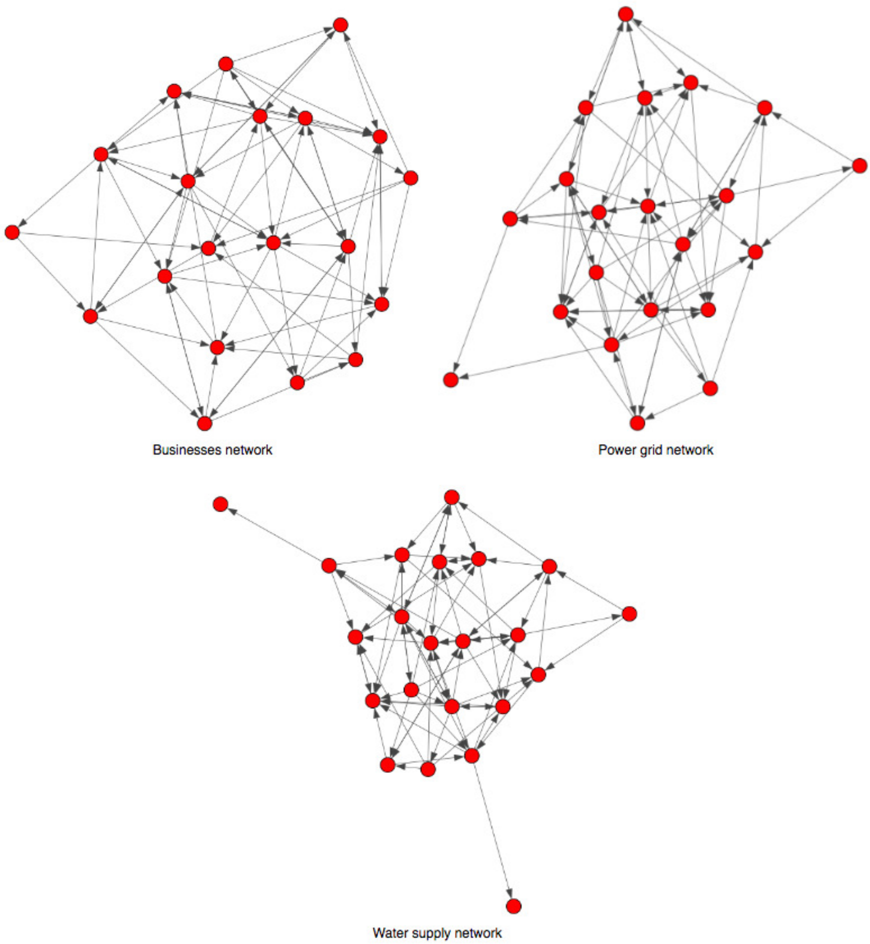


FIGURE 4.3: Topologies of 3 tested networks, with disruptions introduced to nodes for water supply. Interdependency connections existed between corresponding nodes of distinct networks.

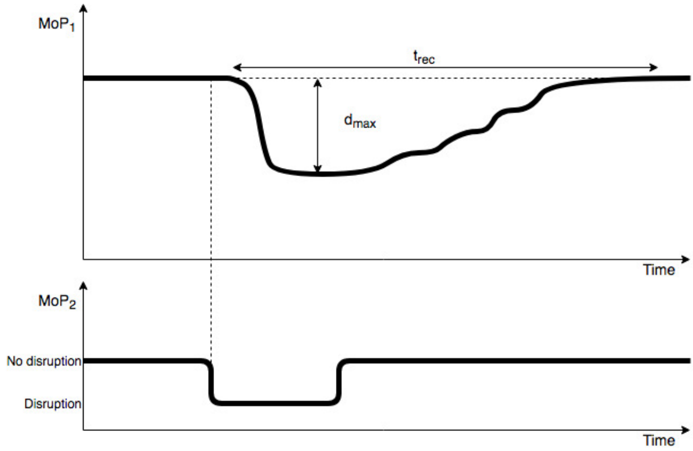


FIGURE 4.4: Disruption was introduced into water supply network (MoP2) and propagated to business network (MoP1). Recovery time (t_{rec}) was defined as interval required for business network to return to at least 99% of original performance level. Maximum disruption size (d_{max}) was maximum deviation from original performance of business network. MoP stands here for measure of performance signifying performance of a network.

99% of its original (pre-disrupted) performance. For our simulation, we were primarily interested in the impact of actual on simulated propagated recovery time, which would then represent the difference in recovery times due to synchronization between federates in the SoS, as defined by time granularity – our key experimental parameter. In this way we could assess the accuracy of the SoS simulation and its dependence on time granularity.

Another dependent variable, maximum simulated disruption size (d_{max}), was defined and measured as the lowest point along the performance curve after a disruption was propagated to that network. Those results indicated the magnitude of such an impact by one system on another, e.g., when a disruption to the water supply interfered with operations by the business network. This approach served as an alternative metric for assessing the accuracy of a simulation based on time granularity.

Our final evaluation involved comparing speeds (in seconds per timestep) among different time granularity configurations so that we could determine how the former changes in conjunction with the latter. This was an important factor because of the trade-off found between speed and accuracy in simulations. Successful design of a framework requires selecting the most appropriate time granularity based on desired speed and some basic knowledge about the network being simulated. All of these were goals of our study here.

4.2.4 *Model implementation*

Planners use distributed modeling frameworks to implement the SoS approach for businesses and infrastructure systems. This involves numerous individual, autonomous systems connected with each other through inputs and outputs to other systems. One such framework is HLA [127][42][38], a tool originated in military applications to simulate battlefield actions, as well as various systems pertaining to simulated battle situations and training. Since then, HLA has been employed in various other applications, including the modeling of civil infrastructure [46].

A particular implementation of HLA features three components: *interface specification*, *object model template (OMT)*, and *rules*. *Interface specification* defines where and how constituent systems ('federates') communicate with RTI, a method used to join all constituent distributed systems. This component serves as the inter-federate communication and synchronization unit of the HLA. Second, *OMT* describes what information is exchanged between constituent federates and what updates about the federation must be communicated to those federates. Finally, *rules* specify what federates have to obey to subscribe to the overall HLA SoS simulation ('federation'). When modeling infrastructure systems, the federates within an HLA simulation can include infrastructure systems, disruption generators, observers and visualization tools, patterns of user services, and businesses. All of these federates introduce dynamic changes to the systems and allow designers to observe their effects on the overall SoS.

Although HLA is perfectly suited to describing and modeling the manner in which constituent systems exchange information and synchronize with each other, it does not indicate the ideal time granularity at which such synchronization and exchange of information should take place. In this context, time granularity means the frequency of exchange of information among federates (i.e., constituent systems), disruption generators, and other components. As such, granularity reflects the frequency of inter-system synchronization. Although specification of HLA provides some mechanisms to perform time management [128][129], it does not identify the best time granularity for that exchange. In fact, the most adequate time granularity varies among types of simulations, where even different disruption events might apply to the same simulation of infrastructures.

Our simulation was developed in C++ v11 [130] and Python. The HLA framework was applied from Portico 2.0.2 HLA [131] implementation, with Portico's HLA being used to define the interfaces between federates, and to manage time in the simulation. Data at given time granularities were synchronized through HLA RTI, as adapted from Portico's implementation, and graph operations were performed with the use of the *igraph* library for C++ and Python, version 0.7.1 [107]. Disruptions were generated and introduced to the system through a disruption generator developed in C++ v11. All infrastructure system networks were developed in Python 3.5 [132], under Anaconda 2.4.0 distribution [106]. We used the following libraries to create those networks: *igraph*, for graph generation, representation, and operations; and *NumPy* version 1.10.1 [108], for linear algebra and numerical operations. The observer was designed with a webpage interface developed in JavaScript, HTML, and Python, using the *CanvasJS* library [109]. This observer enabled us to collect data about the simulations, to visualize their progress, and to view the performance of the system in real time. The simulation was developed, evaluated, and run on a Mac OS High Sierra 10.13.6 operating system.

This implementation shadowed a specific scheme. First, the infrastructure systems were developed based on the definitions established for their interconnections, number of nodes, and working mechanisms, i.e., inputs and outputs. This was followed by the design of HLA interfaces. Finally, the overall HLA simulation was devised to include all components of the infrastructure systems.

Before arriving at our final experimental design, we evaluated the systems for different individual networks, each of which was tested to assess its representation of a real-life system. Our preliminary investigation showed that the networks and HLA SoS simulation performed well individually and as a whole, adequately representing individual networks and propagating and communicating disruptions between them as required.

4.3 RESULTS OF SIMULATION EXPERIMENT

Results from the simulation experiment demonstrated that time granularity, disruption size, and recovery time from disruptions had a significant impact on the outcome of our simulation. Assessments of performance by the business network indicated that the simulated propagated recovery time and disruption size were affected by all experimental factors, but especially time granularity and recovery time.

4.3.1 *Disruption size*

Simulated, propagated disruption size was measured under different experimental configurations to understand which factors had the largest impact on the simulated disruption size. An ANCOVA (Analysis of Covariance) was performed in R to determine the strength of the effect of experimental factors on size. Figure 4.5 presents only those factors and their interactions that had a significant impact on the share in variation of simulated disruption size. The most important factor proved to be time granularity, followed by actual recovery time and then actual disruption size. We found this interesting for several reasons. First, the influence of propagated disruption was decided primarily by time granularity. Second, and more importantly, the time needed to recover from a disruption to the water supply was responsible for a greater share of the variation in simulated disruption size in the business network than the actual disruption size to the water supply network. This finding demonstrated that the recovery time in an SoS federate had a greater effect on the simulated, propagated disruption size in other federates than did the disruption size in the original federate itself. Although interactions among experimental factors also influenced the variations in simulated disruption sizes, they had much less impact than did individual factors. Share of residuals in variation were also lower than the combined share of other factors. Overall, the experimental factors explained 71% of the variation of simulated disruption size. That high percentage indicated that the variation in size could be well-explained by the experimental factors.

Those results above suggested that correctly adjusting the ratio of time granularity to the expected recovery time in a simulation would be of immense importance when simulating the disruption size in an SoS evaluation. Therefore, careful selection of the ratio of time granularity to recovery time would have to be based on the data available to us if we were to determine the optimal time granularity for a simulation and yield the most accurate simulation results.

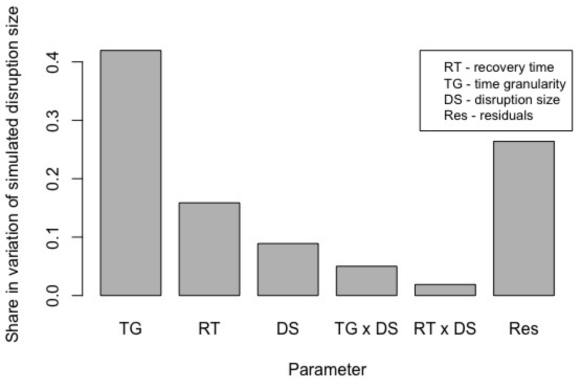


FIGURE 4.5: Share in overall variation for simulated disruption size due to experimental factors (parameters). Greatest impact was associated with time granularity, followed by actual recovery time and actual disruption size. Adequate time granularity is of immense importance in system-of-systems models.

4.3.2 *Recovery time*

Similar to our assessment of disruption size, we analyzed the impact of experimental factors on the variation in simulated recovery time of the business network. Simulated recovery time under various configurations was measured to understand how the recovery time was affected by these factors. As before, we performed ANCOVA in R, using the data obtained when measuring the simulated recovery time. Figure 4.6 presents only the factors and their interactions that had significant impacts on the share in variation for simulated recovery times by the business network. There, the most influential were time granularity of the simulation and the actual recovery time for the water supply network. Furthermore, time granularity had a slightly larger effect on simulated recovery time for the business network. Again, this result underlined the importance of adequate time granularity and its critical influence on the accuracy and outcome of the simulation. The interaction between these two factors also had a significant but smaller share in the variation of simulated recovery time. We noted with interest that the size of the disruption to the water supply had no significant impact on the simulated recovery time for the business network. Similar to our results from examination of disruption sizes, the resid-

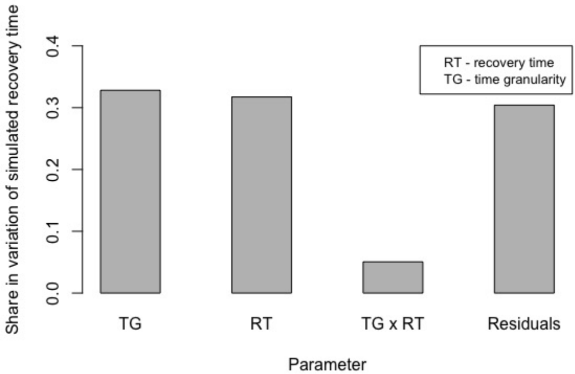


FIGURE 4.6: Variations in simulated recovery time due to experimental factors (parameters). Impact was almost equally shared between time granularity and actual recovery time. This indicated that both factors would require careful adjustments if simulations were to represent actual disruption events adequately.

ual share in variation of simulated recovery time was approximately 30%, which indicated that 70% of the variation (a reasonably high percentage) could be explained by experimental factors.

All of these findings presented above strongly suggested that time granularity was of great importance in an SoS simulation. Making proper adjustments to it in reference to recovery time would be crucial if we were to obtain reliable simulation results. Furthermore, depending upon time granularity, simulation results could change significantly because the impact of actual recovery time and time granularity on the share of variation in simulated recovery time was similar. In both cases of simulated disruption size and recovery time, time granularity accounted for a larger share of the variation than did either the actual recovery time or the actual disruption size.

4.3.3 *Model of visibility of disruption*

One reason that time granularity and actual recovery time had such a great impact on the simulation outcome was that disruptions below a certain recovery time did not get propagated through the SoS simulation to other federates. If the time granularity were large enough, then when such a disruption occurred, the individual system recovered from the disruption before that propagation took place. This implied that time granularity prevented such an occurrence. As such, this phenomenon contributed to the great impact of time granularity on variation of the metrics. Time granularity of the system needed to be finer than the resilience cycle of the system in order to register the propagation of disruption.

Based on these results, we then derived a model of likelihood for disruption visibility that would allow us to select time granularity of the simulation according to the (expected) recovery time of disruptions, making their propagation visible in the system. This model was used to select the maximum time granularity so that one could observe and detect an SoS disruption. Here, visibility of a disruption was understood to be a drop in performance to below 95% of the original level in the network to which disruption should propagate.

This logistical model (fig. 4.7) was developed based on our experimental data, using R and the *glm.fit* function [133]. It depicted the likelihood that a disruption would be visible in a business network, according to the ratio of actual recovery time of the water supply network to time granularity. The primary limitation associated with this model would be the networks to which it could be applied. Here, we used it to select a time granularity for a simulation based on the most important parameters: time granularity and actual recovery time. Those parameters were combined into a ratio so that we could adjust for our desired likelihood of visibility. In most practical applications we can estimate the minimum actual recovery time. Then, by using the model from fig. 4.7, we can derive the time granularity. Our model suggested that the ratio of actual recovery time to time granularity should be at least 0.88. In doing so, for the disruption to propagate to other federates the time granularity should be less than 1.13 of the expected actual recovery time.

Because visibility of a disruption is a key parameter when simulating an SoS infrastructure network, we wished to examine whether a disruption originating in one network could propagate to another network, for how long, and with what impact. This would enable us to understand how businesses respond to a certain disruption in the water supply network. However, if an excessively large time granularity prevented such a propagation, then the simulation would be useless. Consequently, in a real-life scenario, we would not be able to determine whether the disruption

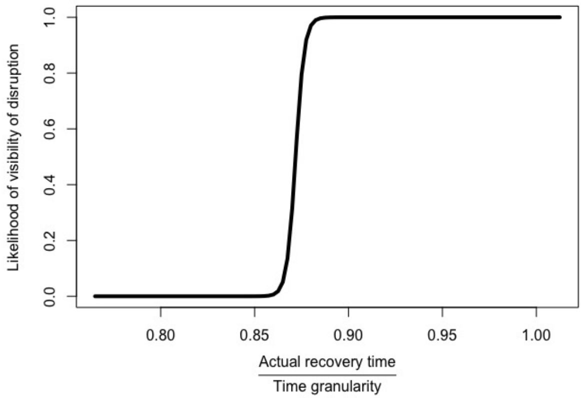


FIGURE 4.7: Model of likelihood for disruption visibility based on ratio of actual recovery time to time granularity. Minimum ratio for disruption to be registered in the simulation with a significant probability is 0.88, meaning that time granularity needs to be less than 1.13 of the actual recovery time.

would propagate. Hence, selection of appropriate time granularity for an SoS simulation is vital.

4.3.4 *Simulation time vs. time granularity trade-off*

Because the SoS approach often entails performing one simulation immediately after another, we want to enable performing as many simulations as possible within a limited period of time to test different scenarios. Our goal was to achieve the most rapid simulation that was also the most accurate. Since simulation speed was affected by time granularity, at any given level of accuracy, a trade-off existed between time granularity and simulation time.

In our experiment, simulation time was expressed in seconds per timestep. As time granularity increased, the simulation time decreased because reduced granularities involved more synchronization between federates. Such synchronizations are time-consuming and computationally expensive, thereby lengthening the simulations. As shown in fig. 4.8, simulation time was roughly inversely proportional to time granularity. Nevertheless, we also noted that the greater the time granularity, the lower the accuracy of the

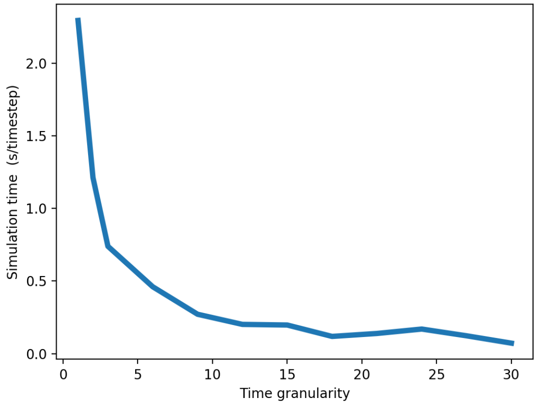


FIGURE 4.8: Inverse relationship that leads to trade-off between simulation time and accuracy, controlled by time granularity.

simulation and the higher the likelihood that a disruption would not propagate to other networks – in our case, the businesses network. This produced a trade-off between simulation speed and accuracy that was controlled by the time granularity parameter. Consequently, when attempting to choose as high a time granularity as possible in order to decrease time, we still had to establish restrictions on the ability of a disruption to propagate.

4.3.5 *Ratio of recovery time to time granularity*

In our SoS simulation, selecting the appropriate time granularity was critical. However, we detected a trade-off between time granularity and the speed of the simulation. The principal factors affecting our results were time granularity and recovery time, both of which influenced the size of the simulated disruption to the business network more than did the size of the disruption to the water supply network. Therefore, we concluded that the ratio of the recovery time for the original disruption to the water supply (i.e., actual recovery time) to the time granularity of the simulation had an even greater impact on the variation among our experimental metrics.

Figure 4.9 presents the results of our ANCOVA analysis. The ratio of actual recovery time of water supply network to time granularity accounted

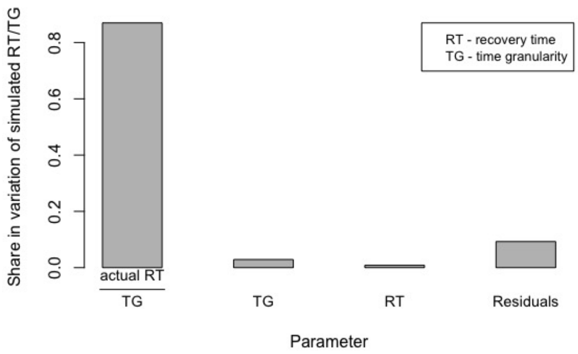


FIGURE 4.9: Variations in ratios of simulated recovery time by business network to time granularity due to experimental factors. Impact was greatest for ratio of original recovery time by water supply to time granularity, proving to be defining factor when modeling simulated recovery time by business network.

for the greatest share, by far (86%), in variation of the ratio of simulated recovery time of the business network to time granularity. This meant that the ratio of actual recovery time to time granularity could be used to explain, with high accuracy, the ratio of simulated recovery time to time granularity in the businesses network. Therefore, the simulated ratio of recovery time to time granularity could be modeled based on the ratio of actual recovery time to time granularity. Because we always know the time granularity of the simulation, we could apply this model to estimate the actual recovery time based on the simulated recovery time.

