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**MODELING FOR LARGE-SCALE DISASTER RESPONSE
SIMULATIONS: A SOCIOTECHNICAL RESILIENCE
APPROACH**

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INTERDISCIPLINARY GRADUATE SCHOOL
INSTITUTE OF CATASTROPHE RISK MANAGEMENT

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**INTERDISCIPLINARY GRADUATE SCHOOL
INSTITUTE OF CATASTROPHE RISK MANAGEMENT**

A thesis submitted to the Nanyang Technological University in partial
fulfillment of the requirement for the degree of
Doctor of Philosophy

2020

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Fredy Tantri

Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

[03.01.2020]

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Date

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Assoc. Prof. Sulfikar Amir

Authorship Attribution Statement

This thesis contains material from a paper published in the following peer-reviewed journal where I was the first author.

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The contributions of the co-authors are as follows:

- Assoc. Prof. Sulfikar Amir provided the initial project direction and edited the manuscript drafts.
- I designed and programmed the model and the simulations, as well as analyzing the data.
- I prepared the manuscript drafts. The manuscript was revised by Assoc. Prof. Sulfikar Amir.

03.01.2020

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Fredy Tantri

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Singapore, January 2020

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Table of Contents

Abstract.....	viii
1. Introduction.....	1
1.1 Background.....	1
1.2 Research Questions	5
1.3 Research Objectives	6
1.4 Thesis Outline	6
2. Literature Review.....	8
2.1 Risk and Safety in Sociotechnical Systems	8
2.1.1 Accident Models in Safety Management	9
2.1.2 Risk: Challenges and Management Strategies	11
2.2 Understanding Sociotechnical Systems and Resilience	13
2.3 Modeling Sociotechnical Systems and Resilience Quantification	17
2.4 Conceptualizing Sociotechnical Resilience	20
2.4.1 Informational Relations	21
2.4.2 Sociomaterial Structures	22
2.4.3 Anticipatory Practices	23
3. Methodology and Computational Experimentation.....	25
3.1 Introduction.....	25
3.2 Modeling Sociotechnical Resilience	26
3.3 Results and Discussion	33
3.4 Conclusions.....	50
4. The Case Study: Jakarta as a Vulnerable City	52
4.1 Disaster and Risk Defined	52
4.2. Jakarta.....	56
4.3. City and Infrastructure Issues of Jakarta	58
4.4 Disaster Risk in Jakarta	61
4.5 Jakarta Healthcare System	71
4.6 Disaster Response in Indonesia.....	73
4.7 Chapter Summary	76
5. Optimizing Hospital Response Strategies.....	78
5.1 Introduction.....	78
5.1.1 Disaster Medicine	78
5.1.2 Modeling and Optimization of Healthcare Systems	83
5.2 Methodology	84
5.2.1 Data Collection.....	86
5.2.2 Model Description	88
5.3 Results and discussion	96
5.4 Conclusions.....	105
6. Conclusions.....	106
7. References.....	109

Abstract

Resilience is generally defined as the ability of a system to plan, prepare, absorb, respond to, and recover from disruptions, as well as to adapt to new conditions. Recently, the concept of resilience has been adopted into the study of sociotechnical systems to analyze resilient capacity of critical urban infrastructures such as power grid, water supply, healthcare, and telecommunication/cyber infrastructures. This research addresses the challenge in modeling sociotechnical resilience by taking into account the hybrid nature of sociotechnical systems. Therefore, this dissertation aims to advance a theoretical framework of sociotechnical resilience by developing a conceptual model and simulation, as well as applying the concept in a real-world urban setting. In order to achieve this goal, this research utilizes a computational modeling approach to observe the behavior of sociotechnical systems during a disruption and to measure its resilient performance. The conceptual model we developed uses the structure of multi-level directed acyclic graph and employs the operational resilience paradigm through the concept of functionality to capture the temporal dimension of system performance. To apply the concept of sociotechnical resilience, the healthcare system in Jakarta was used as the case study. Jakarta is the national capital and also the center of economic activities of Indonesia. It is a megacity with a very high population density. From the perspective of medical emergency, this condition renders the city vulnerable to a large-scale disaster. On top of the existing urban problems, the regulation and organization for disaster management are still relatively new. The coordination strategy they use is a

centralized command center approach without supported by real-time information systems. Therefore, we proposed additional coordination strategies that are feasible to be applied in Jakarta, and then we evaluated the resilience performance of each strategy by simulating the response under a certain disaster event characterized by the number of victims and disaster locations. The computational model and simulation were developed based on regulations, disaster response guidelines, and empirical data from government. This dissertation highlights the importance of system flexibility to allow structural reconfiguration at the organizational level during a disruptions or disasters through planning or institutional policy design. To conclude, the main contribution of this dissertation is to lay a foundation in implementing the concept of sociotechnical resilience to enhance the system capacity of complex infrastructure through modeling and simulation.

Chapter 1

Introduction

1.1 Background

Generally, sociotechnical systems are defined as an integrated structure of human and technical components that performs a specific function. Infrastructures as sociotechnical systems are the backbone of every modern city. They facilitate services and support social life and economic activities of the population. It is a man-made system that functions in a network setting, producing and distributing services and goods in synergy. In the post-911 era, the term “critical infrastructures” emerged to denote the kind of urban infrastructures that play a crucial role for the livelihood of people especially in major cities (Foundations, 1997). It includes electrical power systems, transportation, telecommunication systems, water supply systems, oil and natural gas, banking or financial systems, government services, and emergency services. Furthermore, interconnections and interdependencies between critical infrastructures render the whole systems more vulnerable because a failure in one system can have cascading impact on other systems (Rinaldi et al., 2001).