One limitation associated with this model is its dependence on the type of simulation that is being run. Depending on the chosen federates, the actual difference in actual and simulated recovery times might differ between actual conditions and those that are simulated or propagated. Therefore, the type of simulation, and its internal mechanics, as well as the type and number of interdependencies, have a great impact on this model's accuracy and validity. Likewise, Dubaniowski and Heinimann [122], have demonstrated that such a model that translates the ratio from actual to simulated values might have several regimes depending on whether the ratio is below or above 2. We found it also interesting that such a relationship did not emerge when using the disruption size metric. This further indicated

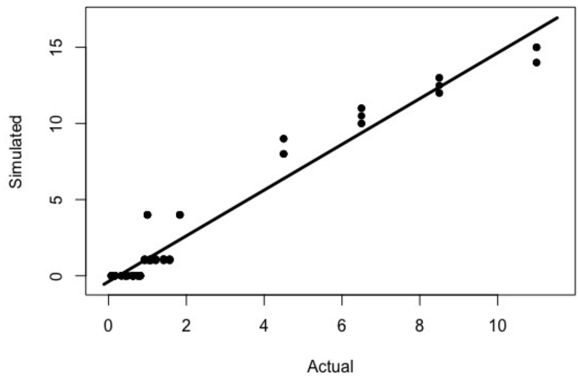


Figure 4.10: Model of relationship between simulated and actual recovery times as fraction of time granularity, which enables users to estimate actual recovery time based on simulated recovery time.

that the selection of an appropriate time granularity is especially sensitive to the recovery time for the major event that is expected in a given simulation. Therefore, the minimum recovery time that is anticipated for major events should be carefully estimated when designing an SoS simulation.

Our proposed generalized linear model (fig. 4.10) was built to consider only the most significant factor, i.e., the ratio of recovery time to time granularity. If we know that the time granularity of a simulation is appropriate, then the model can estimate the actual recovery time based on the simulated recovery time. Conversely, it can be used to quickly estimate simulated, propagated recovery time based on actual recovery time.

We must reiterate our conclusion that this proposed model can vary in its applicability and accuracy, depending upon the networks that are simulated. Although we utilized networks here that resembled infrastructure systems such as water supply, power grid, and businesses, this model might not be fully applicable and yield far different results in other situations. Nevertheless, the outcome from the study described here is valuable for deriving the actual size of a real event based on the simulated event size, and it can aid in choosing the appropriate time granularity, especially in SoS HLA simulations. Finally, it is likely that such a model could have several regimes depending upon the range of value of the ratio of actual recovery time to time granularity.

4.4 CONCLUSIONS

Our experiments were specifically designed to investigate how time granularity, disruption size, and recovery time from a disruption to the water supply might propagate and affect the outcome of a business network under simulated conditions. After developing an HLA system-of-systems simulation that incorporated two infrastructure systems (water supply and power grid), a business network, and a disruption generator, we ran full-factorial simulation experiments to analyze various impacts on the propagation of disruptions. We then developed two models to assist in selecting an adequate time granularity based on expected recovery time and desired accuracy of the simulation.

This research yielded the following major results:

- Time granularity had the greatest influence on both recovery time and size of disruptions in systems to which those disruptions had propagated.

- Recovery time had a larger impact than disruption size on both recovery time and disruption size in systems to which disruptions had propagated.

- Experimental factors explained 70% of the variation in experimental metrics.

- From the model, we determined that the maximum ratio of time granularity to actual recovery time at which the propagation of disruptions was visible was 1.13.

- Simulation time was inversely proportional to time granularity, and the best simulation speeds were achieved at higher granularities.

- The ratio of actual recovery time to time granularity had the greatest effect on the ratio of simulated, propagated recovery time to time granularity. Hence, it was crucial to our simulation that we achieve an adequate ratio of actual recovery time to time granularity. The share of variation in simulated, propagated recovery time to time granularity ratio due to the ratio of actual recovery time to time granularity was 86%.

- We developed a general linear model to estimate the actual recovery time based on simulated recovery time.

Our study about the effect of time granularity on propagation of disruptions in a SoS simulation of infrastructure systems and businesses networks is novel. The time management of such simulations has already been investigated within an HLA environment [134][129]. A few investigations have also been conducted on the impact of time granularity on disruption propagation between infrastructure systems [122]. However, little work has been done on the influence of time granularity on propagation of disruptions of various sizes and with different characteristics within the context of an SoS of businesses and infrastructure systems. Although Eusgeld and Nan [82] and Rinaldi [86] have investigated interdependent infrastructure systems, they have not included the role of time granularity on disruption propagation. Therefore, our introduced model is original in that it translates simulated recovery time into actual recovery time, and considers the selection of an appropriate time granularity.

The HLA approach has been taken in modeling systems-of-systems [42][135], including those associated with infrastructure [136]. However, the concept of disruption propagation within an HLA simulation model has not been studied extensively. Our experiment addressed the issue of modeling disruptions in distributed modeling SoS environments such as the Portico HLA.

Our research findings have several implications. Scientists can utilize them to develop better models of infrastructure systems and business networks. In doing so, they can select the time granularity that yields the most optimal results of SoS simulations in terms of the most accurate disruption propagation representation. The experimental framework presented here can also be used to define time granularity of SoS simulations for applications other than infrastructure systems such as military systems or strictly business systems. Similarly, policymakers and scientists can benefit from the model to estimate the actual impact of a disruption on a system based on its simulated magnitude. For practitioners, policymakers, and scientists, such data can help them achieve better estimates of the size and cost of actual disruptions.

Practitioners and scientists who regularly perform such simulations can benefit from identifying the maximum time granularity required if they are still to register the propagation of disruptions. This will aid in solving the trade-off between speed and accuracy of the simulation, which in turn would allow them to perform more simulations within the same timeframe, thereby leading to savings in both cost and time.

Our study is limited in its ability to apply these results to other networks and infrastructure systems. Although the test system was analyzed for various parameters of disruptions, the topologies and mechanics of the network were constant. In real-world scenarios, the nature of the networks, as well as their sizes, could differ. Similarly, the experimental space and metrics are restricted. Here, we focused on only a subset of possible factors that might influence a disruption. Another limitation was that the model of the ratio of simulated recovery time to time granularity based on the ratio of actual recovery time to time granularity may have several regimes that could be analyzed separately. To address these challenges, future work on this subject might include similar experiments over a broader field of network topologies with different operating parameters. A real-life network could be used to investigate whether the results obtained here remain valid. Finally, a wider range of disruption parameters could be studied, along with more experimental metrics, so that we could determine what other factors can affect the propagation of disruptions, and whether the models obtained through our study still apply.

5

FRAMEWORK FOR MODELING INTERDEPENDENCIES BETWEEN HOUSEHOLDS, BUSINESSES, AND INFRASTRUCTURE SYSTEM, AND THEIR RESPONSE TO DISRUPTIONS - APPLICATION[1]

Learning never exhausts the mind.
— Leonardo da Vinci

This chapter is based on and includes work submitted for publication in Sustainable and Resilient Infrastructure.

5.1 INTRODUCTION

Interdependencies between infrastructure systems, businesses, and households, and the complexity of these systems are increasing as a result of emerging new technologies. These interdependencies have an effect on the way that systems respond to disruptions and on the impact of these disruptions. Due to these interdependencies, the aggregate impact of a disruption on separate systems does not represent the impact of a disruption that cascades from system to system; the latter tends to be greater. Furthermore, disruptions in urban areas are increasing both in impact and frequency. This is due to increasing interdependencies and dependence on technology, and because urban areas are becoming more densely populated, larger in area, and more complex [2]. Understanding the resilience of urban systems through evaluating the impact, propagation, and recovery of these systems from cascading disruptions is relevant to urban communities. Therefore, a comprehensive, easily applicable model is required that can simulate the impact of disruptions on interdependent urban elements, such as infrastructure systems, businesses, and households.

Several models exist that describe cities in terms of urban design patterns that can be used to define urban elements [137][138][139]. In conjunction, these urban element units can be used to create a model of a city [140].

1 This chapter is based on the following publication:
Dubaniowski, M. I. Heinimann, H. R. Framework for modeling interdependencies between households, businesses, and infrastructure system, and their response to disruptions - application. *Sustainable and Resilient Infrastructure*, Submitted (2019).

However, there have been no clear attempts to adapt the concept of urban elements to modeling the response to disruptions in urban areas. Current research approaches include infrastructure modeling for the resilience of an individual system, and the application of these models to systems such as the water supply [84], traffic [43], and power grids [83]. However, these approaches analyze single systems and do not address interdependencies with other systems. A system-of-systems (SoS) methodology has been used to model interdependencies among infrastructure systems by Eusgeld et al. [46]. However, the applicability of this model was not analyzed, and the model was not adapted to a real-world scenario involving businesses and households. Dubaniowski and Heinimann [91] proposed a modeling framework for interdependencies between infrastructure systems, businesses, and households; however, their framework was not applied to urban areas, and the performance of systems for a disruption was not analyzed. Finally, disruptions to infrastructure systems and their impact was analyzed in a number of studies [103][141][142][143]. However, the authors did not consider the impact of interdependencies on various socioeconomic units. Instead, they relied on individual infrastructure systems or expert judgment to arrive at estimates of the urban systems' resilience and the impact of disruptions on the urban systems.

The aim of the present study is to (1) devise an application workflow of a framework for modeling businesses, households, and infrastructure systems, and their response to disruptions; (2) apply the framework to an area of a city; and (3) analyze the response of the simulation to a set of disruption scenarios in order to compare their impact on the system. In particular, our objective was to evaluate the impact of disruptions on a system modeled using our framework for modeling interdependencies between infrastructure systems, businesses, and households.

In this study, we focused primarily on describing the workflow of our modeling framework and applying the framework to an area of a city. Our aim was to establish the framework and demonstrate how it can be used to model a real-world area to evaluate the impact of disruptions in that area. However, the study did not include a wide range of networks or urban areas. In addition, the mechanism for inducing the initial disruption to the systems was beyond the scope of this study.

5.2 MODEL SPECIFICATION

In this study, we designed and developed a model of an agent combined with other agents to form an SoS network of infrastructure systems, businesses, and households. These agents exchange goods and services over infrastructure links represented by edges of a network. In addition, they perform production processes to generate goods and services, and introduce raw materials to the system. The model consists of three integral elements: (1) a network of households and businesses that are connected by infrastructure system links, (2) agents representing socioeconomic units that perform production processes, and (3) disruption generators that introduce disruptions to the system [91].

In infrastructure system networks, business and household agents are nodes, while infrastructure system links are edges. These links correspond to real-life infrastructure connections, such as power lines, water supply pipes, roads, telecommunication lines, and public transport lines. Businesses agents, in contrast, correspond to factories, retail stores, and so on, as well as infrastructure providers, such as power plants and water supply plants. Households represent housing units that provide residence for people and offer human capital resource.

Disruptions can be introduced into the overall SoS through (1) infrastructure system links, such as by removing a link; and (2) agents, such as by introducing changes to an agent's production process or demands. Disruptions may also be introduced by increasing the supply cost of introducing raw material resources to an agent. These disruptions can be modeled as Poisson processes and so can be randomly introduced into the system with a particular distribution pattern. Alternatively, disruptions can follow a pre-designed process that defines how they develop and occur.

Figure 5.1 presents a diagram of our proposed model. The model represents interdependencies between infrastructure systems, businesses, and households. These interdependencies are represented through infrastructure link connections and production processes. The production process of each agent uses an input-output model [97][30] to represent the transformation of a set of input goods and services into another set of output goods and services. In the input-output model, an agent takes certain inputs from the network and performs transformations to produce certain outputs, which are then released into the network. This process is governed by a technology matrix, which specifies the quantities of each resource that are required for producing one unit of another resource by an agent. A disruption may alter this technology matrix.

Each agent possesses a final consumer demand vector, which specifies the amount of resources that the agent consumes without producing any resources in return. This vector corresponds to the final end-user consumption and waste of resources by households and businesses. Each agent also possesses a raw materials supply vector, which specifies the supply price of one unit of raw materials that can be introduced by this agent. Both the final consumer demand vector and raw materials supply vector can be altered by a disruption. The overall SoS network also possesses a total consumer demand vector, which is derived by summing the individual demand vectors for all agents. Each edge has a cost and capacity vector assigned to it that specifies the cost of transferring each resource over that edge.

Disruptions can be introduced to agents and infrastructure links. These disruptions are either randomly generated or preset disruption scenarios, and the scenarios are designed to correspond to real-life events. Disruptions affect different components of the system and can vary spatially or temporally. In addition, various disruption generators can be developed with different specifications and specializations, with each generator modeling a different type of a disruption. These scenarios can then be introduced into the model to evaluate their impact on the simulation of the network.

The main metric in our model is the cost of satisfying the system. The impact of each disruption can be measured by examining its impact on this metric. By assigning probabilities to disruption scenarios, the value-at-risk (VaR) of the system can be further quantified. In addition, by defining a multi-step disruption scenario, a system's response to and recovery from a disruption can be evaluated. Another metric used to evaluate the performance of the system is the variation in the supply curve of the overall system, which represents the effect of the disruption on the supply curve of resources in the simulated network.

In this study, we applied our model to a specific geographical area of a city consisting of households, businesses, and infrastructures. In terms of resources, we modeled power, water, consumer goods, business goods, and human capital (people). As a result, the following infrastructure systems were taken into account: power supply, water supply, consumer and business goods delivery networks (e.g., roads), and public transport. We applied our modeling framework to the geographical area by following

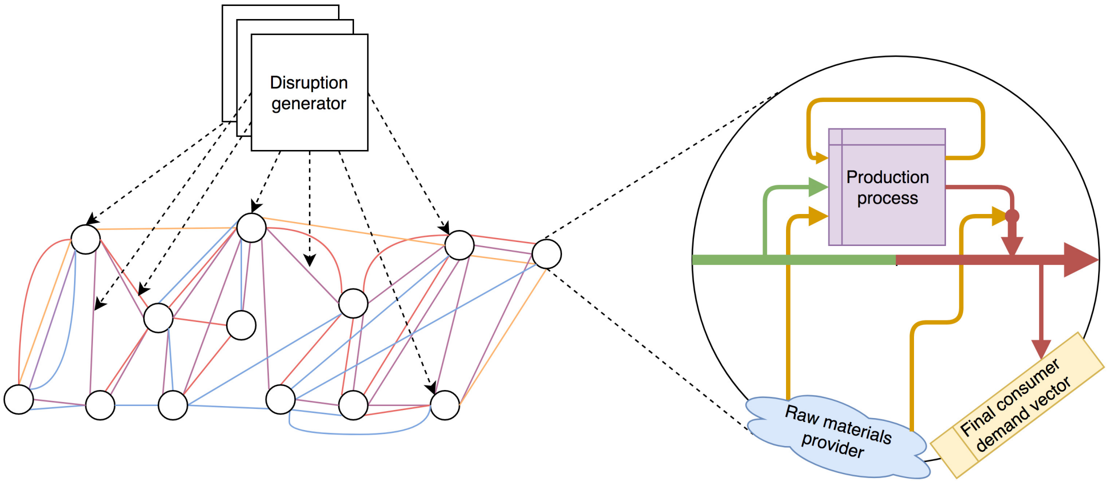


FIGURE 5.1: Conceptual model representing a network of household and business agents connected via infrastructure networks, and the principle mechanism for representing the agents' operations. Agents and the links between them can be disrupted by a disruption generator.

a predefined application workflow. We developed the applied model, ran the simulation, and subsequently evaluated the model's response to various predefined disruption scenarios that were introduced into the system.

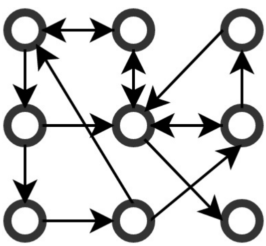
5.3 APPLICATION OF THE MODEL

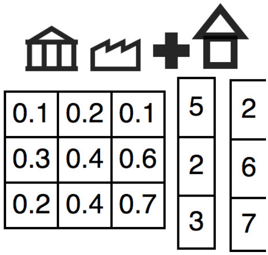
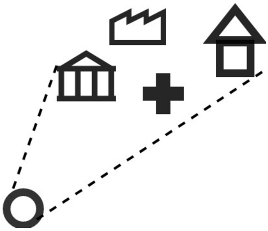
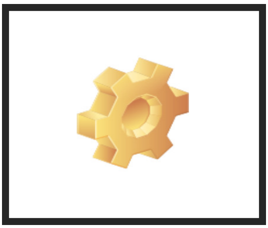
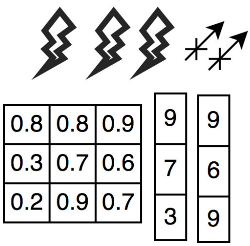
We applied our modeling framework to a geographical area to assess the impact of various disruption scenarios on the infrastructures, businesses, and households of that area. The application of the framework is described by a set of steps performed to use the framework to model a certain area. We first present the workflow of the application, followed by a detailed explanation of each step for our selected geographical area.

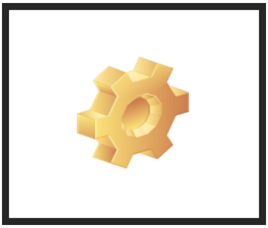
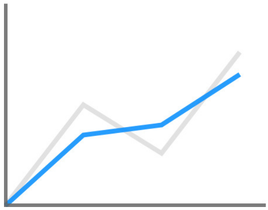
5.3.1 *Application workflow*

We applied our model to a particular geographical area following nine steps, which are outlined in table 5.1. These steps outline the tasks that must be completed and the order of their completion. With these steps, our framework can be used to model a geographical area and simulate the impact of disruptions on the systems in that area.

TABLE 5.1: Process of applying the proposed model to a geographical area. The selected area is divided into a grid, which is transformed into a network. Each element of the grid is defined in terms of building blocks. Disruptions are defined as disruption building blocks or edge malfunctions. A simulation is then run with and without disruptions.

Step no.	Workflow	Procedures
1		Define a geographical area to model.
2		Divide the area into a grid of cells.
3		Create network representations of infrastructure systems based on the grid from Step 2. Assign a cost and capacity to the edges of each network.

Step no.	Workflow	Procedures
4		Define building blocks used to describe the area. Individual units can be used to represent each cell.
5		Define nodes in terms of building blocks. Assign building block coefficients for each cell.
6		Run simulation. Record the base case result and costs.
7		Define disruptions as building blocks and building block coefficient changes or as edge malfunctions.

Step no.	Workflow	Procedures
8		Run simulation with introduced disruptions.
9		Interpret results. Determine cost of each disruption and the effect of disruptions on different cells.

As illustrated in table 5.1, several steps must be completed to convert a real-world problem into a model that can be simulated and analyzed with our framework to evaluate the effects of various disruptions. The initial step involves selecting an area to model and defining the area. This step also includes defining the number and types of resources that must be modeled for determining the scale of the simulation. After selecting a geographical area to model, the area must be divided into a grid whose size will define the spatial granularity of the simulation within the area selected. The larger the grid mesh, the smaller the individual cell, and thus, the finer the granularity of the simulation. Grid size selection is a crucial step in the conversion of a real-world problem into a simulation. It is not required for the grid cells to be of equal size; they can be larger or smaller in different parts of the geographical area, depending on how important the parts are for the simulation results. The area, grid, resources, and systems to be modeled are key high-level parameters of the simulation that must be defined at an early stage.

After dividing the area into a grid, in Step 3 the grid is transformed into a network for each resource and infrastructure system that is modeled. Here, each grid cell is assigned a node of a network, and network connections (i.e. edges) between these nodes are defined for each individual infrastructure system. The edges and nodes for each infrastructure system correspond to the infrastructure system's network for a given area. Nodes correspond to grid cells, and edges correspond to infrastructure system links for each system. Generating a network representation of a real-life infrastructure system is the central element of Step 3. In addition, the capacity and cost of all edges in the network must be defined appropriately to mimic the real-world cost of resources that are transferred through the edges, as well as the capacity of the edges.

After defining the networks in the system, the building blocks that are subsequently used to define individual grid cells must be determined. A building block corresponds to a single unit, which, in combination with other building blocks in certain quantities, represents a cell of the geographical area grid. Building blocks are the smallest functional units used to build an urban area. A building block can be a house, condominium, factory, school, retail outlet, power plant, water supply plant, or similar entity, which, put together, can be used to form an urban area. Each building block is defined in terms of a production process that it is capable of conducting. This production process is represented by a matrix of technical coefficients. In addition, each building block includes a final consumer vector and a raw materials supply vector that represent the internal consumption of the block and the resources that it can supply. The number and type of building blocks have a significant influence on the simulation, and the number of building blocks impacts the granularity of representation of individual grid cells.