On the other hand, the frequency of natural disaster occurrences and its impacts in recent decades have growth almost exponentially, which are mainly caused by poor urban development and climate change (Harrison & Williams, 2016; Cerè et al., 2017). During the period of 2007-2017, on average, there are 352 occurrences of natural disaster, killing about 63,000 and affecting almost 200 million people. They caused economic losses of about US\$ 159 billion, annually (Guha-Sapir et al., 2016; Below & Wallemacq, 2018). Today, more than half of the population in the world lives in cities. Considering the current trends of

urbanization and population growth, it can be expected that 75% of world's population will live in cities by 2030, causing even more vulnerability towards disaster.

The urbanization pattern, climate change, disasters occurrence, and the increased reliance on critical infrastructure have brought worldwide attention to the concept of resilience. Traditionally, risk analysis and risk management methods are employed to identify vulnerabilities of infrastructures from expected disruptive events, and to prepare the system to withstand shock, thus preventing system failure (Linkov et al., 2014). However, since major disasters have repeatedly happened in the past decades (Zio & Aven, 2013), it became evident that not all threats of disasters can be identified and averted. Well-known examples include the natural disasters such as hurricane Katrina in 2005 (Brunkard et al., 2008) and Fukushima Daiichi nuclear disaster in 2011 (Amir & Juraku, 2014), as well as man-made disaster such as the Bhopal chemical accident in 1984 (Bowonder & Linstone, 1987), September 11 attacks on WTC buildings in 2001 (Congress, 2001), North America and Europe blackout in 2003 (Andersson et al., 2005), and global financial crisis in 2008 (Taylor et al., 2009). As a consequence, the preparedness and capability to recover in a timely manner from natural as well as manmade disasters have turned to be a critical factor for human society to cope with sudden and unexpected change of economical, technical, social, and communities condition (Cimellaro, 2016).

In order to deal with these low-probability high-impact events, it is necessary to complement the existing framework of risk analysis and management by developing resilience measurements, frameworks, and models to enable the practice of resilience engineering and management (Linkov et al., 2014). Therefore, the main distinction between risk and resilience assessment and management is that the former focuses on pre-event strategies to

minimize the frequency and impact of a disruption, while the latter covers the whole life-cycle of systems by including the post-event strategy through recovery, reconfiguration, and adaptation (Heinimann, 2016).

Generally, resilience is defined as the systems' capability to survive and maintain its function after absorbing and recovering from internal or external changes. Hollnagel (2014) expands the concept by recognizing the co-existence of both negative and positive outcomes of a system's function, thus suggesting that system resilience should focus on improving the probability of positive outcomes while reducing the probability of negative outcomes. Since the concept of resilience was first introduced in the field of ecology through the seminal work of C.S. Holling (1973), studies on resilience have been rapidly growing across various disciplines. It is used in fields such as, to name a few, institutional resilience (Pidgeon, 1997), coastal resilience (Klein et al., 1998), enterprise management (Sheffi, 2005), social systems (Davidson, 2010), catastrophe management (Park et al., 2013), supply chain (Mensah & Merkurjev, 2014), and disaster resilience (Dahlberg et al., 2015).

While the concept of resilience has been continuously applied in the study of sociotechnical systems, it lacks conceptualization on fundamental features of resilience in sociotechnical systems itself. Most of existing works concentrate only on technical aspects or the aggregation of interactions between technical and organizational or individual components (Carayon, 2006; Park et al., 2013). These perspectives have a limited view on the *hybrid* nature of sociotechnical systems. It means that they embody the elements of social and technical at the same time. Technologies are social constructs while the functioning of the people and organization are supported by the technological components itself (Bijker et al., 1987; Bijker & Law, 1994). Therefore, Amir & Kant (2018) proposed the concept of

sociotechnical resilience which is built on the notion of hybridity. This concept emphasizes transformability as the key feature of sociotechnical resilience. Transformability here refers to the capability of a system to change its internal structure or normal operating procedures in response to shocks.

Sociotechnical systems are designed and built as complex adaptive systems that consist of multiple agents organized around a specific hierarchy, contain feedback loops, and embodies emergent properties (Rinaldi et al., 2001). The functionality of the systems does not arise only from aggregate interactions between the physical and social components, but also from the interactions with their surrounding environment. Furthermore, complex adaptive systems can undergo a variety of possible conditions or states which often result from the process of self-organization that changes the configuration of the system (Oughton et al., 2018).

Due to the complex nature of sociotechnical systems, understanding the behavior of these systems cannot be adequately achieved through a linear formulation since each of the components is interconnected and interacting in a non-linear fashion. Mathematical or statistical modeling approaches are generally can only capture limited processes of the whole systems, while conceptual models have less flexibility to derive further the insights about the behavior of the systems despite being able to represent whole essential characteristics and system components. In such multiplex interactions, the behavior of sociotechnical systems which is influenced by emergent properties from the dynamics of the system is best studied using computer modeling and simulation (Robinson et al., 1998; Miller & Page, 2009). While computational modeling represents the system components and actor's behavior, the computational simulations allow researchers to understand the behavior and outcome of the system performance under certain events and conditions. Modeling and simulation

approaches to understand the behavior and relationship between the components of sociotechnical systems have been largely applied in various fields such as air traffic controller (Agogino & Tumer, 2007; Wolfe, 2007), health care care (Stainsby et al., 2009; Salem et al., 2015; Mustapha & Frayret, 2016), energy systems (Cai et al., 2011; Galus, 2012), complex organization (Tasic et al., 2019), and many more. Given the complex and dynamic nature of sociotechnical systems, computational model allows researchers to simulate the systems under hypothetical disruptive situations such as power outages, disasters, or targeted attacks while freely adjusting parameters to analyze its behavior.