After the building blocks are defined, Step 5 can be commenced. Here, the building blocks defined in Step 4 are used to describe individual grid cells (network nodes), which consist of a certain number of building blocks. In this step, the building blocks are assigned to individual cells. Thus, a simulated urban area is created with the use of model building blocks. For each cell, a vector of building block coefficients whose entries correspond to a weight, or a number of corresponding building blocks in this cell, are assigned. Vectors of building blocks for all cells combined form a matrix of building blocks, which defines the entire modeled network. This matrix includes all the nodes of the network in terms of the building blocks described in Step 4.

Once the urban area is defined in terms of the proposed model, a simulation can be run to determine the cost of satisfying the system with no disruptions. Step 6 enables testing of the simulation system to determine whether the cost of satisfying the system is similar to the expected value or the value that is obtained in the real world. Because there already exists an operational model that can be simulated to obtain results about the system, the base scenario can be evaluated, and data pertaining to it can be collected. From this point, disruptions are introduced to observe their effects on the system in terms of total cost and changes to the supply curve, as well as other metrics of interest.

To simulate disruptions, in Step 7, disruption scenarios are defined. These scenarios are described in terms of disruption building blocks and infrastructure system link malfunctions. Disruption building blocks are building blocks that negatively impact the system. They correspond to a malfunction in a production process, increased final consumer demand, or an increased supply price of resources. Introducing disruption building blocks requires adjusting the matrix of building blocks to specify where and with what impact disruption building blocks affect the model. Similarly, the infrastructure system links that may be faulty for a scenario are defined by specifying how their capacity and cost are affected. In extreme cases, an entire link may be destroyed as a result of a disruption.

Alternatively, a random disruption process generator may be introduced, which follows a Poisson process to simulate disruptions in the system according to a certain set of patterns and parameters. This entails specifying the distributions of multivariate random variables that define disruption building blocks, the matrix of building blocks, and the affected infrastructure links.

Once disruption scenarios or disruption random processes are defined, the simulation can be rerun with a given scenario or with a given disruption process running (Step 8). For each disruption scenario, the data of interest is collected, and the impact of the disruption on the overall system is analyzed (Step 9) by evaluating the overall cost of disruption. In addition, the impact of the disruption on individual cells is analyzed by evaluating the individual costs. Furthermore, the change in shape of the overall supply curve of the system is examined to understand the impact of the disruption on the supply of resources in the system. Once the results are obtained and analyzed, they can be used to generate support for decisions regarding the system or to identify major vulnerabilities.

5.3.2 *Area definition*

In accordance with our application workflow, we began by selecting the area and size of the grid/network and the number of infrastructure systems to be modeled. The area selected is presented in fig. 5.2; it is a part of the Clementi district in Singapore. This area was selected because it represents an effective combination of all units, including households, businesses (both industrial and retail), and a variety of infrastructure systems. Moreover, the area is located near our laboratory in Singapore, and, as such, we are familiar with the area and have a personal interest in it. The size of the area is 2.74 km^2, and we divided it into 49 grid cells in a pattern of 7 x 7 equal cells. With this design, each cell corresponds to an area of size 0.05 km^2; the edge of each cell is thus approximately 250 m long and wide. This is an appropriate grid cell size for a city with a population density such as that of Singapore. The granularity of each cell is reasonable, as each cell includes several buildings. In addition, household, retail, industrial, and infrastructure system cells are generally distinct; however, in several instances, these units are combined into one cell, having both these scenarios is desirable.

We selected the grid to adequately model the system and translated it to a 49-node network with connections defined by roads and infrastructure system connections in the actual district of Clementi in Singapore. The infrastructure system connections thus mimic the real-world infrastructure systems present in the area of interest.

Five infrastructure systems and resources were selected to be modeled. These include the power supply, which was represented by a power supply grid; the water supply, which was represented by a water supply network; and commercial goods, consumer goods, and human capital (people), which were all represented by road networks, albeit with different costs and capacities for each system/resource. These resources were selected as the most crucial to the survival of businesses and households in the city of Singapore. As Singapore has a limited water supply, the water supply system is extremely important. In addition, power is crucial to all commercial and household activities. The physical transportation of goods is also vital in maintaining the operation of all socioeconomic units, and the transportation of people is necessary for maintaining the operation of businesses that require workers. Consequently, the above-mentioned infrastructure systems and resources were selected to be modeled in our system.

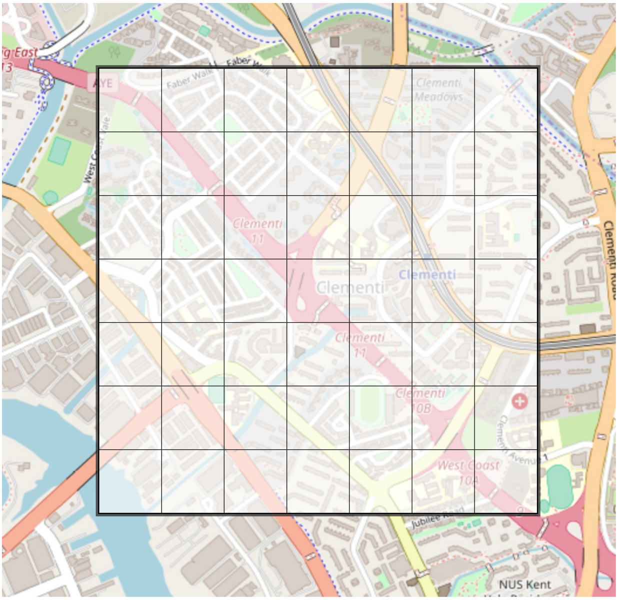


FIGURE 5.2: Area selected for simulation with applied grid. This is an area in the Clementi district in Singapore that has a size of 2.74 km^2. A grid of 49 cells with a size of 7 x 7 was applied. The cells were numbered horizontally from the top left corner to the bottom right corner from 0 to 48. This area represents a combination of residential, retail, and industrial regions.

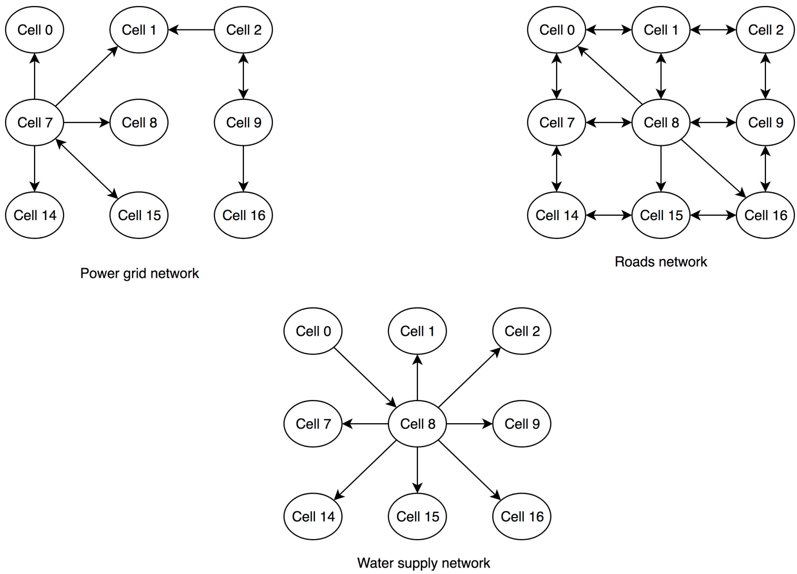


FIGURE 5.3: Section of networks in the area of interest. The selected geographic area is translated into networks of infrastructure systems. These include a water supply network, road network, and power grid network, each consisting of a different topology and specification of edges and 49 nodes. Here, a subset of nine neighboring nodes and the connection between these nodes is presented.

5.3.3 *Networks*

The area illustrated in fig. 5.2 was mapped onto a network for each infrastructure system. The systems were developed into three distinct network topologies: a water supply network, a power supply network, and a road network. The road network was used to create three networks for commercial goods, consumer goods, and human capital with the same topology, but with varying parameters, such as edge costs and capacities.

In these networks, the edges correspond to infrastructure system links, and the network differs for each infrastructure system. Although the networks for commercial goods, consumer goods, and human capital have the same topology, they have different edge parameters. The road networks serve to transfer consumer goods, business goods, and people, while the water supply network supplies water to businesses and households, and the power grid supplies power to businesses and households. The connections in these networks mimic the real-world connections of these modeled systems in the area of interest. As such, the power grid network in the simulation corresponds to the power grid in the area, the water supply network in the simulation corresponds to the water supply system in the area, and the road network corresponds to the road network in the area.

A portion of these networks with a subset of nine cells is presented in fig. 5.3. This figure illustrates nine nodes and the network connections between these nodes for three networks, namely the power grid network, road network, and water supply network. The overall network consists of 49 nodes; however, a subset is presented in fig. 5.3 for simplicity.

5.3.4 *Building blocks*

A set of 13 building blocks was defined to mimic the building blocks of a city. Each building block corresponded to the typical characteristics that the block would have in the real world; in other words, these building blocks defined the characteristics of urban elements that could be seen in a city. The building blocks that we defined included the following: HDBs[2], condominiums, houses, retail business units, office business units, industrial units, water units, power units, highway connection units, external water supply units, external power supply units, recreation area units, and school units. The 13 building blocks were each assigned a matrix of technical coefficients. This matrix defined the resources that a building block could produce and the resources that it required to produce one unit of each resource. The matrix of technical coefficients for each building block was an input-output matrix of this block. In addition, each building block had a final consumer vector assigned that specified the quantity of each resource consumed by this block as the final consumer. Similarly, a raw materials supply vector was defined for each building block to specify the cost of supplying one unit of resources for each building block. An example of a building block corresponding to a house is presented in fig. 5.4. This is one of 13 building blocks; in combination, the blocks are used to describe the nodes of the simulation network. All 13 building blocks used in this study are presented in appendix B.

The building blocks are defined so that they can be easily modified if there arises a need to alter them. They are defined in a spreadsheet and can be easily adjusted in the simulation to ensure that the set of build-

2 HDB – Housing and Development Board – a type of a multi-family residential unit common in Singapore

Building block matrix - T1 - House

$$\begin{bmatrix} 0. & 0. & 0.8 & 0. & 0.8 \\ 0. & 0. & 0.7 & 0. & 0.8 \\ 0. & 0. & 0.5 & 0. & 3. \\ 0. & 0. & 0.1 & 0. & 0.1 \\ 0. & 0. & 0.9 & 0. & 0.4 \end{bmatrix} \text{ Demand: } \begin{bmatrix} 0.1 & 0.2 & 1. & 0.05 & 0.5 \end{bmatrix} \text{ Supply: } \begin{bmatrix} inf & inf & inf & inf & 100. \end{bmatrix}$$

FIGURE 5.4: Description of a house building block used to model the area of Clementi. This block can produce human capital and consumer goods and supply human capital, and it is the final consumer of all resources. There are a total of 13 similar building blocks defined with specific, unique characteristics, including matrices of technical coefficients, final consumer demand vectors, and supply vectors. These blocks are used to define individual cells in the simulation network. Cells are composed of a combination of building blocks.

ing blocks representing individual network nodes is adequate. In addition, these blocks are used to define each cell of the area network. Each cell consists of several blocks, and these blocks are assigned to each cell in accordance with the building block vector of each cell.

Next, we introduced two building blocks that defined disruptions. These building blocks have significantly worse performance in certain respects than functional building blocks. Thus, introducing these blocks into a node decreases the performance of that node and mimics a disruption occurring in the node. In this way, disruptions to cells of the area are represented. The disruptions are introduced into a cell by adjusting the cell's vector of building blocks by including disruption building blocks. The two disruption building blocks used in this study are presented in appendix B.

Defining building blocks makes it possible to quickly assemble an urban area model based on a selected area and a set of building blocks. If the area is altered, the set of previously defined building blocks can be retained, and only the matrix of building blocks must be redefined. The selected area is then divided into a new grid, and the blocks that are already present are assigned to this area, thus accelerating the process of developing a model from a real-world scenario.

5.3.4.1 *Matrix of building blocks*

Combining the vectors of building blocks forms a matrix of building blocks, in which each row corresponds to one cell and represents the combination of building blocks that form that cell. The matrix defines a particular state of the system in terms of building blocks. Changes to the matrix of building blocks serve to alter the composition of the simulated urban area, accommodating changes to the production processes, final consumption, and raw materials supply.

To obtain the actual cell characteristics from a matrix of building blocks, for each row corresponding to one cell in the network, we proportionately apply building blocks to the entries in the row. In this way, each row corresponds to the description of each cell in terms of both normal building blocks and disruption building blocks. The construction of each cell is thus obtained based on the building block coefficients that specify the composition of the cell.

The matrix can be easily modified. Changes to the matrix along with changes to the topology or costs of the edges of the network are two methods of introducing disruptions into the system. Adjustments made to the matrix modify the performance of the network.

A section of the matrix of building blocks is presented in fig. 5.5. The full matrix for our system of interest includes 49 rows and 15 columns. The full matrix is presented in appendix B. The extracted section contains the three top rows of the matrix. This matrix, in conjunction with the building blocks' specifications, can be used to obtain technology matrices and demand and supply vectors for each of the 49 cells in the network. Each row of the matrix corresponds to one cell in the network, and each column corresponds to a building block coefficient of the block in the given row's cell.

5.3.5 *Model execution*

The above-mentioned simulation model was adapted to an interface that allowed for a swift and efficient alteration of building block definitions, building blocks matrices, and network topologies and parameters. To this end, building blocks were defined in an Excel spreadsheet so that they could be read and modified in a simple manner. The spreadsheet contained a matrix of technical coefficients, the final consumer demand vector, and the raw materials supply vector of each building block, and it could be modified in an intuitive fashion.

$$\begin{bmatrix} 2. & 0. & 0. & 0. & 0. & 15. & 55. & 0. & 11. & 50. & 0. & 24. & 0. & 0. & 0. \\ 23. & 0. & 43. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 4. & 0. & 0. & 0. \\ 42. & 0. & 11. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 37. & 0. & 0. & 0. \end{bmatrix}$$

FIGURE 5.5: Section of matrix of building block coefficients. Each row defines the corresponding cell in terms of 15 building blocks (13 actual building blocks and 2 disruption building blocks). In combination with building blocks, this matrix can be used to obtain technology matrices and the demand and supply vectors of each cell in the network. The full matrix consists of 49 rows of 15 building block coefficients, one row corresponding to each cell.

A web interface was used to visualize the graph of a network along with the matrix of technical coefficients for each node. An individual node's matrix of building blocks could be modified; in addition, the network edges and their parameters could also be modified to continuously adjust the simulation. The results were presented on an interactive map, which contained the cost of satisfying the entire system all as well as each individual cell. Similarly, a graph of the supply curve for the simulation was derived. A sample input interface is presented in fig. 5.6.

5.3.6 *Disruption scenarios*

A set of eight disruption scenarios was designed to showcase the application of our model. These disruptions corresponded to events that could take place in the area of interest and result in system malfunctions. These scenarios corresponded to various degrees of disruption to the systems and represented typical events that could occur as a result of a natural disaster, attack, or equipment malfunction. The scenarios developed were used to evaluate the performance of the network and the change in the supply curve resulting from each scenario. This process allowed us to examine the applicability of our model and how it could be applied to assess the resilience of the system in terms of cost.

Adjusting the system to simulate different disruptions can allow operators to observe or predict the impact of various disruption scenarios on a network. This can aid in guiding investment decisions in the area of interest, and different investment options can be presented and evaluated for a set of predefined disruption scenarios.

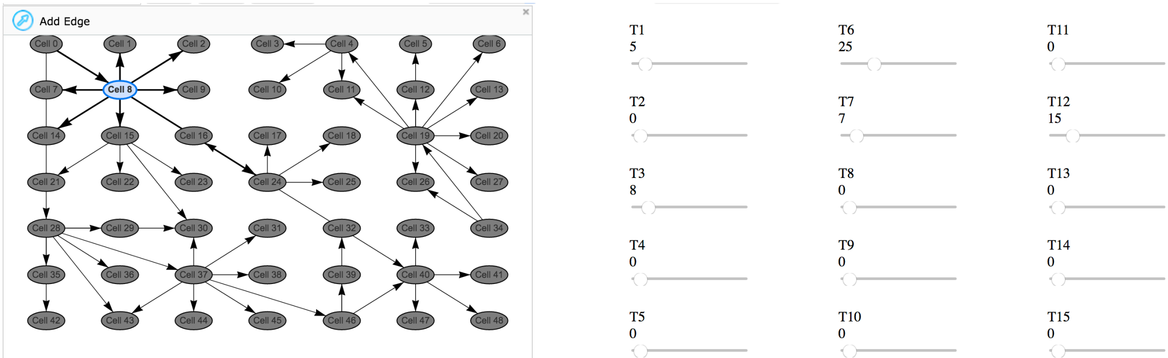
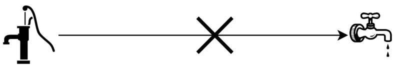
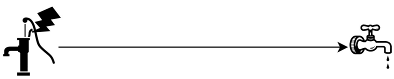
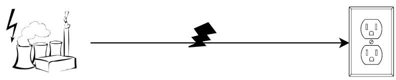
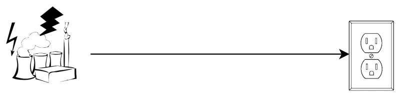
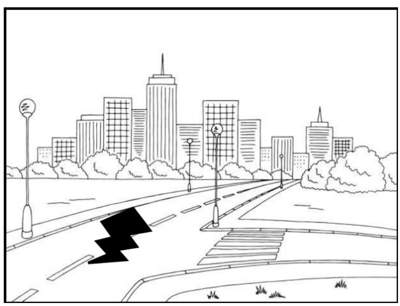


FIGURE 5.6: Sample input interface displaying network links and cells and their composition based on building blocks. Both can be modified, and the simulation can be run to observe the results of the modifications. The network can be modified by removing or adding new edges or changing their costs. The cells/nodes can be modified by adjusting their composition in terms of building blocks.

The set of eight disruption scenarios used in our study is presented in table 5.2.

TABLE 5.2: Simulated disruption scenarios. Each disruption scenario disturbs one or more parts of the system, such as business agents, power supply, power grid, or water grid.

Scenario no.	Diagram	Description
1		Disruption to water supply network only.
2		Disruption to water supply plant only.
3		Disruption to power grid only.
4		Disruption to power plant only.
5		Disruption to road network. Major intersection breakdown only.
6		Disruption to factory only.

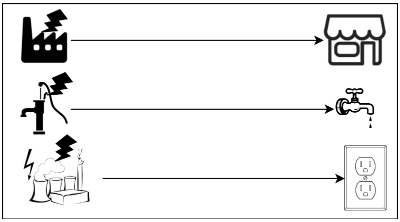
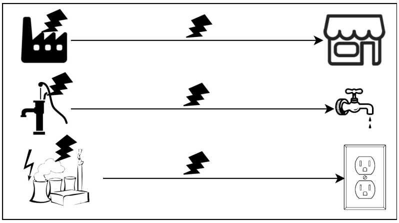
Scenario no.	Diagram	Description
7		Disruption to factories, a water supply plant, and a power plant simultaneously. Major multi-business failure.
8		Disruption to factories, a water supply plant, a power plant, a water supply network, a power grid, and roads simultaneously. Major multi-system failure.

Table 5.2 demonstrates that the severity, causes, and initial impact of the disruption scenarios varied. This enabled us to examine a wide spectrum of disruption scenarios. We began with single system disruption that affected either an infrastructure system network or a single factory, and we gradually moved to complex, major, multi-system failures, in which many infrastructure system networks and businesses were affected.

5.4 RESULTS

To assess the performance of the network, for each disruption scenario the following data was collected:

- Cost of satisfying the overall system given the disruption;
- Supply curve across all cells of the grid given the disruption.

Subsequently, the collected results for each disruption scenario were compared with the base scenario, in which no disruptions were present in the system. This allowed us to evaluate the performance of the system for each disruption scenario. The outcome of this process is presented below.

5.4.1 *Supply curve*

To obtain a supply curve for the overall system, we used the cost of supplying the aggregate quantity of resources for each cell across the system. This involves averaging the price across all resources proportionally to the amount of resource requested in each cell. A supply curve represents the cost to deliver an additional unit of the averaged resource at each aggregated quantity. The shape of the curve indicates the effects on various elements across the grid. Thus, different scenarios have different effects on cells within an area of interest. The supply curve graph can aid in revealing any high-impact areas in which a particular disruption has a significantly greater impact than in other areas.