1.2 Research Questions

Considering the background, challenges, and potential approach to model the sociotechnical resilience, the research questions for this dissertation are as follows:

1. How to model and simulate sociotechnical resilience while taking into account the hybrid nature of sociotechnical systems?

This question addresses the main goal this research aims to achieve. While a plenty of studies on resilience have been done through modeling critical infrastructure, there is a lack of research using the concept of sociotechnical resilience which takes into account the hybrid nature of sociotechnical systems. The fundamental feature in our model is that it does not focus on the micro level where each component is modeled individually and interact with each other through specific chemical, mechanical, or electrical processes. In contrast, it is built on the mesoscale level which has an advantage of incorporating the essential interaction between technical components while being able to capture the main aspects of sociotechnical resilience. This approach can be achieved through simulation processes, which help stakeholders in

designing structures and procedures in response to a disruption and develop proper policy that will improve recovery process during a crisis.

2. How to put the concept of sociotechnical resilience into practice?

This dissertation also provides practical contributions by applying the conceptual model of sociotechnical resilience in a real-world setting. To this end, we draw on a case study of the healthcare system in Jakarta, Indonesia. In this case study, we propose various institutional structures and strategies for the healthcare systems as the addition to the existing emergency response strategy. Using the empirical data of hospitals in Jakarta, the disaster response guidelines as well as the regulations from the government, our study develops a model and simulations to obtain optimum strategies when a disaster event strike the city.

1.3 Research Objectives

By answering the research questions raised above, this dissertation aims to:

1. Build a conceptual model and simulation of sociotechnical resilience.
2. Demonstrate on how to apply the concept of sociotechnical resilience in a real system.
3. Develop a modelling and simulations framework using the case study of emergency healthcare system.

To sum up, the main contribution of this dissertation is to lay a foundation for applying the concept of sociotechnical resilience into a real-world problems to enhance system capacity for responding to large-scale disruptions.

1.4 Thesis Outline

Chapter 1 introduces the topic of this research and provides a general background, research questions, as well as research objectives of this dissertation. A literature review is given in

Chapter 2 to present the development of the fields of resilience, theoretical framework of sociotechnical resilience, and works in sociotechnical systems modeling. Chapter 3 elaborates the proposed conceptual model based on the theoretical concept of sociotechnical resilience. This chapter serves as the basic guidance to develop our model in the later chapter by adjusting the conceptual model further based on the context and objectives. Chapter 4 describes the historical backgrounds, urban problems, healthcare infrastructure, and disaster management of the Jakarta city. This chapter explains the background on Jakarta healthcare system that is selected as the main focus of our case study. In Chapter 5, the development of disaster medicine and modeling in the healthcare system were briefly reviewed before the modeling framework was developed. The aim of the simulations is to obtain the optimum strategies during a disaster event in Jakarta. Lastly, a summary of this research and recommendation for future work are given in Chapter 6.

Chapter 2

Literature Review

This chapter presents a review of the concept of resilience, more specifically sociotechnical resilience, and its related works on modeling and optimization methods. The first section describes the concept of safety and risk in sociotechnical systems. The second section elaborates on studies of resilience, including the theoretical framework and the role of resilience that will be employed in the next chapter as the basis for developing the conceptual model of sociotechnical resilience. The third section discusses the studies of sociotechnical systems modeling and resilience quantification. The fourth section further discusses the theoretical foundation of sociotechnical resilience. Revolving around the notion of transformability, the concept considers sociotechnical resilience to be constituted of three fundamental attributes, namely informational relations, sociomaterial structures, and anticipatory practices.

2.1 Risk and Safety in Sociotechnical Systems

Risk and safety of infrastructures have been extensively studied before the concept of resilience became popular among researchers as the proposed solution to the increased uncertainty in the operation of sociotechnical systems. In this light, safety and risk concepts are closely related to resilience. Risk is a very broad concept and generally defined as the probability and consequences of adverse events. On the other hand, safety is mainly associated with low or acceptable risk. In other words, if an accident is defined as “an unplanned event that results in a specified level of loss” (N. G. Leveson & Weiss, 2009), then “safety is the absence of accident” (N. G. Leveson, 2011). According to Hollnagel & Goteman (2004), the development of accident models for safety management have slowly

followed through three stages, which are cause-effect sequential, epidemiological, and systemic models. This is explained below.

2.1.1 Accident Models in Safety Management

Sequential accident models analyze an accident through a series of events that occur in a logical and predictable order. Major works related to this model include Domino Model (Heinrich, 1941) and Five Whys method (Ohno, 1988). Heinrich's Domino Model described that accident and injury are the last events which are preceded by a series of events that happen sequentially like a domino line, where the initial root causes can be traced back to the worker's social environment which creates the worker's character and working skill, followed by a carelessness, and then the event of unsafe act along with the existence of physical hazards. Five Whys is an investigative method by asking 'why' iteratively to dig further the cause-and-effect of a certain event. It is claimed that five times of asking is enough to find the root cause, even though in practice the 'why's can be taken further to any number. These models offer easy presentation of causal-effect series graphically which may be adequate for industrial systems in the first half of the 20th century. However, these models were criticized for its oversimplification of accident causation in the more complex systems that are common nowadays (Benner, 1975). This makes the epidemiological model started getting attention.

The concept of the epidemiological model can be traced back to the study of causal factors of disease epidemics by Gordon (1949) where he stated that the disease is the results of "... a combination of forces from at least three sources, which are the host – and man is the host of principal interest – the agent itself, and the environment in which host and agent find themselves". Later, Benner (1975) formalized this model through the multilinear event

sequencing methods he proposed. In this model, he suggested multiple causal events have to be investigated entirely with clearly defined of beginning and ending of each event. In this view, accident is interpreted as the outcome of the combination of latent factors that exist simultaneously in space and time (Reason, 1997). The Swiss Cheese Model (SCM) (Reason, 1990) and the Accident Evolution and Barrier Function (AEB) model (Svenson, 1991) are the examples of epidemiological models. However, some researchers argued that epidemiological models are still based on linear cause-effect principles, thus no longer be able to cope with increasing complexity of sociotechnical systems (Rasmussen, 1997; Hollnagel & Goteman, 2004).

The systemic models describe accidents as the result of rational interactions between humans and technologies at a local level but are unknowingly pushing the systems' state to unsafe boundaries while remaining uncorrected (Underwood & Waterson, 2013). Comprehensive analysis should be used to understand how a precursor to an accident emerges in a sociotechnical system where the perspective and the role of operators, engineers, managers, regulatory agencies, and even the government should be represented in the analysis at the same time (N. Leveson, 2004).

In a similar vein, Rasmussen & Svedung (2000) suggested that a proactive risk management strategy is needed to ensure that operations (decision making and the work process) in a system work within the boundaries of safe performance. This management strategy focuses on the decision-makers and the scope of their control. To ensure safe outcomes, the structures of communication networks should be identified. Next, the objectives, status information, capability, awareness, and priorities of the decision-makers should be considered. These safe boundaries should be visible and understood by every decision-maker, in order to ensure that

efforts can be made to keep the system performance within safe boundaries. Examples of systemic models are the AcciMap (Rasmussen, 1997), Systems Theoretic Accident Modeling and Process (STAMP) model (N. Leveson, 2004), and Functional Resonance Analysis Method FRAM (Hollnagel & Goteman, 2004). While these models are able to provide comprehensive analysis of accident causation, it takes considerable resources and domains knowledge to be applicable.

The STAMP and AcciMap models have a fundamental similarity in the lower level of the system where the socio and technical elements interact (see Figure 1). The structure of ‘Management-Staff-Work’ in AcciMap is related to the STAMP model as the ‘Operations Management’ level and ‘Operating Process’ which consists of human and automated controllers. Recognizing the importance of these components in sociotechnical systems, this dissertation adopts the notion as the main building block of sociotechnical systems. The interactions between agents in our model are assumed to take place in this level of structure.

2.1.2 Risk: Challenges and Management Strategies

There are three major challenges in managing risk, namely complexity, uncertainty, and ambiguity (Renn & Graham, 2006). Complexity refers to the challenges in identifying and assessing causal relationships between multiple factors which lead to adverse events. Complexity is related to uncertainty, in which high complexity systems favour the emergence of uncertainty. From the perspective of decision theory, uncertainty represents the ‘unmeasurable uncertainty’, a situation where not all possible outcomes and probability distribution are known (Knight, 1921). This leads to the next definition of ambiguity as the unknown probability of a known outcome as the results of missing of relevant information

(Frisch & Baron, 1988). Ambiguity can also be defined as the variation of interpretations from similar observations and data assessments (Aven & Renn, 2009).

(a)

(b)

Figure 1. Simplified (a) Accimap model and (b) System Operations component of STAMP.

Each challenge requires different strategies. There are three management styles in risk management: risk-informed, precautionary, and discursive strategies (Klinke & Renn, 2002). The risk-informed strategy refers to the avoidance or reduction of risk. This strategy is suitable for the systems whose probability or damage of its disruption can be well measured such as nuclear energy, chemical facilities, or dams. The precautionary strategy highlights the features and tools such as containment of risk over time and space, constant monitoring, diversification, flexibility, organizational capacity, building high-reliability organizations, and development of redundancy and substitutes (Aven, 2016). It emphasizes on reading signals and being well-prepared in responding to the adverse event, therefore it is suitable for relatively high uncertainty systems. The discursive strategy involves building collective consciousness, strengthening trustworthiness in government or regulatory bodies, clarification of facts, and public participations.

The key factor that connects risk and resilience is uncertainty. The increased complexity of modern infrastructure systems has increased the uncertainty factor. When this component becomes more dominant, risk management started to fail in coping with the ‘surprise’ damage to the systems. This gives rise to the concept of resilience that not only focuses on preventing loss of system performance, but also deals with the capability to ‘bounce-back’ from a disruptive event.