The supply curves in fig. 5.7 reveal that disruption scenarios can have a different impact on various cells in the area of interest. In particular, Scenarios 2 and 8 have a disproportionately large impact on the cells that are impacted the most (i.e., at higher aggregate quantities). This suggests that some areas are significantly more affected by these disruptions than other areas. Therefore, infrastructure investments may be useful in these areas to lower the supply curves on the right side of the graph.

Figure 5.7 illustrates Scenarios 2, 7, and 8, and the base case with no disruptions. The changes in the supply curve represent the self-adjustment of prices in response to the disruptions. An upward change in the supply curves and an increase in their gradient correspond to the cost adjustment that occurs throughout the system in response to a disruption introduced to the system. Figure 5.7 suggests that Scenarios 2 and 8 are the costliest and therefore the most impactful on the system for the cost metric.

It is worth noting that as the quantity increases, the price variation between different disruption scenarios increases (heteroskedasticity). This confirms our predictions that there tends to be a greater impact on some of the most vulnerable units of the urban area. These units suffer the implications of disruptions to a larger degree than the other units. This finding is consistent with the results of disruptions in a real-life setting.

Similarly, standard deviations of simulations of disruption scenarios are important to note, as they can aid in confirming where and why crucial state transitions occur in a given area. Standard deviation of the average

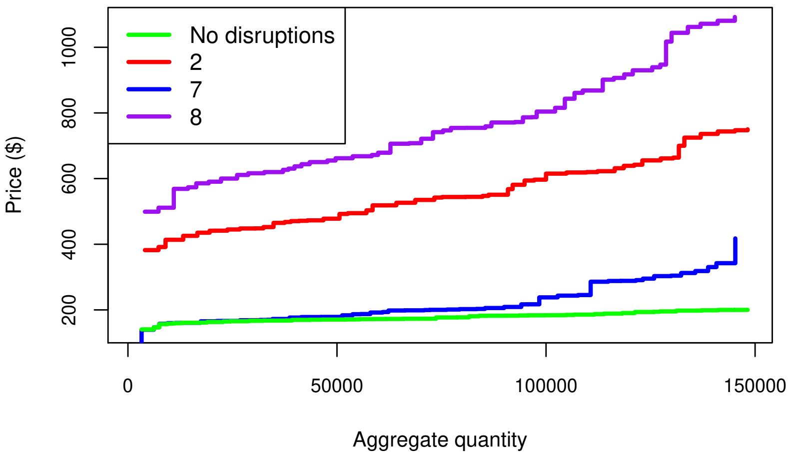


FIGURE 5.7: Simulation results for three disruption scenarios (numbered in top left corner) averaged across 10 stochastic simulation runs. The supply curve, which is the cost curve of the averaged resource unit, is presented for three disruption scenarios and the base case. There are variations of supply curves in both location and shape. The changes in the supply curve represent the self-adjustment of prices in response to disruptions. The most impactful disruption is the multi-system failure of various systems (Scenario 8), followed by a major failure of the water supply system (Scenario 2). The other scenarios have a lower impact on the performance of the system.

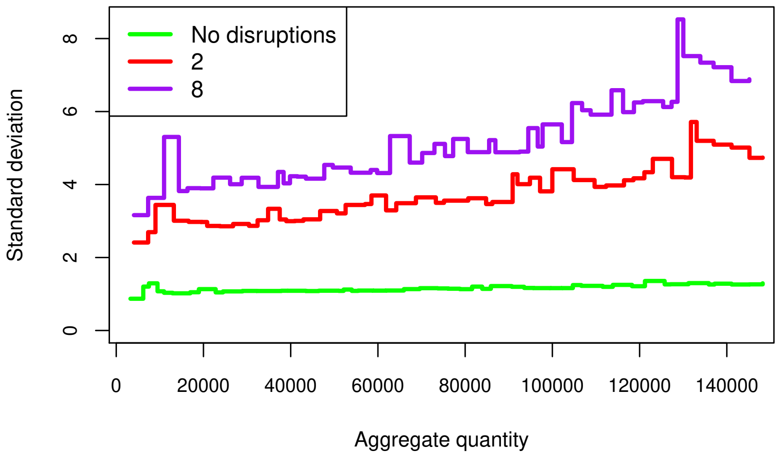


FIGURE 5.8: Standard deviations of average resource price for each agent across 10 stochastic simulation runs for disruption scenarios 2 and 8, and the base case (no disruption). Standard deviation generally increases with increasing price of resources. Peaks tend to appear near major shifts in price thus confirming particular vulnerability of these agents.

resource price for each agent across several simulation runs can be computed. On fig. 5.8, a graph of standard deviations of average resource price for each agent across 10 simulation runs for 2 disruption scenarios (Scenarios 2 and 8) and the base case is shown. It can be noted that standard deviation is growing in general proportionally with price, however, large shifts in supply curve correspond to large increases in standard deviation. This is an interesting result, which shows that standard deviation tends to peak around major shifts in supply curve. This might be because agents at these points are particularly affected by any, even minor, changes to the system. Even very small random variation to the system at such boundary agent becomes amplified, thus resulting in a larger standard deviation at these agents.

5.4.2 *Total cost*

Another metric for assessing the impact of disruptions is the total cost of satisfying the system for a disruption scenario. The evaluation of the system according to this metric is illustrated in fig. 5.9. The difference between the cost of each disruption scenario and the base scenario is an important metric, as it reveals the additional cost suffered by the system caused by introducing the disruption scenario.

Figure 5.9 demonstrates that with the exception of Scenario 1, which is omitted from the graph due to infinite total cost, Scenarios 2 and 8 result in the most costly disruptions. Scenario 8 has the largest impact in the entire simulation, with multiple systems failing simultaneously. Scenario 2, in contrast, involves the failure of a water plant, which provides a critical resource for the overall network. This disruption to the water supply propagates to all cells and substantially affects many production processes, thus increasing the cost of the disruption.

The total cost metric can also be used to examine the opposite case in which an improvement is introduced into the system; here, the cost of the improvement can be measured to determine the impact of the improvement. This approach can then be used to guide infrastructure development planning and investments. Different approaches can be evaluated to identify the approach that provides the largest decrease in the overall cost of satisfying the system.

Identifying and calculating the cost of disruption scenarios can aid in arranging the various scenarios in terms of their impact on a system. This can allow emergency and contingency planners to understand the failures

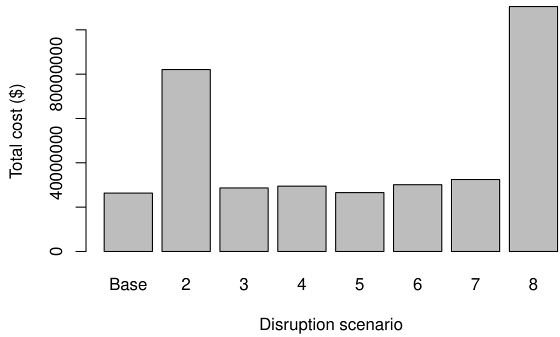


FIGURE 5.9: Total cost of satisfying the system for all disruption scenarios with the exception of Scenario 1, in which the cost of satisfying the system is infinite. These results reveal that the cost of satisfying the system is the greatest for Scenarios 2 and 8.

that would have the largest impact on the system. In addition, it can also help risk managers better calculate and estimate the VaR if the probability of each disruption appearing in the system can also be estimated.

Of the disruption scenarios used in our study, the disruption to the water supply system resulted in the largest negative impact on the system. In addition, as expected, the combination of several simultaneous system disruptions had a massive impact on the performance of the system in the area of interest. The results indicate that a disruption to the power system resulted in a lower cost than a disruption to the water supply system, unless the disruption to the water supply system was combined with a disruption to the power supply, as in Scenario 8.

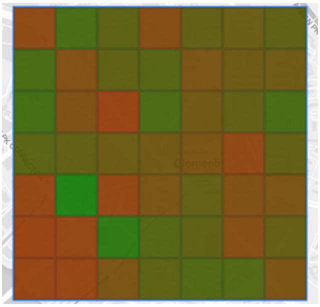
5.4.3 *Resilience cycle*

Behavior of agents over a resilience cycle can be tracked in our simulation. By collecting data on an agent's behavior, we can see how an agent's production and consumption changes when a disruption is introduced to the system and as it develops and propagates through the system. This progress of a disruption can be tracked and shown for various agents, and at an individual agent level too. Here we present the impact of a disruption on several agents and on an individual agent as the disruption progresses in the system through 5 different stages of resilience cycle: before (awareness), introduction of a disruption (resistance), during the disruption (resistance), recovery (re-establishment and rebuilding), after the disruption retracts (re-configuration and adaptation).

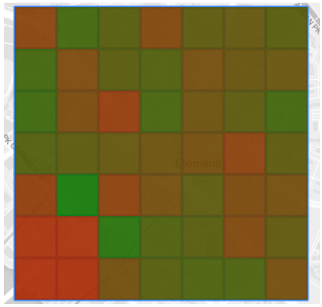
Figure 5.10 demonstrates the progress of agents in the area through 5 stages of resilience cycle mentioned, under a disruption (based on disruption scenario 4) being introduced. Using colors, grid cells represent changes and effects of the disruption scenario on the geographical area considered in this study in terms of average costs of resources. It can be seen that cost of resources is low initially, then as the disruption is introduced the costs start to rise, and they peak as disruption fully propagates and takes effect on the area. Then, as disruption recedes, we can see the system improving and going back to the original performance and even adapting by decreasing the costs as compared to before the disruption had occurred.

On fig. 5.11 bar charts show how a single agent (agent no. 35) behaves in terms of amount of resources demanded by this agent throughout a resilience cycle of the same disruption being introduced. This behavior is captured by the changes in external demand (inputs) of the agent throughout the corresponding resilience cycle. The amount of resources requested by the agent varies as disruption happens in the system. We can see that the agent requires more input resources right after the disruption occurs to the system in order to resist the disruption. The agent maintains higher demand throughout the disruption, and then changes its profile during recovery in order to adapt itself to the disruption occurring in the future. This resilience cycle representation demonstrates an individual agent's response to a disruption and how its input varies as disruption develops and progresses through the system.

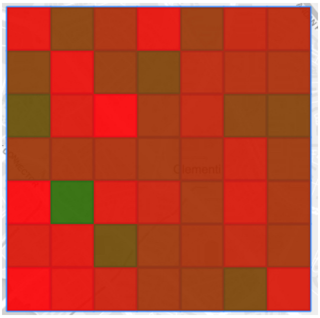
A resilience cycle episode was presented at two different granularities and for 2 different metrics here. We could see how cost of resources in an area varied and progressed with a disruption scenario introduced to the system. Furthermore, we could notice how a single agent responded to a disruption in terms of amount of resources that the agent demanded from the system. Both these approaches allow stakeholders to infer different characteristics of the system and assess resilience by looking at a particular resilience cycle for different disruption scenarios' episodes. This can be particularly useful and beneficial for resilience assessment of the system.



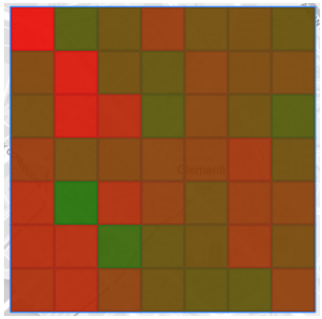
(a) Before the disruption occurs - awareness



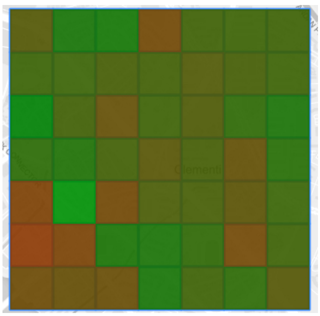
(b) Beginning of the disruption, just after disruption is introduced - resistance



(c) During the disruption, the highest impact of the disruption - resistance



(d) Recovery from the disruption - reestablishment and rebuilding



(e) Disruption fully retracted - reconfiguration and adaptation

FIGURE 5.10: Averaged cost of resources in the area considered throughout 5 stages of resilience cycle. On the color spectrum, red corresponds to a higher cost, while green to a lower cost to provide resources in the given cell. Each cell corresponds to one cell of the geographical area from fig. 5.2. Resilience cycle can be clearly seen.

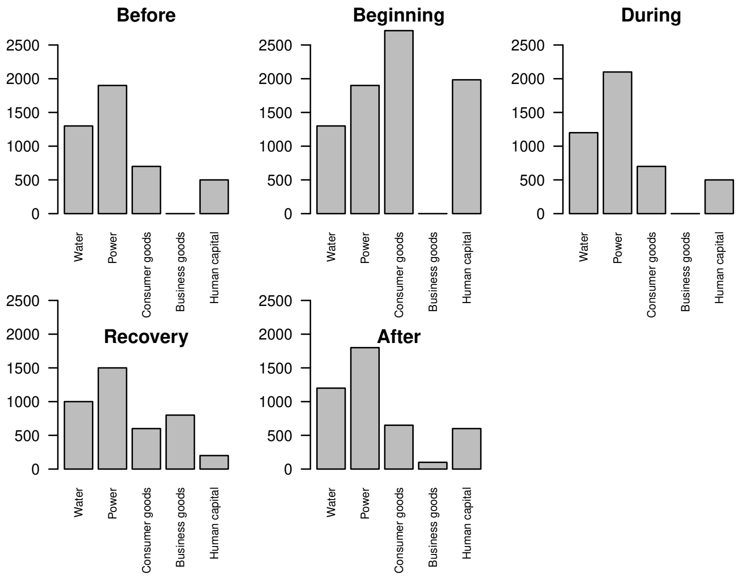


FIGURE 5.11: External demand (input) changes in a single agent throughout a resilience cycle. The demand profile of an agent varies as disruption propagates through the system. Resilience cycle can be clearly seen.

5.5 CONCLUSIONS

The goals of this study were to (1) devise an application workflow of a framework for modeling businesses, households, and infrastructure systems and their response to disruptions; (2) apply the framework to an area of a city; and (3) analyze the response of the simulation to a set of predefined disruption scenarios to compare the impact of the disruptions on the system. In particular, our objective was to evaluate the impact of disruptions on the system to confirm that the proposed modeling framework can be applied to model interdependencies between infrastructure systems, businesses, and households to assess their resilience.

Our study resulted in the following findings. First, a nine-step application workflow for our modeling framework was developed, which can be used to apply the framework to any geographical urban area. Second, the modeling framework was applied using the workflow to a 2.74 km^2 area of Singapore's Clementi district. We modeled five infrastructure systems and resources in this area, including the water supply, power supply, consumer goods, industrial goods, and human capital. Third, a set of eight disruption scenarios was applied to the simulation model, and the response to these scenarios was examined.

The above process yielded the following major results:

- As expected, the impact of major multi-system disruptions resulted in the largest impact on the SoS.
- Disruptions tended to have a disproportionately large effect on small vulnerable populations, especially as the overall size of the disruption increased.
- Disruptions to key utility systems such as the water supply or power supply were more impactful than disruptions to businesses or transportation networks. Thus, utility networks tended to be less resilient than transportation networks.
- The application of the model to the area of interest revealed that the model can be used to assess the resilience of a system in terms of disruption cost. In addition, it can be used to assess the impact of prospective improvements to a system.

Our application of the framework to a certain geographical area to assess its resilience is novel. The modeling framework that we used has been described in the literature [91]; however, the application of the model to an actual area in the city of Singapore, and the development of a workflow defining the method for using the simulation, is original. Similarly, there exist different modeling frameworks for infrastructure systems [5][92][86]; however, most of these approaches do not take into account the role of businesses and households, which are considered in our study. Likewise, the input-output model has been applied to modeling infrastructure systems [144], economies [117], and individual businesses [27]; however, it has not been utilized in an applied SoS model in which all applications are combined within one model. Modeling frameworks and models are presented for many infrastructures [87] and locations [145]; however, the application workflows for these frameworks are not available. This study has bridged this gap.

The results of this study have several implications for scientists, policymakers, and practitioners. Scientists can utilize our results to better model infrastructure systems, businesses, and households to assess their resilience. The workflow can be used to apply the model to different configurations of urban areas to evaluate the performance of the different configurations for various disruptions. Policymakers can apply the proposed model to support decisions regarding infrastructure development and investments. Risk managers can use the model with a set of randomly generated stochastic disruption scenarios to assess the VaR of the area. Furthermore, infrastructure and city planners can utilize the model to understand which parts of a city are affected the most by disruptions and generate the highest costs when disrupted. Domain experts can then draw conclusions regarding the causes of these costs and suggest system improvements that may decrease the overall cost.

The primary limitations of our study are its applicability to the selected area, infrastructure systems, and resources, and its reliance on the definitions of building blocks. The results obtained for this area and these networks may differ for a different set of networks. Similarly, if altered, the selection of building blocks may yield different results. There is a wide range of building blocks that can be used to simulate the system, and adding more blocks or redefining the blocks may change the results. Similarly, introducing different types of disruptions and increasing the number of disruption scenarios can alter our model in terms of the cost of disruptions.

Another limitation of this study is the type of data collected about the system and the accuracy of the model, which may vary depending on the granularity of the model and the number of resources modeled. To address these challenges, future work on this topic can involve similar experiments using a different area and a different set of resources. The application workflow can be used to apply the model to a larger area of the simulation with finer granularity. In addition, a different and wider range of disruptions and building blocks can be used to better model the performance of individual units. This will likely improve the accuracy of the simulation. Finally, a structured comparison between the model application and actual real-world urban area can be performed to further investigate the shortcomings and advantages of the proposed model and workflow.

6 SYNTHESIS

I dream my painting and I paint my dream.
— Vincent van Gogh

The aim of this study was to develop a framework for modeling interdependencies between infrastructure systems, households, and businesses, which would allow for an analysis of the impact of these interdependencies on the effect of disruptions on the system. First, the aim was to develop a model of interdependencies that would allow for introduction of disruptions into the system to evaluate their impact on performance of the system. Second, our objective was to investigate how synchronization of such models can be performed to represent a real-world system as accurately as possible. Third, our aim was to combine the above ideas to apply the model of interdependencies between infrastructure systems, businesses, and households to an actual urban area. The scope of this study covered the development of an agent representing metabolism of a socioeconomic unit, such as a business or a household, interacting with infrastructure systems within an urban area. Moreover, the scope covered development and description of the simulation model and experiments to assess performance of the models and their scalability and applicability. This included the application of the developed model to a certain real-world case study area.

6.1 OUTCOMES

This study resulted in the following outcomes:

- distributed simulation model representing metabolism of business or household units, infrastructure system links, and disruptions,
- price mechanism for allocation of resources to represent the self-organizing capability of the model, and to estimate disruption magnitudes,
- concurrent disruptions to the water and power network have higher impact than those to the transportation network,

- disruption impacts exhibit emergent behavior,
- propagation effects of disruptions in a system-of-systems model are heavily dependent on time granularity,
- time granularity of a system-of-systems should be less than 1.13 of the smallest expected recovery time of the constituent systems,
- disruptions to key utility systems are costlier than to transportation systems or other businesses, and
- disruptions have a disproportionately large effect on small vulnerable populations, especially as the overall size of the disruption increases.

Major outcomes of this study are presented above. The primary outcome achieved by this study was the design and development of an agent that simulated the metabolism of a socioeconomic unit such as a business or a household. The agent applied Leontief's input–output model to describe production as a transformation of a set of input goods and services into a set of output goods and services. Moreover, the agent included interfaces to other agents and final consumers of resources and raw material producers that could be used to introduce primary materials into the modeling environment.

In this study, the agents were joined to form a network of agents, and combined with a price mechanism used to coordinate allocation of goods and services. Such simulation model was self-organizing through automatically attempting to fulfill the requirements of the agents when a disruption was introduced into the system. The resources in the network were dynamically assigned to agents based on transportation and production costs. In our model, the allocation of resources was affected by introduction of disruptions to the system, and increasing disruption magnitudes yielded price increases.

The above model consisting of a network of agents is a novel approach to modeling interdependencies of infrastructure systems, businesses, and households. Most of the research paths thus far have focused on modeling individual infrastructure systems [111] or on modeling several infrastructure systems; however, they have excluded socioeconomic agents in their approaches [86]. Our approach of a network of agents fills the gap in the current state of the art by including households and businesses in infrastructure system models, thus making these models more accurate by representing the real world better.

Similarly, the adaptation of the input–output model [12] and the introduction of a self-organizing mechanism to model interdependencies of infrastructures, businesses, and households, and their impact on propagation of disruptions is original. The input–output model has been applied to analyze production processes within businesses [95]; however, the model has not been attempted beyond that—in the context of urban areas and infrastructure systems modeling. This pushes the boundary of the current state of the art by applying the input–output model and complex networks' self-organization mechanisms to model interdependencies between infrastructure systems, businesses, and households.