2.2 Understanding Sociotechnical Systems and Resilience

Sociotechnical systems are complex adaptive systems that have several nonlinear characteristics and embody emergent properties (Miller & Page, 2009). They contain feedback loops, and consist of multiple heterogeneous components organized around hierarchies/subsystems (Rinaldi et al., 2001). The term ‘sociotechnical systems’ was first

coined by Emery and Trist (1960) to describe systems that involve a complex interaction between humans, machines, and the environmental aspects of the work system. They suggest that the characteristics and interactions between human-machine-environment should be considered when building and managing a work system (e.g. industry). Later, Trist (1981) elaborated on the sociotechnical analysis of three interrelated levels: primary work systems (e.g. service unit), whole organization systems (e.g. plants, corporations, public agencies), and macrosocial systems (e.g. industrial sectors and institutions). In principle, the design of sociotechnical systems should reflect social and technical components in equal weight (Mumford, 2006). There are five characteristics of sociotechnical systems. First, they are interdependent. Second, they are meant to adapt and pursue goals in external environments. Third, they comprise of social subsystems (people, work context, and organizations). Fourth, they have equifinality (more than one ways to achieve a goal). And finally, their performances rely on joint optimization of technical and social components (Baxter & Sommerville, 2011).

Systems can be characterized according to its interaction and coupling levels. There are linear and complex interactions. Linear interactions indicate that the interactions of one component with the other components are sequential and predictable, while complex interactions have unpredictable sequences of interactions. In term of the coupling levels, the two ends of spectrum represent loose and tight coupling. The components in former type tend to have flexible and decentralized processes, while the latter works in a centralized and highly interdependent manner. Due to its complexity and tight coupling interactions, complex technological sociotechnical systems are prone to accidents because these systems are mutually constrained, and therefore the normal operating conditions represent compromises. While a part of a system can be made less prone to one type of shortcomings, another part

would at the same time become more prone to other type of shortcoming. Therefore, the designers and users would eventually settle on compromises to make the systems largely functional but susceptible to many different types of failures.

This condition is encapsulated in the notion of ‘normal accidents’ (Perrow, 2011). Many works have elaborated on the cases of normal accidents. To name a few, Vaughan (1996) found how normalization of deviance in organization led to Columbia space shuttle disaster, and Amir & Juraku (2014) showed how institutional, political, and epistemological problems lead to crisis in the Fukushima nuclear disaster. There are also other disasters related to technological systems such as gas production (Hopkins, 2000), transportation (Koetse & Rietveld, 2009), oil & gas drilling (Tabibzadeh & Meshkati, 2015), and ferry accidents (Kee et al., 2017).

On the other stream, several scholars studied reliability of highly complex technological systems. Although reliability is never defined explicitly, those scholars agree that “reliability is the ability to maintain and execute error-free operations” (S. Shrivastava et al., 2009). This study, which is then referred to as ‘high reliability theory’, was initially conducted in certain technological systems such as air traffic control systems (La Porte, 1988), submarines (Bierly III & Spender, 1995), nuclear power plant (Bourrier, 1996), space shuttles (Vaughan, 1996), and naval aircraft carrier (Rochlin et al., 1998). According to Flach et al. (2015), the safety of a system depends on the performance of the interaction between communications, constraints, decisions, and goals of the components or system. In the same vein, Weick et al. (Weick et al., 2000) proposed an essential condition of reliability, namely ‘mindfulness’. This notion aims to facilitate the discovery and correction of anomalies that could cumulate with other anomalies and grow into a catastrophe.

In the past few decades, as technological changes, economic pressures, and socio-political dynamics rapidly increase the risk of crisis and disruptions on critical infrastructures, the study of resilience in various fields has emerged. For example, the study of resilience in the field of psychology (Schoon, 2006; Luthar & Sexton, 2007), social-ecological systems (B. H. Walker et al., 2006), organization and management (Weick, 1995; Roberts & Grabowski, 1999; Gittell et al., 2006), safety management (Woods, 2006), and disaster management (Janssen & Ostrom, 2006). In the view of traditional safety, controlling the adverse outcome of a system is the main focus. It assumes that the working of a system results from good design and correct procedures, while the failure probability should be maintained as low as possible by system design and safety management.

In contrast to this view, resilience engineering accepts both (positive and negative) outcomes as the result of the same underlying processes (Hollnagel, 2014). This idea focuses on improving the probability of positive outcomes while reducing the probability of negative outcomes. This approach is argued to be more effective than the traditional view in managing risks and sustaining the required function under expected and unexpected conditions. He thus posits four main abilities to build resilience, which include monitoring, responding, learning, and anticipation. These four abilities, combined with four crisis/emergency responses (mitigation, preparedness, response, and recovery) are used as the resilience framework in the model built by Lundberg and Johansson (2015) in their Systemic Resilience (SyRes) model. This model is argued to be able to incorporate all four concepts of resilience: resilience as rebound, resilience as robustness, resilience as the opposite of brittleness, and resilience as sustained adaptability (Woods, 2015).

A novel perspective on the concept of resilience was proposed by Amir & Kant (2018). It incorporates insights from interdisciplinary fields such as human factors, organizational studies, science and technology studies, safety science, and systems engineering. In this framework, the technical and social components are addressed as a hybrid entity, which emphasize the constructedness of sociotechnical systems. Revolving around transformability, the concept of sociotechnical resilience centers on three main interrelated aspects. First, informational relations, which refer to the pathways of information between machines, individual operators and managers, subsystems, and/or organizations. Second, sociomaterial structures, which are the constitutive entanglement of materials and human organization in sociotechnical systems. Third, anticipatory practices that are defined as a set of recovery protocols designed for an organization to rapidly bounce back from crisis or disruption to normal operational state. A healthcare infrastructure can be used as an example. The doctors, nurses, technicians, drivers, hospitals, ambulance, beds, medicine, equipment, etc. are the sociomaterial structures, while the communication and coordination between doctor, nurses, driver, public health officers, and hospital managements during an emergency situation are the informational relations. Meanwhile, the medical emergency training, disaster response plan, and victim transfer procedures are embodied in anticipatory practices. This research will be built upon this theoretical framework to model and simulate the sociotechnical resilience.