Simulation experiments were conducted on the developed model to evaluate the usefulness of the model in assessing resilience and the impact of disruptions on an urban area. This approach allowed us to expand the body of knowledge by providing a more comprehensive framework for modeling resilience of urban areas that includes households and businesses alongside infrastructure systems in the model. The simulation experiments showed that combined disruptions to water and power supply networks resulted in the most severe impacts, and that disruptions to both infrastructure system lifelines and socioeconomic agents are most damaging followed by disruptions to socioeconomic agents only. Furthermore, the experiments emphasized the emergent nature of disruptions impacts, where the impact of a small disruption gets amplified by cascading effects. This stressed the need for robust water and power supply networks, and the importance of system-of-systems models of disruption impacts.

The impact of time granularity of exchange of information between constituent systems in a system-of-systems simulation on propagation of disruptions between these systems was evaluated with different simulation parameters. This has shown that the exchange of information has a significant impact on mapping and propagation of disruptions. Depending on the recovery time after a disruption, time granularity of a system-of-systems simulation needs to be carefully selected. Constituent systems need to have a finer time granularity than the expected length of resilience cycle. However, to register propagation of a disruption, the ratio of time granularity to the expected recovery time from a major disruption needs to be at most 1.13. This result means that the time granularity in the SoS simulation needs to be less than 113% of the smallest expected recovery time from a disruption of constituent systems to register the propagation of disruption from one constituent system to the others. The experiments conducted have also enabled us to devise a model of actual recovery time of a system based on the simulated recovery time for a given simulation. These findings are helpful in establishing the real-world impact of disruptions simulated in a system-of-systems simulation model.

Time management and synchronization of simulations have been studied and investigated [128][134]. However, there is no consideration of how propagation of disruptions is affected by changes in time granularity of the simulation. The appropriate time granularity of exchange of data between constituent models is a gap that this study fills in the field of distributed SoS modeling. The analysis of the impact that time granularity has on simulations is crucial to designing good simulations and subsequently to obtaining valid results in SoS models and simulations of infrastructure systems. Selection of appropriate time granularity is a substantial concern, which this study has determined, thus confirming expectations and expanding the body of knowledge of distributed SoS simulations.

The system-of-systems simulation model was applied to a real-world case, the area of Clementi in Singapore following the application workflow described. This revealed that the model can be used to assess resilience of systems in terms of costs of disruptions. The simulation experiments performed on the application of the model showed that disruptions to key utility systems such as the water supply or power supply result in costlier impacts than disruptions to businesses or transportation networks. Similarly, the experiment demonstrated that in the area considered disruptions tend to have disproportionately large effect on small areas with vulnerable populations. This effect gets magnified as disruption size increases.

The development of application workflow used to apply the model to a use case pushes the boundary of the body of knowledge by allowing modeling frameworks to be applied to real-world systems to improve their design and performance. The modeling frameworks have been developed in the past [5]; however, there was little research available on the processes leading to application of these frameworks. This shortcoming was addressed in this study by providing a methodical workflow that can be used to apply a framework for modeling interdependencies between systems that follows certain principles to an actual urban area.

The simulation experiments conducted allowed for identification of infrastructure systems and areas which are especially vulnerable to disruptions. These experiments are a novel contribution to the field of resilience modeling and assessment. The ability to model disruptions' impact on infrastructure systems, businesses, and households and evaluate these in terms of cost in a particular region of a city is a substantial achievement that makes a worthwhile contribution to the body of knowledge in this field. There have existed many approaches to modeling individual infrastructure systems in various locations [92][146]; however, these have not been applied to a particular physical location and have not included businesses and households present in the area. This study has clearly outlined benefits of applying the model to a real-world context.

6.2 LIMITATIONS

A major limitation for this study is the limited scope of experimentation conducted on the proposed framework. The developed agent was utilized and combined in a network with other agents to represent an SoS network of infrastructure systems, businesses, and households. This network was tested and compiled with a particular topology. Only one medium-size topology was applied to evaluate and describe the system, and the impact of topology of the network on the system was thus not considered. Furthermore, only a subset of data was collected about the system to evaluate the network's performance and the model's applicability. This study focused on measuring the cost to satisfy a critical demand to estimate and compare resilience of the SoS in the face of disruptions. There exist other indicators that can be used to evaluate resilience and performance of a system. In this study, the primary metric considered was the cost of producing the required amount of goods and services. Other metrics and influence of regulatory frameworks on the model were not analyzed and used in organizing the system.

Disruption generation models that were used to evaluate performance of the system were limited in scope. There was a limited number of disruption scenarios randomly selected from a limited set of distributions to represent disruptions that can be generated in the system. There was no analysis of various differing disruption generators and differences between those. Disruption generators have a significant impact on evaluating resilience and adequacy of the model of interdependencies; hence, limitation in the study of disruption generators limited the scope of outcomes of this study.

Data obtained from the model can be primarily adapted to compare systems on a high level and to see interesting relationships between different systems or systems with additional developments added. This is because a large number of stochastic processes that are combined together and cascaded together in an SoS simulation make the exact numerical results very difficult to interpret. Hence, the model presented in this study could be primarily used to compare system designs and developments with other developments and to understand major relationships between certain factors of system design. This is a limitation that is natural and very difficult to overcome for a complex SoS simulation with such a great degree of stochasticity inherent in the model.

Partly because of reasons stated in the previous paragraph, it was difficult to validate and test the model beyond very simple cases where the outcome of the model is obvious. The outcome can only be compared with expert opinions on what the outcome should be in a given situation. In SoS modeling, especially with a significant amount of randomness present, it is difficult to utilize traditional validation techniques as the emergent outcome of cascaded random processes is not easily foreseeable.

In the study of impact of time granularity on propagation of disruptions, the selection of factors varied to evaluate the impact of these on propagation of disruptions was limited. Three factors were considered, and their impact was evaluated. This is a limitation as other factors also affect the propagation of disruptions to other systems. Similarly, the SoS was analyzed with a given set of three topologies and three networks; however, this is a limited scope as different topologies and larger quantities of networks can present different results. However, the results presented provide a good estimate of what factors are especially important for selecting time granularity of SoS simulations of infrastructure systems.

Moreover, the impact of factors on propagation of disruptions was studied on an abstract, generated network that followed principles similar to those of infrastructure system networks; however, it did not represent an actual physical area. The application of the model to a given physical area was a limitation of this study.

The model of infrastructure systems, businesses, and households was applied to a geographical area to evaluate the impact of disruptions on the model and, hence, evaluate resilience of the region. This was applied to a geographical area; however, the data used to apply the model were generated based on informed estimates and expert knowledge of the systems of interest. Consequently, the system was not evaluated with detailed real-world data. Similarly, the number of areas to which the model was applied was limited, having applied the model only to one city area of Singapore. Application of the model is a resource-consuming process that does not necessarily present any value in terms of conceptual model development.

The application of the model made use of certain building blocks for the city socioeconomic units. These blocks could be redefined, and their application can follow a different process, such as different composition of building blocks or different spatial granularity. These were limited in scope to one case and configuration of building blocks.

6.3 Implications

This study and approaches presented in the previous chapters may have the following implications:

6.3.1 *Scientists*

Scientists might benefit from the scalable approach outlined to evaluate infrastructure systems, businesses, and households in a geographical area. Interactions and the impact of these interactions on the outcomes and propagation of disruptions between the systems can be studied by scientists at a fine granularity of individual households and businesses. Moreover, researchers can use the model to evaluate how different communities are affected by various disruptions. Furthermore, this study can help scientists in selecting an appropriate time granularity for such system-of-systems models of various infrastructure systems. The study emphasizes the importance of an appropriate time granularity for simulations to obtain substantive results. This can be applied by scientists to other fields beyond infrastructure system simulations, such as business or military settings. Similarly, scientists can utilize the framework for translating simulated to actual disruption magnitudes to more adequately assess the impact of disruptions on systems.

The application workflow of the model to a geographical area can be used by the scientific community as a blueprint for modeling interdependencies between infrastructure systems, households, and businesses in other regions. This can help researchers to better estimate costs of disruptions being introduced into the system, and to compare various areas in terms of their resilience and to compare hypothetical disruption scenarios against one another. This is a valuable implication that can provide scientists with a uniform method of evaluating resilience of urban area ecosystems and infrastructure development projects in these areas.

6.3.2 *Policymakers*

For policymakers, this study presents several implications. Decision makers can use methods developed in this study as a support tool, which would help them in making decisions about policies that they design. They can use the tool to make decisions about direction to take when planning infrastructure development projects. The models developed in this study could be utilized in devising contingency plans in cases of major disruptions. Policymakers can adapt the method presented in this study to aid them in making critical decisions on the go while a disruption is developing and progressing. Inclusion of households and businesses in the model can help the decision makers to identify the most vulnerable groups, that is, groups that are affected the most by a potential disruption within an urban area. Moreover, business leaders and corporate policymakers can use the methods presented in the study to better predict the behavior of businesses in the face of disruptions, especially to see how regional units are affected by the disruptions.

Policymakers can make use of the findings of this study to estimate the actual impact of disruptions based on simulations of these disruptions. They can apply these findings in their decision-making processes regarding infrastructure system development and policies. Furthermore, policymakers can utilize the application framework and the applied model to support their decisions regarding investments in infrastructure. They can utilize the application workflow to apply the model to various situations to create a complex decision support tool for their policies. They can utilize the findings of this study to find the value at risk of urban areas and infrastructure systems and to estimate the benefits from development of additional infrastructure.

6.3.3 *Professionals*

Professionals such as urban and infrastructure planners and asset managers can adapt methods developed in this study for stress-testing and assessing systems. Urban planners can use the tool to compare different topologies and configurations of areas in terms of their resilience. This can help infrastructure planners to introduce more redundancy and to focus their design efforts on particular segments of the system that are the most critical to preserving operation of the system in the face of adversities. Infrastructure asset managers can use the tool to understand better where their infrastructure needs to be reinforced. The costliest vulnerabilities to the system given a certain range of disruptions can be located using the adaptation of the model presented in this study. This knowledge can aid infrastructure planners to better plan infrastructure. Risk managers can adapt the model to estimate the value at risk of infrastructure systems in a certain area and to estimate the infrastructure systems' exposure to adverse events in that area. This in turn can help underwriters and risk engineers to better calculate insurance premiums for large infrastructure systems and projects. Planners can utilize the model to create experimentation that would enable them to identify parts of the systems that need the most investments. Consequently, the application of this study can be helpful in determining where to expand infrastructure projects such as power grids or water supply networks.

Furthermore, the study can aid risk managers, infrastructure planners, and other professionals to better estimate the actual impact of cascaded disruptions based on simulation results. The study can aid in devising better simulation parameters that would make the simulation more efficient for such professionals by decreasing their cost and time required to run simulations, which could present significant savings in the case of running thousands of simulations. Infrastructure and city planners can use the model to identify areas of cities that accrue the most cost due to a disruption. Domain experts can then use this information to investigate causes for these costs and possibly counteract them or come up with ideas to mitigate the costs.

6.4 PATHWAYS TO FUTURE WORK

To tackle challenges and limitations to this study, presented in this chapter, and to further increase the scope of the study, the following pathways to future work have been identified.

The primary pathway for future work is to apply the models presented in this study to more topologies and areas to investigate the impacts of these topologies and areas on performance of systems under disruptions. This would mean introducing a different topology to the model, applying the model to different areas, and applying several different granularities for cells in the application of the model. This would help scientists to evaluate the model's accuracy for various environments and to see how the systems of concern are affected by disruptions in these new areas with different topologies and systems included in the simulation.

Additionally, an alternative system for resource allocation in the model could be attempted. The current mechanism focuses primarily on cost; however, there are other regulatory frameworks that might alter this mechanism. Implementing and including these in the model could present different results and expand the model further. Such mechanisms could include emergency protocols or limits on consumption or production of resources by different entities in the event of emergency defined by reaching a certain price level. An independent rules-based operator could introduce these limits to the system. Investigating the performance and behavior of such an operator and then modeling this could be attempted.

Another significant pathway for future research is to introduce a wider range of disruption generators into the systems. Disruption generators can follow more carefully designed stochastic processes that correspond better to particular real-world events that are threatening infrastructure systems. Such disruption models are an important field to study, since the type of disruptions that could happen to the system is crucial to evaluating the risks involved in the system accurately. This study focused primarily on modeling interdependencies between different components of urban areas; hence, the complement—accurate disruption generation—would be the natural pathway forward. Furthermore, additional, more commensurate with the real-world mechanisms and supply curves could be used to model supply of raw materials to the system, as well as final consumer demands in the system.

The time granularity of exchange of data between the systems could be evaluated on a greater range of systems. Including a larger amount of systems would allow for obtaining better and more comprehensive results about the systems and the importance and influence of time granularity on the results of simulations. Similarly, a wider range of factors could be used to evaluate the propagation of disruptions between the systems. This could include factors such as size of the network and number of systems included and affected by the disruption. Hence, a pathway forward here would be to perform such experimentation on a wider range of systems with different networks and parameters of the networks involved.

The data collected in the system and the presentation of results could be improved and further investigated. Since in complex system-of-systems simulations, the amount of data collected is massive, investigating the options to visualize and succinctly compress the results of the simulations could be an important way forward. There are also plenty of metrics for performance that could be devised based on the model and simulations presented in this study. These metrics could be described and evaluated for their usefulness in terms of assessing resilience of networks in the future. Similarly, including other metrics besides costs could help to evaluate sustainability of the system and its impact on the environment in the face of disruptions.

The application of the model could be attempted with more accurate data that could be obtained from operators, researchers, and experts in the respective fields. This would ensure that the model is more accurate and representative of the actual urban area in the real world. More accurate representation of the model would mean more accurate results of the simulation experiments. Additional building blocks for the application of the simulations could be developed and experimented on. This would help to model urban areas more accurately and, more importantly, to model disruptions within these areas better.

Moreover, an alternative mechanism for deriving technology matrices of socioeconomic units and network topologies within the framework presented in this study could be researched, which could include machine learning and pattern recognition approaches. Such approaches would help to automate the application of the framework to an urban area given access to certain sensors within the area. This would be a more ambitious path for future research; however, having considered the rapid development and access to data and sensors, it does not seem too far-fetched.

Furthermore, a more general pathway forward for this study could be to incorporate models developed by particular infrastructure systems' experts to create a large system-of-systems simulation modeling various systems with differing intrinsic simulations joined together. This study has laid the groundwork for such application. Moreover, an application of the ideas presented in this study could be applied to other fields of research that could benefit from complex SoS simulation modeling such as health care and financial systems.

BIBLIOGRAPHY

1. United Nations Department of Economic and Social Affairs. *The World's Cities in 2016* (2016).
2. Heinimann, H. R. & Hatfield, K. *Infrastructure Resilience Assessment, Management and Governance – State and Perspectives* in *Resilience and Risk* (Springer, 2017), 147.
3. Swyngedouw, E. Circulations and metabolisms: (Hybrid) Natures and (Cyborg) cities. *Science as Culture* **15**, 105 (2006).
4. Rinaldi, S., Peerenboom, J. & Kelly, T. Identifying, understanding, and analyzing critical infrastructure interdependencies. *IEEE Control Systems Magazine* **21**, 11 (2001).
5. Ouyang, M. Review on modeling and simulation of interdependent critical infrastructure systems. *Reliability Engineering & System Safety* **121**, 43 (2014).
6. Francis, R. & Bekera, B. A metric and frameworks for resilience analysis of engineered and infrastructure systems. *Reliability Engineering & System Safety* **121**, 90 (2014).
7. Park, J., Seager, T. P., Rao, P. S. C., Convertino, M. & Linkov, I. Integrating risk and resilience approaches to catastrophe management in engineering systems. *Risk Analysis* **33**, 356 (2013).
8. McAslan, A. The concept of resilience: Understanding its origins, meaning and utility. *Adelaide: Torrens Resilience Institute*, 1 (2010).
9. Jackson, S. A multidisciplinary framework for resilience to disasters and disruptions. *Journal of Integrated Design and Process Science* **11**, 91 (2007).
10. Cutter, S. L., Ahearn, J. A., Amadei, B., Crawford, P., Eide, E. A., Galloway, G. E., Goodchild, M. F., Kunreuther, H. C., Li-Vollmer, M., Schoch-Spana, M., Scrimshaw, S. C., Stanley, E. M., Whitney, G. & Zoback, M. L. Disaster resilience: A national imperative. *Environment: Science and Policy for Sustainable Development* **55**, 25 (2013).
11. Leichenko, R. Climate change and urban resilience. *Current Opinion in Environmental Sustainability* **3**, 164 (2011).

12. Leontief, W. W. Quantitative Input and Output Relations in the Economic Systems of the United States. *The Review of Economics and Statistics* **18**, 105 (1936).
13. Leontief, W. W. *The Structure of American Economy, 1919-1939: An Empirical Application of Equilibrium Analysis* 2Rev Ed edition (Oxford University Press, 1951).
14. Miller, R. E. & Blair, P. D. *Input-Output Analysis: Foundations and Extensions* (Cambridge University Press, 2009).
15. Baumol, W. J. Leontief's Great Leap Forward: Beyond Quesnay, Marx and von Bortkiewicz. *Economic Systems Research* **12**, 141 (2000).
16. Akita, T. & Kataoka, M. Interregional Interdependence and Regional Economic Growth: An Interregional Input-Output Analysis of the Kyushu Region. *Review of Urban & Regional Development Studies* **14**, 18 (2002).
17. Franke, R. & Kalmbach, P. Structural change in the manufacturing sector and its impact on business-related services: an input–output study for Germany. *Structural Change and Economic Dynamics* **16**, 467 (2005).
18. Hui-jiong, W. *Interregional Input-output Analysis Of The Chinese Economy* (World Scientific, 2003).
19. Ozkan, B., Akcaoz, H. & Fert, C. Energy input–output analysis in Turkish agriculture. *Renewable Energy* **29**, 39 (2004).
20. Machado, G., Schaeffer, R. & Worrell, E. Energy and carbon embodied in the international trade of Brazil: an input–output approach. *Ecological Economics* **39**, 409 (2001).
21. Fletcher, J. E. Input-output analysis and tourism impact studies. *Annals of Tourism Research* **16**, 514 (1989).
22. Leontief, W. Environmental Repercussions and the Economic Structure: An Input-Output Approach. *The Review of Economics and Statistics* **52**, 262 (1970).
23. Hendrickson, C. T., Lave, L. B. & Matthews, H. S. *Environmental Life Cycle Assessment of Goods and Services: An Input-output Approach* (Resources for the Future, 2006).
24. Joshi, S. Product Environmental Life-Cycle Assessment Using Input-Output Techniques. *Journal of Industrial Ecology* **3**, 95 (1999).

25. Van Ittersum, M. K. & Rabbinge, R. Concepts in production ecology for analysis and quantification of agricultural input-output combinations. *Field Crops Research* **52**, 197 (1997).

26. Hazari, B. R. & Krishnamurty, J. Employment Implications of India's Industrialization: Analysis in an Input Output Framework. *The Review of Economics and Statistics* **52**, 181 (1970).

27. Lin, X. & Polenske, K. R. Input—output modeling of production processes for business management. *Structural Change and Economic Dynamics* **9**, 205 (1998).

28. Oliva, G., Panzieri, S. & Setola, R. Agent-based input–output interdependency model. *International Journal of Critical Infrastructure Protection* **3**, 76 (2010).

29. Haimes Yacov Y., Horowitz Barry M., Lambert James H., Santos Joost R., Lian Chenyang & Crowther Kenneth G. Inoperability Input-Output Model for Interdependent Infrastructure Sectors. I: Theory and Methodology. *Journal of Infrastructure Systems* **11**, 67 (2005).

30. Haimes Yacov Y., Horowitz Barry M., Lambert James H., Santos Joost, Crowther Kenneth & Lian Chenyang. Inoperability Input-Output Model for Interdependent Infrastructure Sectors. II: Case Studies. *Journal of Infrastructure Systems* **11**, 80 (2005).

31. Setola, R., De Porcellinis, S. & Sforna, M. Critical infrastructure dependency assessment using the input–output inoperability model. *International Journal of Critical Infrastructure Protection* **2**, 170 (2009).

32. Jonkeren, O. & Giannopoulos, G. Analysing Critical Infrastructure Failure with a Resilience Inoperability Input–Output Model. *Economic Systems Research* **26**, 39 (2014).

33. Heermann, D. W. *Computer-simulation methods* in *Computer Simulation Methods in Theoretical Physics* 8 (Springer, 1990).

34. Fujimoto, R. M. *Parallel and distributed simulation systems* (John Wiley & Sons, Inc., 2000).

35. Law, A. M., Kelton, W. D. & Kelton, W. D. *Simulation modeling and analysis* (McGraw-Hill New York, 2000).

36. Fujimoto, R. *Parallel and distributed simulation* in *2015 Winter Simulation Conference (WSC)* (2015), 45.

37. Hofer, R. C. & Loper, M. L. DIS today [Distributed interactive simulation]. *Proceedings of the IEEE* **83**, 1124 (1995).

38. Dahmann, J. S., Kuhl, F. & Weatherly, R. Standards for Simulation: As Simple As Possible But Not Simpler The High Level Architecture For Simulation. *SIMULATION* **71**, 378 (1998).
39. Schlesselman, J. M., Pardo-Castellote, G. & Farabaugh, B. *OMG data-distribution service (DDS): architectural update* in *IEEE MILCOM 2004. Military Communications Conference, 2004.* **2** (2004), 961.
40. Bonabeau, E. Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences* **99**, 7280 (2002).
41. Pardo-Castellote, G. *OMG Data-Distribution Service: architectural overview* in *23rd International Conference on Distributed Computing Systems Workshops, 2003. Proceedings.* (2003), 200.
42. Dahmann, J. S., Fujimoto, R. M. & Weatherly, R. M. *The Department of Defense High Level Architecture* in *Proceedings of the 29th conference on Winter simulation - WSC '97* (ACM Press, 1997), 142.
43. Klein, U., Schulze, T. & Straßburger, S. *Traffic Simulation Based on the High Level Architecture* in *Proceedings of the 30th Conference on Winter Simulation* (IEEE Computer Society Press, Los Alamitos, CA, USA, 1998), 1095.
44. Ippolito, C. & Pritchett, A. *Software architecture for a reconfigurable flight simulator* in (2000), 4501.
45. Julier, S., King, R., Colbert, B., Durbin, J. & Rosenblum, L. *The software architecture of a real-time battlefield visualization virtual environment* in *Proceedings IEEE Virtual Reality (Cat. No. 99CB36316)* (1999), 29.
46. Eusgeld, I., Nan, C. & Dietz, S. "System-of-systems" approach for interdependent critical infrastructures. *Reliability Engineering & System Safety* **96**, 679 (2011).
47. Müller, S. C., Georg, H., Rehtanz, C. & Wietfeld, C. *Hybrid simulation of power systems and ICT for real-time applications* in *2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe)* (2012), 1.
48. Farmer, J. D. & Foley, D. The economy needs agent-based modelling. *Nature* **460**, 685 (2009).
49. Epstein, J. M. Modelling to contain pandemics. *Nature* **460**, 687 (2009).
50. An, G., Mi, Q., Dutta-Moscato, J. & Vodovotz, Y. Agent-based models in translational systems biology. *Wiley Interdisciplinary Reviews: Systems Biology and Medicine* **1**, 159 (2009).

51. Heppenstall, A. J., Crooks, A. T., See, L. M. & Batty, M. *Agent-Based Models of Geographical Systems* (Springer Science & Business Media, 2011).

52. Bazghandi, A. Techniques, advantages and problems of agent based modeling for traffic simulation. *International Journal of Computer Science Issues (IJCSI)* **9**, 115 (2012).

53. Sterman, J. *Business Dynamics: Systems Thinking and Modeling for a Complex World* (McGraw-Hill, 2000).

54. Richardson, G. P. *Feedback thought in social science and systems theory* (University of Pennsylvania Press, 1991).

55. Boardman, J. & Sauser, B. *System of Systems - the meaning of of* in *2006 IEEE/SMC International Conference on System of Systems Engineering* (2006), 118.

56. Jamshidi, M. *System of Systems Engineering: Innovations for the Twenty-First Century* (Wiley, 2009).

57. Nomaguchi, Y. & Fujita, K. A Framework of System of Systems Design with Scenario, Multi-Agent Simulation and Robustness Assessment. *Procedia CIRP. Complex Systems Engineering and Development Proceedings of the 27th CIRP Design Conference Cranfield University, UK 10th – 12th May 2017* **60**, 133 (2017).

58. Keating, C., Rogers, R., Unal, R., Dryer, D., Sousa-Poza, A., Safford, R., Peterson, W. & Rabadi, G. System of Systems Engineering. *Engineering Management Journal* **15**, 36 (2003).

59. Jackson, M. C. & Keys, P. Towards a System of Systems Methodologies. *Journal of the Operational Research Society* **35**, 473 (1984).

60. Jackson, M. C. Beyond a System of Systems Methodologies. *Journal of the Operational Research Society* **41**, 657 (1990).

61. DeLaurentis, D. A. & Ayyalasomayajula, S. Exploring the Synergy Between Industrial Ecology and System of Systems to Understand Complexity. *Journal of Industrial Ecology* **13**, 247 (2009).

62. Garrett Jr., R. K., Anderson, S., Baron, N. T. & Moreland Jr., J. D. Managing the interstitials, a System of Systems framework suited for the Ballistic Missile Defense System. *Systems Engineering* **14**, 87 (2011).

63. Owens, W. A. *The Emerging U.S. System-of-Systems* tech. rep. 63 (National Defense University, Institute for National Strategic Studies, Washington, DC, USA, 1996).

64. Hadian, S. & Madani, K. A system of systems approach to energy sustainability assessment: Are all renewables really green? *Ecological Indicators* **52**, 194 (2015).

65. Carlock, P. G. & Fenton, R. E. System of Systems (SoS) enterprise systems engineering for information-intensive organizations. *Systems Engineering* **4**, 242 (2001).

66. Logan, B. & Theodoropoulos, G. The distributed simulation of multiagent systems. *Proceedings of the IEEE* **89**, 174 (2001).

67. Georg, H., Wietfeld, C., Müller, S. C. & Rehtanz, C. *A HLA based simulator architecture for co-simulating ICT based power system control and protection systems* in *2012 IEEE Third International Conference on Smart Grid Communications (SmartGridComm)* (2012), 264.

68. Kleijnen, J. P. C. *Design and Analysis of Simulation Experiments* 2nd ed. (Springer International Publishing, 2015).

69. Barton, R. R. *Simulation experiment design* in *Proceedings of the 2010 Winter Simulation Conference* (IEEE, Baltimore, MD, USA, 2010), 75.

70. Barton, R. R. *Graphical Methods for the Design of Experiments* (Springer Science & Business Media, 2012).

71. Donohue, J. *Experimental designs for simulation* in *Proceedings of the 26th conference Winter Simulation* (IEEE, Lake Buena Vista, FL, USA, 1994), 200.

72. Sargent, R. G. *Verification and validation of simulation models* in *Proceedings of the 2010 Winter Simulation Conference* (IEEE, Baltimore, MD, USA, 2010), 166.

73. Rutherford, A. *Introducing Anova and Ancova: A GLM Approach* (SAGE, 2001).

74. Bagdatli, B., Griendling, K. & Mavris, D. Challenges for Simulating Stochastic Behavior in Systems of Systems. *INSIGHT* **15**, 29 (2012).

75. Thomas, J. J. & Cook, K. A. *Illuminating the Path: The Research and Development Agenda for Visual Analytics* (IEEE Computer Society, Los Alamitos, US-CA, 2005).

76. United Nations. *World urbanization prospects: the 2014 revision* (United Nations, Department of Economic and Social Affairs, and Population Division, 2014).

77. Holling, C. S. Understanding the Complexity of Economic, Ecological, and Social Systems. *Ecosystems* **4**, 390 (2001).

78. Committee on Adaptation to a Changing Climate. *Adapting Infrastructure and Civil Engineering Practice to a Changing Climate* (ed Olsen, J. R.) (American Society of Civil Engineers, Reston, VA, 2015).

79. Dueñas-Osorio, L. & Vemuru, S. M. Cascading failures in complex infrastructure systems. *Structural Safety*. *Risk Acceptance and Risk Communication* **31**, 157 (2009).

80. Boin, A. & McConnell, A. Preparing for Critical Infrastructure Breakdowns: The Limits of Crisis Management and the Need for Resilience. *Journal of Contingencies and Crisis Management* **15**, 50 (2007).

81. Amin, M. Toward self-healing infrastructure systems. *Computer* **33**, 44 (2000).

82. Eusgeld, I. & Nan, C. *Creating a simulation environment for critical infrastructure interdependencies study* in *2009 IEEE International Conference on Industrial Engineering and Engineering Management* (2009), 2104.

83. Espinoza, S., Panteli, M., Mancarella, P. & Rudnick, H. Multi-phase assessment and adaptation of power systems resilience to natural hazards. *Electric Power Systems Research* **136**, 352 (2016).

84. Liu, X., Liu, J., Zhao, S. & Tang, L. C. *Modeling and Simulation on a Resilient Water Supply System Under Disruptions* in *Proceedings of the Institute of Industrial Engineers Asian Conference 2013* 1385 (Springer, Singapore, 2013).

85. Tamvakis, P. & Xenidis, Y. Resilience in Transportation Systems. *Procedia - Social and Behavioral Sciences*. *Transport Research Arena 2012* **48**, 3441 (2012).

86. Rinaldi, S. M. *Modeling and simulating critical infrastructures and their interdependencies* in *Proceedings of the 37th Annual Hawaii International Conference on System Sciences, 2004.* (Big Island, HI, USA, 2004).

87. Dudenhoeffer, D., Pederson, P., Hartley, S. & Permann, M. *Critical infrastructure interdependency modeling: a survey of U.S. research* in (2006).

88. Panzieri, S., Setola, R. & Ulivi, G. *An agent based simulator for critical interdependent infrastructures* in *Securing Critical Infrastructures* (Grenoble, 2004).

89. Cardellini, V., Casalicchio, E. & Galli, E. *Agent-based Modeling of Interdependencies in Critical Infrastructures Through UML* in *Proceedings of the 2007 Spring Simulation Multiconference - Volume 2* (Society for Computer Simulation International, San Diego, CA, USA, 2007), 119.

90. Casalicchio, E., Galli, E. & Tucci, S. *Federated Agent-based Modeling and Simulation Approach to Study Interdependencies in IT Critical Infrastructures* in *Proceedings of the 11th IEEE International Symposium on Distributed Simulation and Real-Time Applications* (IEEE Computer Society, Washington, DC, USA, 2007), 182.

91. Dubaniowski, M. I. & Heinimann, H. R. *A framework modeling flows of goods and services between businesses, households, and infrastructure systems* in *Resilience The 2nd International Workshop on Modelling of Physical, Economic and Social Systems for Resilience Assessment : 14-16 December 2017, Ispra* **I** (Publications Office of the European Union, 2017), 182.

92. Zhang, P. & Peeta, S. A generalized modeling framework to analyze interdependencies among infrastructure systems. *Transportation Research Part B: Methodological* **45**, 553 (2011).

93. Chang, S. E. Socioeconomic Impacts of Infrastructure Disruptions. *Oxford Research Encyclopedia of Natural Hazard Science* (2016).

94. Buzna, L., Issacharoff, L. & Helbing, D. The evolution of the topology of high-voltage electricity networks. *International Journal of Critical Infrastructures* **5**, 72 (2009).

95. Wang, J.-W. & Rong, L.-L. Robustness of the western United States power grid under edge attack strategies due to cascading failures. *Safety Science* **49**, 807 (2011).

96. Cardillo, A., Scellato, S., Latora, V. & Porta, S. Structural properties of planar graphs of urban street patterns. *Physical Review E* **73** (2006).

97. Leontief, W. W. *Input-output Economics* (Oxford University Press, 1986).

98. Bowles, S. The Production Process in a Competitive Economy: Walrasian, Neo-Hobbesian, and Marxian Models. *The American Economic Review* **75**, 16 (1985).

99. Hackman, S. T. & Leachman, R. C. A General Framework for Modeling Production. *Management Science* (1989).

100. Yu, G. & Qi, X. *Disruption Management: Framework, Models and Applications* (World Scientific, 2004).

101. Blackhurst, J., Craighead, C. W., Elkins, D. & Handfield, R. B. An empirically derived agenda of critical research issues for managing supply-chain disruptions. *International Journal of Production Research* **43**, 4067 (2005).

102. Snyder, L. V., Scaparra, M. P., Daskin, M. S. & Church, R. L. *Planning for Disruptions in Supply Chain Networks* in *Models, Methods, and Applications for Innovative Decision Making* 234 (INFORMS, 2006).

103. Rose, A. & Liao, S.-Y. Modeling Regional Economic Resilience to Disasters: A Computable General Equilibrium Analysis of Water Service Disruptions. *Journal of Regional Science* **45**, 75 (1980).

104. Cimellaro, G. P., Reinhorn, A. M. & Bruneau, M. Framework for analytical quantification of disaster resilience. *Engineering Structures* **32**, 3639 (2010).

105. Albino, V., Izzo, C. & Kühtz, S. Input–output models for the analysis of a local/global supply chain. *International Journal of Production Economics* **78**, 119 (2002).

106. Anaconda Inc. *Anaconda 2.4.0 for Python 3.5* 2015.

107. igraph.org. *python-igraph 0.7.1* 2014.

108. SciPy.org. *NumPy Reference — NumPy v1.10 Manual* 2015.

109. Fenopix, Inc. *CanvasJS 1.8.5 beta* en-US. 2013.

110. INCOSE & Walden, D. D. *Systems engineering handbook: A guide for system life cycle processes and activities* Fourth Edition (John Wiley & Sons, 2015).

111. Kinney, R., Crucitti, P., Albert, R. & Latora, V. Modeling cascading failures in the North American power grid. *The European Physical Journal B - Condensed Matter and Complex Systems* **46**, 101 (2005).

112. Sterbenz, J. P. G., Çetinkaya, E. K., Hameed, M. A., Jabbar, A., Qian, S. & Rohrer, J. P. Evaluation of network resilience, survivability, and disruption tolerance: analysis, topology generation, simulation, and experimentation. *Telecommunication Systems* **52**, 705 (2013).

113. Panteli, M., Trakas, D. N., Mancarella, P. & Hatziargyriou, N. D. Boosting the Power Grid Resilience to Extreme Weather Events Using Defensive Islanding. *IEEE Transactions on Smart Grid* **7**, 2913 (2016).

114. Furuta, K., Komiyama, R., Kanno, T., Fujii, H., Yoshimura, S. & Yamada, T. *Resilience Analysis of Critical Infrastructure* in *Recent Advances in Information Science* (WSEAS Press, 2016), 21.

115. Kotzanikolaou, P., Theoharidou, M. & Gritzalis, D. *Interdependencies between Critical Infrastructures: Analyzing the Risk of Cascading Effects* in *Critical Information Infrastructure Security* (Springer, Berlin, Heidelberg, 2011), 104.

116. Little, R. G. Controlling Cascading Failure: Understanding the Vulnerabilities of Interconnected Infrastructures. *Journal of Urban Technology* **9**, 109 (2002).

117. Isard, W. Interregional and Regional Input-Output Analysis: A Model of a Space-Economy. *The Review of Economics and Statistics* **33**, 318 (1951).

118. Santos, J. R. Inoperability input-output modeling of disruptions to interdependent economic systems. *Systems Engineering* **9**, 20 (2006).

119. Baumann, D. D., Boland, J. & Hanemann, W. M. *Urban water demand management and planning* (McGraw-Hill New York, 1998).

120. Neuman, M. Infrastructure planning for sustainable cities. *Geographica Helvetica* **66**, 100 (2012).

121. Boer, C. *Distributed Simulation in Industry* (Erasmus University Rotterdam, 2005).

122. Dubaniowski, M. I. & Heinimann, H. R. *Time Granularity in System-of-Systems Simulation of Infrastructure Networks* in *Complex Networks and Their Applications VII - Volume 1 Proceedings The 7th International Conference on Complex Networks and Their Applications COMPLEX NETWORKS 2018, Cambridge, UK, December 11-13, 2018.* (eds Aiello, L. M., Cherifi, C., Cherifi, H., Lambiotte, R., Lió, P. & Rocha, L. M.) (Springer, 2019), 482.

123. Gao, J., Buldyrev, S. V., Stanley, H. E. & Havlin, S. Networks formed from interdependent networks. *Nature Physics* **8**, 40 (2012).

124. Olsson, A. M. J. & Sandberg, G. E. Latin Hypercube Sampling for Stochastic Finite Element Analysis. *Journal of Engineering Mechanics* **128**, 121 (2002).

125. Erdős, P. & Rényi, A. On Random Graphs I. *Publicationes Mathematicae (Debrecen)* **6** (1959).

126. Bollobás, B. *Random Graphs* in *Modern Graph Theory* (ed Bollobás, B.) 215 (Springer New York, 1998).

127. Topçu, O. & Oztüzün, H. *High Level Architecture* in *Guide to Distributed Simulation with HLA* (eds Topçu, O. & Oztüzün, H.) 29 (Springer International Publishing, 2017).

128. Fujimoto, R. M. Time Management in The High Level Architecture. *SIMULATION* **71**, 388 (1998).

129. Fujimoto, R. M. & Weatherly, R. M. *Time Management in the DoD High Level Architecture* in *Proceedings of the Tenth Workshop on Parallel and Distributed Simulation* (IEEE Computer Society, Washington, DC, USA, 1996), 60.

130. Josuttis, N. M. *The C++ Standard Library: A Tutorial and Reference* (Addison-Wesley Professional, 2012).

131. Calytrix Technologies. *The Portico Project*

132. Python.org. *Python Release Python 3.5.0* 2015.

133. Lewis, B. *An R Interface to SciDB*

134. Jansen, R. E. J., Huiskamp, W. & Boomgaardt, J. Real-time Scheduling of HLA Simulator Components. null. *TNO Fysisch en Elektronisch Laboratorium* (2004).

135. Ferenci, S. L., Choi, M., Evans, J., Fujimoto, R. M., Alspaugh, C. & Legaspi, A. K. *Experiences integrating NETWARS with the naval simulation system using the high level architecture* in *IEEE MILCOM 2004. Military Communications Conference, 2004.* **3** (2004), 1395.

136. Jain, A., Robinson, D., Dilkina, B. & Fujimoto, R. *An approach to integrate inter-dependent simulations using HLA with applications to sustainable urban development* in *2016 Winter Simulation Conference (WSC)* (IEEE, Washington, DC, USA, 2016), 1218.

137. Alexander, C. *A Pattern Language: Towns, Buildings, Construction* (Oxford University Press, 1977).

138. Beirão, J. N. & Duarte, J. P. Urban design with patterns and shape rules. *Model Town, Using Urban Simulation in New Town Planning. Egbert Stolk and Marco te Brömmelstroet. SUN, Amsterdam* (2009).

139. Steino, N. *Parametric Thinking in Urban Design* in *28th Conference of Future Cities. eCAADe* **28** (2010).

140. Von Richthofen, A., Knecht, K., Miao, Y. & König, R. The 'Urban Elements' method for teaching parametric urban design to professionals. *Frontiers of Architectural Research* **7**, 573 (2018).

141. Chang, S. E., McDaniels, T., Fox, J., Dhariwal, R. & Longstaff, H. Toward Disaster-Resilient Cities: Characterizing Resilience of Infrastructure Systems with Expert Judgments. *Risk Analysis* **34**, 416 (2014).

142. Little, R. G. *Toward more robust infrastructure: observations on improving the resilience and reliability of critical systems* in *Proceedings of the 36th Annual Hawaii International Conference on System Sciences, 2003.* (2003).

143. Chang, S. E. Infrastructure Resilience to Disasters. *The Bridge* **44**, 36 (2014).

144. Haimes Yacov Y. & Jiang Pu. Leontief-Based Model of Risk in Complex Interconnected Infrastructures. *Journal of Infrastructure Systems* **7**, 1 (2001).

145. Kang, H.-Y. & Schoenung, J. M. Estimation of future outflows and infrastructure needed to recycle personal computer systems in California. *Journal of Hazardous Materials* **137**, 1165 (2006).

146. Pederson, P., Dudenhoeffer, D., Hartley, S. & Permann, M. *Critical infrastructure interdependency modeling: a survey of US and international research* tech. rep. INL/EXT-06-11464 (Idaho National Laboratory, Idaho Falls, ID, USA, 2006).

A

APPENDIX

In this appendix, we present the matrices of technical coefficients for all 14 agents used in the simulation experiment in chapter 3 under 3 disruption levels (no disruption, medium disruption, heavy disruption) used in the experiment. Similarly, we present transfer cost vectors for all the links in the simulation experiment model under 3 disruption levels (no disruption, medium disruption, heavy disruption) used in the experiment.