2.3 Modeling Sociotechnical Systems and Resilience Quantification

Generally, sociotechnical systems consist of interdependent interactions between the human and technical components in an integrated structure to perform a specific function. One powerful method to study such systems is through modeling and simulation. Modeling and simulation are a computer-based representation of a certain characteristics of a real system,

which aims to provide experimentations and analysis of the system behavior. For example, Vespignani (2012) reviewed the studies of epidemic outbreaks, information spreading, and internet packet routing using data-driven computational modeling.

Generally, there are four simulation approaches: discrete event simulation, system dynamics simulation, agent-based simulation, and hybrid simulation (Hettinger et al., 2015). Since the present research draws on the notion of transformability of sociotechnical systems, the hybrid model of discrete event simulation and agent-based method is considered most suitable for the simulation purpose, as it has greater flexibility to incorporate heterogeneity of network and agent interactions under a generated event such as disruptions (Macal & North, 2005). Furthermore, this method offers decision support in a context of sociotechnical system. For example, the study by Van Dam (2009) applied agent-based model to determine the location of intermodal freight hub while considering the objectives of each stakeholders, or to make optimum response to unexpected disturbance in oil refinery supply chain system.

The use of computational modeling in various fields has become ubiquitous, including the study of sociotechnical systems, for example in air traffic controller (Blom et al., 2006; Agogino & Tumer, 2007; Wolfe, 2007; Sharpanskykh & Stroeve, 2011), health care (Stainsby et al., 2009; Salem et al., 2015; Mustapha & Frayret, 2016), and energy systems (Cai et al., 2011; Galus, 2012). However, existing works mostly focus on the optimization of performances in engineering realms or safety. In contrast to that, this research focuses on the holistic interaction of a sociotechnical structure to capture the critical components and interactions for improving the system's resiliency based on the concept of sociotechnical resilience. The quantification of resilience of our model uses the approach from operational resilience.

From the perspective of operational resilience, a system's resilience is generally quantified according to its *normal functionality* (can also be referred as performance), K , which can be determined by stakeholders through integrated measurements. In other words, K depends on the systems' context and objectives. For example, the performance of a power systems can be measured by the number of operating plants and transmission grid, or its availability of service to customers. The performance usually ranges from 0% for total disruption to 100% for normal operations. For a single disaster/disruption event E , resilience can be calculated as

$$R_E = \left(\frac{1}{T}\right) \int_{t_0}^{t_0+T} K(t) dt \quad (1)$$

where t_0 and T are the event time and the time horizon investigated by the analysis, respectively. This approach of resilience quantifications has been used in various field such as civil infrastructure (Bocchini et al., 2014), networked infrastructure (Reed et al., 2009), and disaster resilience (Cimellaro et al., 2010).

Since the existing framework of resilience remains fragmented between those emphasizing engineered features and those focusing on social and organizational conditions, we develop our model by emphasizing the hybrid nature of sociotechnical systems as they consist of the social constructs of people and technologies. Thus, the concept of sociotechnical resilience (Amir & Kant, 2018) is adopted in our model. This model also incorporates the paradigm of resilience as the complementary attribute of risk management which emphasizes strategies on minimizing loss or increasing the recovery rate (Linkov et al., 2014). The quantification of the system's resilience adopts the use of functionality function, a concept that is embodied in operational resilience. The following section will introduce the theoretical framework, which we have adopted in our model.

2.4 Conceptualizing Sociotechnical Resilience

To date, works on sociotechnical modeling continue to grow. We note substantial shortcomings in existing models in which the hybrid nature of sociotechnical systems is not strongly reflected. Some of these models are nearly completely devoid of social elements, or at best take into account marginal social variables (Cavallaro et al., 2014; Adjetey-Bahun et al., 2016; Guidotti et al., 2016; Almoghatawi et al., 2019). It is this gap that we wish to fill in this dissertation by offering a new approach in developing a sociotechnical model, and at the same time, using this model to create a computational simulation in sociotechnical systems.

Studies on sociotechnical systems are abundant, and concepts of resilience are plenty. Yet, studies that combine the two are quite a few. As mentioned earlier, one of them is conducted by Amir and Kant (2018) who have proposed the concept of sociotechnical resilience. Recognizing the hybrid nature of sociotechnical systems, sociotechnical resilience is characterized as an inherent capacity built around transformability. In contrast to Walker *et al.* (2004) in defining resilience, adaptability, and transformability in the context of socioecological systems, transformability is placed at the core of sociotechnical resilience. Amir and Kant maintain a distinction of transformability in sociotechnical systems from the one in socioecological systems. This distinction is the result of the difference in temporal and spatial scale of the systems of interest. While Walker *et al.* focus on socioecological systems that center on social and natural environments, sociotechnical systems are artificial systems where humans and technological components interact in a structured configuration such as transportation systems, water supply systems, telecommunication systems, healthcare, and energy systems. As a result, sociotechnical resilience revolves around the idea that the ‘building block’ of sociotechnical systems are intentional hybrids (Kroes et al., 2006; Vermaas et al., 2011; Leonardi, 2012), meaning they are both technical as well as social at

the same time; both are entangled entities where the humans and technologies are social constructs.

Given its unique characterization of sociotechnical resilience, our model adopts this concept and frames the resilience of sociotechnical systems as an integrative capacity to cope with internal failures or external shock. This capacity lies in system agility to transform its configuration from one form to another. The process of transformation is extremely crucial because it facilitates repair and adaptation in the aftermath of crisis and disruption. The aftermath transformations involve technical, organizational, and even institutional reconfiguration following the changing environment after a disruption. Thus, it is transformability—the ability to transform, which constitutes sociotechnical resilience (Amir & Kant, 2018). A distinctive feature of this concept appears from its emphasis on key attributes of sociotechnical networks rather than emphasizing protocols and processes of resilience enhancement as found in mainstream resilience analysis (Memarzadeh & Pozzi, 2016; Panteli et al., 2017; Li et al., 2017). Looking further into the way in which transformability is internally built within a sociotechnical system, there are three key attributes of transformability, namely informational relations, sociomaterial structures, and anticipatory practices. We found the composition of these attributes to be more suitable for our purpose to develop our sociotechnical modeling of resilience. To grasp the meaning of these attributes and how it can be translated into a computational model, it is instructive to elaborate each of them as follows.

2.4.1 Informational Relations

Informational relations represent the production and distribution of information that are extremely crucial in crisis response. These aspects can be emphasized as one that “deals with how information flows in the systems to support continued operations.” As information is

instrumental in determining how effective and efficient the coordination to respond to crisis (Fraustino et al., 2012; Appleby, 2013; Sutton et al., 2014; Tasic & Amir, 2016), any sociotechnical system cannot afford to have weak informational relations. In the concept of sociotechnical resilience, informational relations refer to the pathways of information between machines, individual operators and managers, subsystems, and/or organizations. Informational links between various types of elements contain a specific meaning or context, which defines how it is received. The information flow from machine to human may involve engineering medium and require technical knowledge (e.g. temperature level monitoring in a chemical plant, or electrical load monitoring of a power grid by engineers), while information sharing between humans serves to manage interdependencies or coordination purposes (Malone & Crowston, 1990; Bjerger et al., 2016). In our sociotechnical model, we treat informational relations as the reporting lines from operational units to command center or local coordinator to inform the disruption impacts. The information will allow the command center to decide and perform an optimum system recovery.

2.4.2 Sociomaterial Structures

The constitutive entanglement of the materials and human organization in sociotechnical systems creates what Amir and Kant called as sociomaterial structures. It is ‘structures’ as they are defined by how each entity is interconnected with one another in a hybrid configuration. The entities in sociotechnical systems belong to social realm such as individuals, groups, and organizations, while at the same time belong to the material realm, thus hybrid in nature. An interesting example is a study by Orlikowski et al. (2007) on the use of BlackBerry phones in a firm called Plymouth Investments. The company claimed itself that they respect individual and work-life balance. However, 4 years after the company issued BlackBerry for all company members (when the study was conducted), the ‘push email’

feature of the device had changed the organization's communication norms by altering people's expectations of availability, intensifying interactions, and redefining the working time boundaries. One of the company members shared their experiences associated with BlackBerry as follows: *"One of the things that I've noticed more and more is that people will BlackBerry me in the evening, you know, after 8:30 in the evening. I'm pretty much settled in and people know that it [BlackBerry] sits next to me, my cup of tea is there, my knitting is in my lap, something's on television and I just take care of business. "Linda, do you think you can order this, this and this for me?" Fine. Sure"*. Her experiences show how the BlackBerry, a technological unit that is designed and configured by humans, in turn, changes the organization's communication culture.

Another aspect that comes along with the hybridity is interpretive flexibility (Bijker et al., 1987). In the previous example, while Blackberry was intentionally designed to ease email communication, the pressure in the workplace may push people to intentionally use it beyond traditional communication norms. In terms of sociotechnical systems, this aspect determines how flexible the entities are structured or undergo reconfiguration during disruptions in sociotechnical systems. Therefore, in order to improve the resilience of sociotechnical systems, it is important to incorporate the characteristics of hybridity and interpretive flexibility when optimizing correct functioning and minimizing the malfunction probability of the technical dimension. In our proposed model, sociomaterial structures are embodied in agents as the operational units and represented as a network with a specific topology.

2.4.3 Anticipatory Practices

The last aspects of sociotechnical resilience are anticipatory practices, defined as a set of recovery protocols designed for an organization to rapidly bounce back from crisis or disruption to normal operational state. In addition to this definition, the scope of anticipatory

practices includes routine activities aiming to anticipate possibilities of future occurrences of events (Comfort et al., 2001; Poli, 2010). Since anticipatory practices are highly dependent on the context of a system to function as disaster prevention and management, the conceptual model we designed only incorporates anticipatory practices as recovery strategies during a disruption. In this way, the recovery protocols are reflected as the strategies of the command center in determining the order of nodes to be repaired.

Chapter 3

Methodology and Computational Experimentation

This chapter presents a conceptual model to simulate the responsive behavior of a sociotechnical system during a crisis. The model draws on the concept of “sociotechnical resilience” described in Chapter 2. The first section elaborates on how the conceptual model was developed. Our model aims to capture the complex interactions within a sociotechnical system during a recovery process by incorporating the core attributes of sociotechnical resilience in the operational units embedded in a multi-level directed acyclic graph, reporting lines structure, and recovery protocols. The second section presents the results and discussions of the simulation results. The simulation results suggest the importance of system flexibility to allow structural reconfiguration at the organizational level. The last section concludes this chapter. Our proposed model complements the theoretical principles of sociotechnical resilience while laying a practical foundation for sociotechnical modelling in resilience management for real-world settings.