In matrix of technical coefficients entries of "0" throughout the whole column mean that the particular resource cannot be produced by the agent. Otherwise, the entries represent units of resource from the row required in production of a unit of resource from the column.

Alongside each matrix of technical coefficients (each table) a short paragraph justifying the particular selection of values for that matrix is presented. This is to provide explanation of reasonableness of the values selected for the simulation experiment, and so of the overall system. Furthermore, a short commentary on the physical reasonableness of each agent is provided. In general, the matrices of technical coefficients of agents were derived in order to ensure close correspondence with the case study system. As such, types and ratios of amounts of resources produced and used in production mimicked real-world production processes. Therefore, the system mimicked real-world physical production processes of resources.

In overall, after running the base case scenario, the following agents were producers for different goods and services. Power was produced by agent $A1$ for all consumers. Water was produced by agent $A2$ for all consumers. Gas was imported and supplied through agent $A1$ into the system. Petrol was imported and supplied to the system through agent $A0$. Capital goods were imported, or generated from scratch, and supplied to the system by agent $A0$. Consumer goods and services were produced and supplied by multiple agents at multiple levels depending on cost of these goods at each consumer. The above account of producer agents throughout the system complies with our prior expectations and common sense, which also suggests that the system is physically reasonable.

The above process corresponds to a small community in a physically reasonable way, where consumer goods and services are often produces and obtained in a distributed fashion close to the final demand points.

Conversely, utilities and capital goods are provided by central providers such as power plants, water plants, and major factories. Gas and petrol are imported into small communities from outside areas, where access to ports and major pipelines can be obtained. Finally, consumer households present a wide and diverse portfolio of consumption and production patterns varying due to their diverse needs on all income levels. All the above notions are precisely reflected in our system model. What is more, a company that produces resources, which are not described within our model, is represented to show how such agent would behave under our model – as a final consumer. This also corresponds to what we would expect of a reasonable model of such physical system.

In conclusion, the system presents a good physical reasonableness. The model corresponds to a real, physical world adequately. The small-scale proof-of-concept simulation allowed us to represent and to simulate crucial relationships of the system in our model effectively. The results of such simulation followed what we would expect in a real-world setting. It can be noted that the agents behaved in a reasonable manner producing resources at the most efficient points throughout the network, which coincided with the experts' assessment. Consequently, by comparing the similarities between the physical systems and our simulation model system, we can conclude that our system model is physically reasonable for the case study scenario considered.

TABLE A.1: Agent $A0$ - matrix of technical coefficients - no disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0
	Water	0	0	0	0	0	0
	Gas	0	0	0	0	0	0
	Petrol	0	0	0	0	0	0
	CapG	0	0	0	0	0	0
	CG&S	0	0	0	0	0	0

This agent does not perform any production processes. The agent supplies petrol and capital goods as raw materials. The agent's purpose is to supply raw materials from outside of the network and inject them into the system. This mimics a real-world situation, where petrol would not normally be produced locally in a small community but rather it would be imported into the local system. Similarly, a part of capital goods would be imported rather than produced by the local system in a small neighborhood. Consequently, the matrix of technical coefficients of this agent is empty, filled with "0", as the agent does not perform any production processes.

a CapG - Capital goods
b CG&S - Consumer goods and services

TABLE A.2: Agent $A1$ - matrix of technical coefficients - no disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0.05	0	0	0	0	0
	Water	0.02	0	0	0	0	0
	Gas	0.10	0	0	0	0	0
	Petrol	0.05	0	0	0	0	0
	CapG	0.05	0	0	0	0	0
	CG&S	0.10	0	0	0	0	0

This agent performs large-scale power production and supplies water and gas as raw materials into the system. The main purpose is to provide power to the overall system and introduce water and gas imported from outside of the small community. The agent corresponds to a real-world situation, where a power plant is present, producing energy for the neighborhood, and connections to outside water and gas suppliers are introduced through this agent too. The power production is focused mainly on gas followed by petrol, and these are the main resources needed for operation of the power producing capacity of this agent. Furthermore, capital goods, and consumer goods and services are used in this production process. This corresponds to the capital cost of running the production plant and employees of the plant consuming resources. As this is a large plant benefiting from high efficiency, it uses relatively little gas (0.10), petrol (0.05), and capital goods (0.05) in producing one unit of power. Also, 0.10 is a constant cost in terms of consumer goods and services for running a power plant in our model. The plant uses also minimal water (0.02) for cooling and maintenance, and self-consumes limited amount of power (0.05). This corresponds adequately to a power plant in a small community.

a CapG - Capital goods
b CG&S - Consumer goods and services

TABLE A.3: Agent $A2$ - matrix of technical coefficients - no disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0.18	0.90	0	0	0	0.20
	Water	0.30	0.10	0	0	0	0.30
	Gas	0.76	0.10	0	0	0	0.40
	Petrol	0.30	0.08	0	0	0	0.30
	CapG	0.14	0.05	0	0	0	0.20
	CG&S	0.10	0.05	0	0	0	0

This is the most comprehensive agent. It produces power, water and consumer goods and services. The agent's power production is less efficient than that of agent A1, with it requiring more primary resources to produce one unit of power. Consequently, under normal circumstances and low cost of energy transfer, power would be primarily produced by agent $A1$ (table A.2) for the whole system. Similarly, this agent produces water largely with the use of power (0.90) and small amounts of other resources ($\leq$0.10) corresponding with real-world water plants, which operate using electrical power. This large intake of power to produce one unit of water corresponds to the expensive nature of water in the small neighborhood considered. However, under normal operating circumstances water supplied by this agent should still be cheaper than imported from outside of the network. Finally, the agent also produces consumer goods and services. This is a process that utilizes all resources in relatively similar quantities (0.20-0.40) and is represented by the "shop" in the case study diagram. In real-world, this agent would correspond to a large distribution and provision center for some resources. It would be an infrastructure hub of the modeled area.

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.4: Agent $A3$ - matrix of technical coefficients - no disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.20
	Water	0	0	0	0	0	0.30
	Gas	0	0	0	0	0	0.40
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.20
	CG&S	0	0	0	0	0	0

This agent produces consumer goods and services that can subsequently be transferred to households. It does so by utilizing most of the resources in similar quantities (0.20-0.40). This agent mimics shop behavior described already for agent $A2$ (table A.3). Furthermore, it conveys resources from preceding agents. In real-world this agent corresponds to a very small neighborhood store and petrol station, a sub-area of a bigger neighborhood.

a CapG - Capital goods
b CG&S - Consumer goods and services

TABLE A.5: Agent $A4$ - matrix of technical coefficients - no disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.60
	Water	0	0	0	0	0	0.20
	Gas	0	0	0	0	0	0.50
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.20
	CG&S	0	0	0	0	0	0.01

This agent produces consumer goods and services that can subsequently be transferred to households. It does so by utilizing most of the resources in similar quantities (0.20-0.60). However, this agent is a bit more expensive in producing consumer goods and services than the previous two agents. This is because of older equipment and a more remote location of the neighborhood. Such circumstances warrant a more expensive production process. Furthermore, this agent conveys resources from preceding agents. In real-world this agent corresponds to a very small neighborhood store and petrol station, a subarea of a bigger neighborhood in a more remote location and with more rundown and thus less efficient facilities.

a CapG - Capital goods
b CG&S - Consumer goods and services

TABLE A.6: Agent $A5$ - matrix of technical coefficients - no disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.20
	Water	0	0	0	0	0	0.10
	Gas	0	0	0	0	0	0.20
	Petrol	0	0	0	0	0	0.20
	CapG	0	0	0	0	0	0.15
	CG&S	0	0	0	0	0	0

This agent represents a company that provides services which are not represented by the network. Consequently, they are represented as a final consumer that can also produce some resources very efficiently but only for own consumption. This corresponds to a company or a business unit that produces resources that are not covered by our model. In our case study this agent can include for example medical or financial services, which are not included as one of resources in our simulation model.

a CapG - Capital goods
b CG&S - Consumer goods and services

TABLE A.7: Agent $A6$ - matrix of technical coefficients - no disruption.

		To					
		Power	Water	Gas	Petrol	CapG[a]	CG&S[b]
From	Power	0	0	0	0	0	0.20
	Water	0	0	0	0	0	0.30
	Gas	0	0	0	0	0	0.20
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.10
	CG&S	0	0	0	0	0	0

This agent corresponds to a household with a low level of income. For such households, consumption is low, however, cost of producing consumer goods and services at the household level is similar to a "shop" as they are unable to take advantage of more advanced equipment and cannot perform production efficiently, but have less sophisticated demands for resources. This is reflected by a moderate number of resources required for production of consumer goods and services at the agent (0.10-0.30).

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.8: Agent $A7$ - matrix of technical coefficients - no disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.20
	Water	0	0	0	0	0	0.15
	Gas	0	0	0	0	0	0.50
	Petrol	0	0	0	0	0	0.10
	CapG	0	0	0	0	0	0.30
	CG&S	0	0	0	0	0	0

This agent corresponds to a household with a medium level of income. For such households, consumption is high, and the cost of producing consumer goods and services by the household level is different than at low income level as they are able to take advantage of more advanced equipment and can perform production more efficiently but require more sophisticated products. Still, this agent does not require luxurious products where cost of production in terms of resources is high. This is reflected by a larger difference in the amounts of resources required for production (0.10-0.50), and an increased need for gas and capital goods signifying more sophisticated resources being produced and consumed by this household.

a CapG - Capital goods
b CG&S - Consumer goods and services

TABLE A.9: Agent $A8$ - matrix of technical coefficients - no disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.25
	Water	0	0	0	0	0	0.22
	Gas	0	0	0	0	0	0.40
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.80
	CG&S	0	0	0	0	0	0

This agent corresponds to a household with a high level of income. For such households, consumption is high, and cost of producing certain resources and goods at the household level is higher as they are able to take advantage of more advanced equipment, which requires more resources. These households aim to consume and produce also more sophisticated luxurious products, which are costlier. This is reflected in the larger amount of capital goods needed to produce one unit of these goods (0.80).

a CapG - Capital goods
b CG&S - Consumer goods and services

TABLE A.10: Agent $A9$ - matrix of technical coefficients - no disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.20
	Water	0	0	0	0	0	0.40
	Gas	0	0	0	0	0	0.60
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.40
	CG&S	0	0	0	0	0	0

This agent corresponds to a household with a medium level of income. For such households, consumption is high, and cost of producing certain resources and goods at the household level is different as they are able to take advantage of more advanced equipment and can perform production efficiently but require more sophisticated products. Still they do not require luxurious products were cost of production in terms of resources is high. This is reflected by a larger difference in the amounts of resources required for production (0.20-0.60), and an increased need for gas and capital goods signifying more sophisticated resources being produced.

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.11: Agent $A10$ - matrix of technical coefficients - no disruption.

		To					
		Power	Water	Gas	Petrol	CapG[a]	CG&S[b]
From	Power	0	0	0	0	0	0.20
	Water	0	0	0	0	0	0.30
	Gas	0	0	0	0	0	0.40
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.20
	CG&S	0	0	0	0	0	0

This agent corresponds to a household with a low level of income. For such households, consumption is low, however, cost of producing consumer goods and services at the household level is moderate as they are unable to take advantage of more advanced equipment and cannot perform production efficiently in contrary to a shop. This is reflected by a relatively slightly higher number of resources required for production of consumer goods and services at the agent (0.20-0.40).

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.12: Agent $A11$ - matrix of technical coefficients - no disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.80
	Water	0	0	0	0	0	0.40
	Gas	0	0	0	0	0	0.60
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.40
	CG&S	0	0	0	0	0	0

This agent corresponds to a household with a low level of income. Here the production cost in terms of resources is high (0.30-0.80), as the household has no access to machinery but still might need to produce certain resources and the occupiers might be unskilled. This agent is meant to represent a household that cannot produce goods and services efficiently but is forced to do so, as they cannot be supplied otherwise at the agent level.

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.13: Agent $A12$ - matrix of technical coefficients - no disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.50
	Water	0	0	0	0	0	0.30
	Gas	0	0	0	0	0	0.40
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.50
	CG&S	0	0	0	0	0	0

This agent corresponds to a household with a medium level of income. Here the production cost in terms of resources is medium (0.30-0.50), as the household has some access to machinery when it might need to produce certain resources with medium skilled occupiers. This agent corresponds to a medium income household that is forced to produce certain goods and services, however, it can take advantage of equipment and help from employees or society due to their socioeconomic status.

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.14: Agent $A13$ - matrix of technical coefficients - no disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.10
	Water	0	0	0	0	0	0.30
	Gas	0	0	0	0	0	0.40
	Petrol	0	0	0	0	0	0.11
	CapG	0	0	0	0	0	0.40
	CG&S	0	0	0	0	0	0

This agent corresponds to a household with a high level of income. Here the production cost in terms of resources is low (0.10-0.40), as the household has access to machinery when it might need to produce certain resources and has skills to perform production efficiently when needed. Furthermore, the household can employ further workers to perform this production at their residence for the main occupiers. This agent represents a high-income household that can take advantage of efficient production mechanisms due to its socioeconomic status.

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.15: Agent $A0$ - matrix of technical coefficients - medium disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0
	Water	0	0	0	0	0	0
	Gas	0	0	0	0	0	0
	Petrol	0	0	0	0	0	0
	CapG	0	0	0	0	0	0
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.16: Agent $A1$ - matrix of technical coefficients - medium disruption.

		To					
		Power	Water	Gas	Petrol	CapG[a]	CG&S[b]
From	Power	0.40	0	0	0	0	0
	Water	0.70	0	0	0	0	0
	Gas	0.15	0	0	0	0	0
	Petrol	0.07	0	0	0	0	0
	CapG	0.05	0	0	0	0	0
	CG&S	0.15	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.17: Agent $A2$ - matrix of technical coefficients - medium disruption.

		To					
		Power	Water	Gas	Petrol	CapG[a]	CG&S[b]
From	Power	0.30	0.95	0	0	0	0.31
	Water	0.50	0.30	0	0	0	0.31
	Gas	0.80	0.20	0	0	0	0.40
	Petrol	0.31	0.40	0	0	0	0.30
	CapG	0.10	0.10	0	0	0	0.40
	CG&S	0.50	0.10	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.18: Agent $A3$ - matrix of technical coefficients - medium disruption.

		To					
		Power	Water	Gas	Petrol	CapG[a]	CG&S[b]
From	Power	0	0	0	0	0	0.80
	Water	0	0	0	0	0	0.50
	Gas	0	0	0	0	0	0.60
	Petrol	0	0	0	0	0	0.40
	CapG	0	0	0	0	0	0.20
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.19: Agent $A4$ - matrix of technical coefficients - medium disruption.

		To					
		Power	Water	Gas	Petrol	CapG[a]	CG&S[b]
From	Power	0	0	0	0	0	0.70
	Water	0	0	0	0	0	0.30
	Gas	0	0	0	0	0	0.60
	Petrol	0	0	0	0	0	0.34
	CapG	0	0	0	0	0	0.40
	CG&S	0	0	0	0	0	0.08

a CapG - Capital goods
b CG&S - Consumer goods and services

TABLE A.20: Agent $A5$ - matrix of technical coefficients - medium disruption.

		To					
		Power	Water	Gas	Petrol	CapG[a]	CG&S[b]
From	Power	0	0	0	0	0	0.70
	Water	0	0	0	0	0	0.50
	Gas	0	0	0	0	0	0.25
	Petrol	0	0	0	0	0	0.21
	CapG	0	0	0	0	0	0.20
	CG&S	0	0	0	0	0	0.10

a CapG - Capital goods
b CG&S - Consumer goods and services

TABLE A.21: Agent $A6$ - matrix of technical coefficients - medium disruption.

		To					
		Power	Water	Gas	Petrol	CapG[a]	CG&S[b]
From	Power	0	0	0	0	0	0.20
	Water	0	0	0	0	0	0.30
	Gas	0	0	0	0	0	0.20
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.10
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.22: Agent $A7$ - matrix of technical coefficients - medium disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.20
	Water	0	0	0	0	0	0.15
	Gas	0	0	0	0	0	0.50
	Petrol	0	0	0	0	0	0.10
	CapG	0	0	0	0	0	0.30
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.23: Agent $A8$ - matrix of technical coefficients - medium disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.25
	Water	0	0	0	0	0	0.22
	Gas	0	0	0	0	0	0.40
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.80
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.24: Agent $A9$ - matrix of technical coefficients - medium disruption.

		To					
		Power	Water	Gas	Petrol	CapG[a]	CG&S[b]
From	Power	0	0	0	0	0	0.20
	Water	0	0	0	0	0	0.40
	Gas	0	0	0	0	0	0.60
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.40
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.25: Agent $A10$ - matrix of technical coefficients - medium disruption.

		To					
		Power	Water	Gas	Petrol	CapG[a]	CG&S[b]
From	Power	0	0	0	0	0	0.20
	Water	0	0	0	0	0	0.30
	Gas	0	0	0	0	0	0.40
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.20
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.26: Agent $A11$ - matrix of technical coefficients - medium disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.80
	Water	0	0	0	0	0	0.40
	Gas	0	0	0	0	0	0.60
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.40
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.27: Agent $A12$ - matrix of technical coefficients - medium disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.50
	Water	0	0	0	0	0	0.30
	Gas	0	0	0	0	0	0.40
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.50
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

TABLE A.28: Agent $A13$ - matrix of technical coefficients - medium disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.10
	Water	0	0	0	0	0	0.30
	Gas	0	0	0	0	0	0.40
	Petrol	0	0	0	0	0	0.11
	CapG	0	0	0	0	0	0.40
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

TABLE A.29: Agent $A0$ - matrix of technical coefficients - heavy disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0
	Water	0	0	0	0	0	0
	Gas	0	0	0	0	0	0
	Petrol	0	0	0	0	0	0
	CapG	0	0	0	0	0	0
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.30: Agent $A1$ - matrix of technical coefficients - heavy disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0.40	0	0	0	0	0
	Water	0.90	0	0	0	0	0
	Gas	0.90	0	0	0	0	0
	Petrol	0.50	0	0	0	0	0
	CapG	0.60	0	0	0	0	0
	CG&S	0.20	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.31: Agent $A2$ - matrix of technical coefficients - heavy disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0.40	0.99	0	0	0	0.31
	Water	0.70	0.35	0	0	0	0.40
	Gas	0.90	0.40	0	0	0	0.40
	Petrol	0.31	0.40	0	0	0	0.30
	CapG	0.30	0.30	0	0	0	0.40
	CG&S	0.80	0.30	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

TABLE A.32: Agent $A3$ - matrix of technical coefficients - heavy disruption.

		To					
		Power	Water	Gas	Petrol	CapG[a]	CG&S[b]
From	Power	0	0	0	0	0	0.80
	Water	0	0	0	0	0	0.80
	Gas	0	0	0	0	0	0.60
	Petrol	0	0	0	0	0	0.70
	CapG	0	0	0	0	0	0.50
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

TABLE A.33: Agent $A4$ - matrix of technical coefficients - heavy disruption.

		To					
		Power	Water	Gas	Petrol	CapG[a]	CG&S[b]
From	Power	0	0	0	0	0	0.80
	Water	0	0	0	0	0	0.70
	Gas	0	0	0	0	0	0.60
	Petrol	0	0	0	0	0	0.34
	CapG	0	0	0	0	0	0.70
	CG&S	0	0	0	0	0	0.30

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.34: Agent $A5$ - matrix of technical coefficients - heavy disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.90
	Water	0	0	0	0	0	0.80
	Gas	0	0	0	0	0	0.90
	Petrol	0	0	0	0	0	0.40
	CapG	0	0	0	0	0	0.50
	CG&S	0	0	0	0	0	0.20

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.35: Agent $A6$ - matrix of technical coefficients - heavy disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.20
	Water	0	0	0	0	0	0.30
	Gas	0	0	0	0	0	0.20
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.10
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.36: Agent $A7$ - matrix of technical coefficients - heavy disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.20
	Water	0	0	0	0	0	0.15
	Gas	0	0	0	0	0	0.50
	Petrol	0	0	0	0	0	0.10
	CapG	0	0	0	0	0	0.30
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.37: Agent $A8$ - matrix of technical coefficients - heavy disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.25
	Water	0	0	0	0	0	0.22
	Gas	0	0	0	0	0	0.40
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.80
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.38: Agent $A9$ - matrix of technical coefficients - heavy disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.20
	Water	0	0	0	0	0	0.40
	Gas	0	0	0	0	0	0.60
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.40
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.39: Agent $A10$ - matrix of technical coefficients - heavy disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.20
	Water	0	0	0	0	0	0.30
	Gas	0	0	0	0	0	0.40
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.20
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.40: Agent $A11$ - matrix of technical coefficients - heavy disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.80
	Water	0	0	0	0	0	0.40
	Gas	0	0	0	0	0	0.60
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.40
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.41: Agent $A12$ - matrix of technical coefficients - heavy disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.50
	Water	0	0	0	0	0	0.30
	Gas	0	0	0	0	0	0.40
	Petrol	0	0	0	0	0	0.30
	CapG	0	0	0	0	0	0.50
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.42: Agent $A13$ - matrix of technical coefficients - heavy disruption.

		To					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From	**Power**	0	0	0	0	0	0.10
	Water	0	0	0	0	0	0.30
	Gas	0	0	0	0	0	0.40
	Petrol	0	0	0	0	0	0.11
	CapG	0	0	0	0	0	0.40
	CG&S	0	0	0	0	0	0

a CapG - Capital goods
b CG&S - Consumer goods and services

TABLE A.43: Transfer cost vectors under no disruption.

		Resource					
		Power	**Water**	**Gas**	**Petrol**	**CapG[a]**	**CG&S[b]**
From agent to agent	**A0 → A2**	0.78	0.55	0.42	0.23	0.64	0.74
	A0 → A4	0.11	0.13	0.60	0.21	0.89	0.49
	A0 → A3	0.94	0.53	0.46	0.73	0.72	0.42
	A1 → A3	0.10	0.07	0.35	0.05	0.16	0.82
	A1 → A2	0.50	0.23	0.06	0.30	0.62	0.84
	A1 → A5	0.73	0.20	0.19	0.67	0.19	0.82
	A2 → A6	0.27	0.92	0.36	0.30	0.87	0.82
	A2 → A7	0.95	0.90	0.18	0.77	0.03	0.08
	A2 → A4	0.83	0.68	0.36	0.80	0.11	0.71
	A4 → A8	0.57	0.54	0.02	0.56	0.48	0.03
	A4 → A9	0.75	0.27	0.23	0.57	0.39	0.01
	A4 → A10	0.70	0.09	0.32	0.64	0.59	0.92
	A3 → A11	0.33	0.17	0.39	0.15	0.95	0.97
	A3 → A12	0.62	0.42	0.87	0.72	0.32	1.00
	A3 → A13	0.09	0.05	0.42	0.90	0.40	0.52
	A2 → A1	0.17	0.54	0.74	0.92	0.69	0.20

a CapG - Capital goods
b CG&S - Consumer goods and services

Table A.44: Transfer cost vectors under medium disruption.

		Resource					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
From agent to agent	**A0 → A2**	0.78	0.55	0.42	0.23	0.64	0.74
	A0 → A4	∞[c]	∞	∞	∞	∞	∞
	A0 → A3	∞	∞	∞	∞	∞	∞
	A1 → A3	0.10	0.07	0.35	0.05	0.16	0.82
	A1 → A2	0.50	0.23	0.06	0.30	0.62	0.84
	A1 → A5	0.73	0.20	0.19	0.67	0.19	0.82
	A2 → A6	0.27	0.92	0.36	0.30	0.87	0.82
	A2 → A7	0.95	0.90	0.18	0.77	0.03	0.08
	A2 → A4	0.83	0.68	0.36	0.80	0.11	0.71
	A4 → A8	0.57	0.54	0.02	0.56	0.48	0.03
	A4 → A9	0.75	0.27	0.23	0.57	0.39	0.01
	A4 → A10	0.70	0.09	0.32	0.64	0.59	0.92
	A3 → A11	0.33	0.17	0.39	0.15	0.95	0.97
	A3 → A12	0.62	0.42	0.87	0.72	0.32	1.00
	A3 → A13	0.09	0.05	0.42	0.90	0.40	0.52
	A2 → A1	0.17	0.54	0.74	0.92	0.69	0.20

a CapG - Capital goods
b CG&S - Consumer goods and services
c ∞ – infinity, meaning that the link is fully broken.

TABLE A.45: Transfer cost vectors under heavy disruption.

		Resource					
		Power	**Water**	**Gas**	**Petrol**	**CapG**[a]	**CG&S**[b]
	A0 → A2	0.78	0.55	0.42	0.23	0.64	0.74
	A0 → A4	∞[c]	∞	∞	∞	∞	∞
	A0 → A3	∞	∞	∞	∞	∞	∞
	A1 → A3	0.10	0.07	0.35	0.05	0.16	0.82
	A1 → A2	0.50	0.23	0.06	0.30	0.62	0.84
	A1 → A5	0.73	0.20	0.19	0.67	0.19	0.82
From agent to agent	**A2 → A6**	0.27	0.92	0.36	0.30	0.87	0.82
	A2 → A7	0.95	0.90	0.18	0.77	0.03	0.08
	A2 → A4	0.83	0.68	0.36	0.80	0.11	0.71
	A4 → A8	0.57	0.54	0.02	0.56	0.48	0.03
	A4 → A9	0.75	0.27	0.23	0.57	0.39	0.01
	A4 → A10	0.70	0.09	0.32	0.64	0.59	0.92
	A3 → A11	0.33	0.17	0.39	0.15	0.95	0.97
	A3 → A12	0.62	0.42	0.87	0.72	0.32	1.00
	A3 → A13	0.09	0.05	0.42	0.90	0.40	0.52
	A2 → A1	0.82	0.94	0.94	0.92	0.99	0.90

a CapG - Capital goods
b CG&S - Consumer goods and services
c ∞ – infinity, meaning that the link is fully broken.

B

APPENDIX

In this appendix, we present all the building blocks used in the simulation experiment in chapter 5. This includes 13 building blocks and 2 disruption building blocks devised for use in that experiment. Similarly, we present the matrix of building blocks used in the base case of the experiment in chapter 5. The matrix consists of 49 rows, one for each cell; and 15 columns: 13 for the 13 building blocks, and 2 for the 2 disruption building blocks.

B.1 BUILDING BLOCKS

Building block matrix - T1 - House

$$\begin{bmatrix} 0. & 0. & 0.8 & 0. & 0.8 \\ 0. & 0. & 0.7 & 0. & 0.8 \\ 0. & 0. & 0.5 & 0. & 3. \\ 0. & 0. & 0.1 & 0. & 0.1 \\ 0. & 0. & 0.9 & 0. & 0.4 \end{bmatrix} \text{ Demand: } \begin{bmatrix} 0.1 & 0.2 & 1. & 0.05 & 0.5 \end{bmatrix} \text{ Supply: } \begin{bmatrix} \infty & \infty & \infty & \infty & 100. \end{bmatrix}$$

Building block matrix - T2 - HDB

$$\begin{bmatrix} 0. & 0. & 0. & 0. & 0.2 \\ 0. & 0. & 0. & 0. & 0.2 \\ 0. & 0. & 0. & 0. & 1. \\ 0. & 0. & 0. & 0. & 0.02 \\ 0. & 0. & 0. & 0. & 0.1 \end{bmatrix} \text{ Demand: } \begin{bmatrix} 5. & 10. & 15. & 3. & 10. \end{bmatrix} \text{ Supply: } \begin{bmatrix} \infty & \infty & \infty & \infty & 400. \end{bmatrix}$$

Building block matrix - T3 - Condominium

$$\begin{bmatrix} 0. & 0. & 0.7 & 0. & 0.4 \\ 0. & 0. & 0.5 & 0. & 0.6 \\ 0. & 0. & 0.6 & 0. & 2. \\ 0. & 0. & 0.1 & 0. & 0.05 \\ 0. & 0. & 0.7 & 0. & 0.2 \end{bmatrix} \text{ Demand: } \begin{bmatrix} 4. & 8. & 13. & 2.5 & 15. \end{bmatrix} \text{ Supply: } \begin{bmatrix} \infty & \infty & \infty & \infty & 250. \end{bmatrix}$$

Building block matrix - T4 - Retail establishment

$$\begin{bmatrix} 0. & 0. & 0.1 & 0. & 0. \\ 0. & 0. & 0.1 & 0. & 0. \\ 0. & 0. & 0.1 & 0. & 0. \\ 0. & 0. & 0.3 & 0. & 0. \\ 0. & 0. & 0.2 & 0. & 0. \end{bmatrix} \text{Demand: } \begin{bmatrix} 6. & 10. & 2. & 6. & 2. \end{bmatrix} \text{Supply: } \begin{bmatrix} \infty & \infty & \infty & \infty & \infty \end{bmatrix}$$

Building block matrix - T5 - Office

$$\begin{bmatrix} 0. & 0. & 0. & 0. & 0.2 \\ 0. & 0. & 0. & 0. & 0.2 \\ 0. & 0. & 0. & 0. & 0.5 \\ 0. & 0. & 0. & 0. & 0.1 \\ 0. & 0. & 0. & 0. & 0.6 \end{bmatrix} \text{Demand: } \begin{bmatrix} 4. & 8. & 10. & 4. & 1. \end{bmatrix} \text{Supply: } \begin{bmatrix} \infty & \infty & \infty & \infty & \infty \end{bmatrix}$$

Building block matrix - T6 - Industrial establishment

$$\begin{bmatrix} 0. & 0. & 0. & 0.3 & 0. \\ 0. & 0. & 0. & 0.4 & 0. \\ 0. & 0. & 0. & 0.1 & 0. \\ 0. & 0. & 0. & 0.2 & 0. \\ 0. & 0. & 0. & 0.3 & 0. \end{bmatrix} \text{Demand: } \begin{bmatrix} 10. & 15. & 6. & 8. & 2. \end{bmatrix} \text{Supply: } \begin{bmatrix} \infty & \infty & \infty & \infty & \infty \end{bmatrix}$$

Building block matrix - T7 - Water supply

$$\begin{bmatrix} 0.15 & 0. & 0. & 0. & 0. \\ 0.1 & 0. & 0. & 0. & 0. \\ 0.01 & 0. & 0. & 0. & 0. \\ 0.2 & 0. & 0. & 0. & 0. \\ 0.2 & 0. & 0. & 0. & 0. \end{bmatrix} \text{Demand: } \begin{bmatrix} 4. & 10. & 4. & 8. & 3. \end{bmatrix} \text{Supply: } \begin{bmatrix} \infty & \infty & \infty & \infty & \infty \end{bmatrix}$$

Building block matrix - T8 - Power supply

$$\begin{bmatrix} 0. & 0.2 & 0. & 0. & 0. \\ 0. & 0.4 & 0. & 0. & 0. \\ 0. & 0.1 & 0. & 0. & 0. \\ 0. & 0.4 & 0. & 0. & 0. \\ 0. & 0.3 & 0. & 0. & 0. \end{bmatrix} \text{Demand: } \begin{bmatrix} 8. & 6. & 5. & 10. & 6. \end{bmatrix} \text{Supply: } \begin{bmatrix} \infty & \infty & \infty & \infty & \infty \end{bmatrix}$$

Building block matrix - T9 - Neighbor road connection

$$\begin{bmatrix} 0. & 0. & 0. & 0. & 0. \\ 0. & 0. & 0. & 0. & 0. \\ 0. & 0. & 0. & 0. & 0. \\ 0. & 0. & 0. & 0. & 0. \\ 0. & 0. & 0. & 0. & 0. \end{bmatrix} \text{Demand: } \begin{bmatrix} 0. & 0. & 5. & 5. & 6. \end{bmatrix} \text{Supply: } \begin{bmatrix} \infty & \infty & 1000. & 1000. & 350. \end{bmatrix}$$

Building block matrix - T10 - Neighbor water connection

$$\begin{bmatrix} 0. & 0. & 0. & 0. & 0. \\ 0. & 0. & 0. & 0. & 0. \\ 0. & 0. & 0. & 0. & 0. \\ 0. & 0. & 0. & 0. & 0. \\ 0. & 0. & 0. & 0. & 0. \end{bmatrix} \text{Demand: } \begin{bmatrix} 0. & 0. & 0. & 0. & 0. \end{bmatrix} \text{Supply: } \begin{bmatrix} 1000. & \infty & \infty & \infty & \infty \end{bmatrix}$$

Building block matrix - T11 - Neighbor power connection

$$\begin{bmatrix} 0. & 0. & 0. & 0. & 0. \\ 0. & 0. & 0. & 0. & 0. \\ 0. & 0. & 0. & 0. & 0. \\ 0. & 0. & 0. & 0. & 0. \\ 0. & 0. & 0. & 0. & 0. \end{bmatrix} \text{Demand: } \begin{bmatrix} 0. & 0. & 0. & 0. & 0. \end{bmatrix} \text{Supply: } \begin{bmatrix} \infty & 1000. & \infty & \infty & \infty \end{bmatrix}$$

Building block matrix - T12 - Park

$$\begin{bmatrix} 0. & 0. & 0. & 0. & 0.1 \\ 0. & 0. & 0. & 0. & 0.1 \\ 0. & 0. & 0. & 0. & 0.3 \\ 0. & 0. & 0. & 0. & 0.1 \\ 0. & 0. & 0. & 0. & 0.1 \end{bmatrix} \text{Demand: } \begin{bmatrix} 5. & 5. & 5. & 5. & 4. \end{bmatrix} \text{Supply: } \begin{bmatrix} \infty & \infty & \infty & \infty & \infty \end{bmatrix}$$

Building block matrix - T13 - School

$$\begin{bmatrix} 0. & 0. & 0. & 0. & 0.1 \\ 0. & 0. & 0. & 0. & 0.2 \\ 0. & 0. & 0. & 0. & 0.7 \\ 0. & 0. & 0. & 0. & 0.05 \\ 0. & 0. & 0. & 0. & 0.09 \end{bmatrix} \text{Demand: } \begin{bmatrix} 8. & 6. & 12. & 4. & 30. \end{bmatrix} \text{Supply: } \begin{bmatrix} \infty & \infty & \infty & \infty & \infty \end{bmatrix}$$

Building block matrix - T14 - Disruption 1

$$\begin{bmatrix} 0.9 & 0. & 0. & 0. & 0. \\ 0.9 & 0. & 0. & 0. & 0. \\ 0.9 & 0. & 0. & 0. & 0. \\ 0.9 & 0. & 0. & 0. & 0. \\ 0.9 & 0. & 0. & 0. & 0. \end{bmatrix} \text{ Demand: } \begin{bmatrix} 0. & 0. & 0. & 0. & 0. \end{bmatrix} \text{ Supply: } \begin{bmatrix} \infty & \infty & \infty & \infty & \infty \end{bmatrix}$$

Building block matrix - T15 - Disruption 2

$$\begin{bmatrix} 0. & 0. & 0. & 0.9 & 0. \\ 0. & 0. & 0. & 0.9 & 0. \\ 0. & 0. & 0. & 0.9 & 0. \\ 0. & 0. & 0. & 0.9 & 0. \\ 0. & 0. & 0. & 0.9 & 0. \end{bmatrix} \text{ Demand: } \begin{bmatrix} 0. & 0. & 0. & 0. & 0. \end{bmatrix} \text{ Supply: } \begin{bmatrix} \infty & \infty & \infty & \infty & \infty \end{bmatrix}$$

B.2 MATRIX OF BUILDING BLOCKS

$$
\begin{bmatrix}
2. & 0. & 0. & 0. & 0. & 15. & 55. & 0. & 11. & 50. & 0. & 24. & 0. & 0. & 0. \\
23. & 0. & 43. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 4. & 0. & 0. & 0. \\
42. & 0. & 11. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 37. & 0. & 0. & 0. \\
30. & 0. & 3. & 0. & 0. & 37. & 8. & 0. & 13. & 0. & 0. & 8. & 0. & 0. & 0. \\
0. & 61. & 0. & 13. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
0. & 62. & 0. & 16. & 0. & 0. & 0. & 0. & 19. & 10. & 11. & 11. & 0. & 0. & 0. \\
0. & 70. & 0. & 8. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 19. & 9. & 0. & 0. \\
0. & 0. & 40. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 11. & 0. & 0. & 0. \\
5. & 0. & 8. & 0. & 0. & 25. & 7. & 0. & 0. & 0. & 0. & 15. & 0. & 0. & 0. \\
44. & 0. & 21. & 8. & 6. & 0. & 0. & 0. & 0. & 0. & 0. & 22. & 0. & 0. & 0. \\
22. & 0. & 13. & 10. & 7. & 0. & 0. & 0. & 0. & 0. & 0. & 9. & 7. & 0. & 0. \\
0. & 0. & 17. & 11. & 12. & 16. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
0. & 42. & 0. & 17. & 0. & 4. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
0. & 46. & 0. & 16. & 10. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
61. & 0. & 28. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
29. & 0. & 13. & 47. & 7. & 0. & 0. & 0. & 0. & 0. & 0. & 20. & 0. & 0. & 0. \\
3. & 0. & 0. & 39. & 11. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
0. & 0. & 30. & 0. & 8. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
0. & 25. & 0. & 15. & 19. & 0. & 0. & 0. & 0. & 0. & 0. & 14. & 0. & 0. & 0. \\
0. & 56. & 0. & 0. & 9. & 0. & 0. & 0. & 0. & 0. & 0. & 14. & 0. & 0. & 0. \\
0. & 53. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 9. & 26. & 0. & 0. \\
13. & 0. & 24. & 0. & 16. & 44. & 0. & 0. & 0. & 0. & 0. & 12. & 33. & 0. & 0. \\
100. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 39. & 0. & 0. & 0. \\
100. & 0. & 0. & 0. & 0. & 10. & 0. & 61. & 0. & 0. & 55. & 57. & 0. & 0. & 0. \\
0. & 38. & 0. & 17. & 0. & 18. & 0. & 0. & 0. & 18. & 15. & 0. & 0. & 0. & 0. \\
0. & 42. & 0. & 33. & 7. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
0. & 30. & 0. & 96. & 27. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
0. & 79. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
0. & 0. & 0. & 0. & 14. & 86. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
44. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 53. & 0. & 0. \\
61. & 0. & 0. & 39. & 9. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
17. & 33. & 0. & 46. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
0. & 34. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
0. & 54. & 0. & 67. & 31. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
0. & 61. & 0. & 0. & 0. & 0. & 42. & 0. & 0. & 52. & 0. & 0. & 0. & 0. & 0. \\
0. & 0. & 0. & 0. & 0. & 100. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
0. & 0. & 0. & 0. & 0. & 74. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
0. & 0. & 0. & 16. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 42. & 0. & 0. \\
0. & 84. & 20. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
0. & 0. & 51. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 100. & 0. & 0. & 0. \\
0. & 0. & 0. & 50. & 26. & 0. & 0. & 0. & 0. & 0. & 0. & 100. & 0. & 0. & 0. \\
0. & 68. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 49. & 0. & 0. & 0. \\
0. & 0. & 0. & 0. & 0. & 100. & 19. & 0. & 0. & 46. & 0. & 0. & 0. & 0. & 0. \\
0. & 0. & 0. & 0. & 0. & 100. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
0. & 51. & 0. & 0. & 0. & 56. & 0. & 0. & 0. & 0. & 0. & 0. & 5. & 0. & 0. \\
0. & 78. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
44. & 49. & 39. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
30. & 15. & 30. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\
0. & 0. & 0. & 0. & 0. & 0. & 0. & 62. & 0. & 0. & 72. & 0. & 0. & 0. & 0.
\end{bmatrix}
$$

CURRICULUM VITAE

PERSONAL DATA

Name	Mateusz Iwo Dubaniowski
Date of Birth	25 April 1993
Place of Birth	Warsaw, Poland
Citizen of	Poland

EDUCATION

March 2016 –	ETH Zurich Zürich, Switzerland *Doctoral student*
September 2014 – November 2015	University of Edinburgh Edinburgh, United Kingdom *Final degree:* Master of Science
September 2011 – June 2014	University of Edinburgh Edinburgh, United Kingdom *Final degree:* Bachelor of Engineering with Honours
August 2009 – May 2011	United World College of South East Asia Singapore, Singapore *Final diploma:* International Baccalaureate Bilingual Diploma
March 2009 – June 2009	Overseas Family School Singapore, Singapore
September 2006 – March 2009	Gimnazjum Dwujęzyczne nr 59 Warsaw, Poland

WORK EXPERIENCE

October 2015 –	PhD Researcher *Singapore-ETH Centre*, Singapore, Singapore
August 2015 – October 2015	Securities Strategist Summer Analyst *Goldman Sachs*, London, United Kingdom
August 2014	IT Intern *PL.2012+*, Warsaw, Poland
July 2014	Software Tester Intern *Pentacomp*, Warsaw, Poland