3.1 Introduction

In this chapter, we proposed a computational model to simulate sociotechnical resilience while taking into account the three core attributes discussed in previous chapter, namely sociomaterial structures, informational relations, and anticipatory practices. Each of these attributes is translated into the model as a multi-level directed acyclic graph (DAG) of sociotechnical units, reporting lines, and recovery protocols. The simulation is designed to show the performance and resilience of various information flow strategies for a given disruption scenario and physical network configuration. By incorporating information flow in the model, we are aiming to expand the understanding of the complexity of sociotechnical

resilience thus helping researchers and practitioners to plan, design, build, and develop organizational and technical aspects in infrastructural systems.

3.2 Modeling Sociotechnical Resilience

Following the concept of sociotechnical resilience discussed above, our model of sociotechnical resilience is constituted by a graph $G(N, L)$, where N is a set of nodes connected by a set of links L . The graph has α levels of nodes. Each node represents a basic structure of a typical control loop as illustrated by Leveson (2004) in which an automated controller is supervised by a human controller (N. Leveson, 2004). For our purpose, we simplified this control loop into what we called as “operational unit” that serves as the building block of sociotechnical systems in our model. Figure 2 shows our model of *operational unit* which consists of human operators and machine. Each unit serves a certain amount of demand in its service area, producing output O each T_o timestep for the system. The output is assumed to be used as a resource for recovery cost during disruption. The recovery of each disrupted node requires C resources of the system. The operation of the unit may depend on the service of other units. In that case, a directional link is created from the ‘dependee’ node to the ‘dependent’ node. A link can only be created from the upstream unit (upper level) to the downstream unit (lower level). Creating a link between units at the same level or from a lower to a higher level is not allowed. When a unit is disrupted, all of the downstream units which are connected to the disrupted unit will be disabled. Consequently, units that are disrupted, disabled, or both cannot produce output and service to other units.

The physical nature of sociotechnical systems can vary from one system to another. Systems such as public health, security, or financial services does not connected through physical structure with one another, while systems such as power systems, transportation, or water

supply form a physical network structure through cables, tracks, or pipes. For simplicity, our model considers one type of connected system, e.g. power systems that are serving population/households in many cities, or subway systems operating across the city to serve mobility demands of commercial, industrial, or residential areas. However, our model allows researchers to study other type of systems, e.g. healthcare systems, by changing how the operational units operate in the system. For example, the operational units are not necessarily connected through links to form a network. They can operate in a more independent manner while still being a part of the sociotechnical resilience modelling and simulations, as long as they embody the sociomaterial structures, informational relations, and anticipatory practices.

Figure 2: Node is modelled as operational unit which represents human or organization controlling automated machine. The operation of unit may depend on the service of other upstream units. Each unit serves a certain amount of demand in their service area, producing output O for the system.

The performance or the normal functionality K at time t for our model is defined as the normalized total output of the active nodes A_t in the system (as shown in Equation 2). Active nodes are the nodes that are not in disrupted or disabled state. The output of each node is generated randomly between 0.01 to 1. The output becomes 0 when the node is in disrupted or disabled state and returns to its initial value after it is recovered or being active again. The resilience R_E for each recovery strategy as the results of adverse event E is calculated using Equation 3, where T and S are the simulation duration and number of simulations, respectively. Adverse event E determines how the disruption is generated in the system. Since it is not possible to consider all kinds of disruption events, we evaluate the system on a

certain event E where a certain percentage of disruption takes place on each level of the system. For example, if 10% disruption is generated on the system, 10% nodes of each level are disrupted. The resilience variable R_E will be simplified as R for the rest of the chapter.

$$K(t) = \frac{\sum_{i \in A_t} O_i}{\sum_{i \in N} O_i} \quad (2)$$

$$R_E = \left(\frac{1}{T}\right) \left(\frac{1}{S}\right) \sum_{s=1}^S \sum_{t=1}^T K_s(t) \quad (3)$$

Figure 3. Random recovery strategy. (1) Initial configuration of the system. Green node indicates that the node is active and operates normally. (2) Disruption is generated. Red nodes and purple nodes are the disrupted and disabled nodes, respectively. A node will be disabled when at least one of its upstream nodes is disrupted or disabled. (3) A disrupted node which was chosen randomly is recovered. The rectangle indicates the recovered node. In this case, the node is still inactive since one of its upstream nodes is still disrupted. (4) Another disrupted node was chosen and has recovered. Its downstream nodes will be activated in the next time step. (5) Last disrupted node has recovered. (6) All nodes are recovered and activated.

In this model, we applied two recovery strategies, namely, *random recovery* and *informed recovery*. The former represents the less prepared mode of response during a disruption. For example, when some sections in a subway system are disrupted, the recovery team may be sent to the disruption sites without particular patterns. It is primarily based on received emergency reports without considering the number of passengers in each affected station and trains at that time. This is due to the lack of information and coordination at the

organizational level. Therefore, the system responds to the crisis in a sub-optimum manner. The latter refers to a situation in which the system takes into account the impact of each disrupted node to the system performance, thus allowing the command centre to prioritise the most ‘rewarding’ nodes to be repaired. Using the previous example, the command centre of the subway system will take action based on the information of the number of affected passengers sent by all station heads and train staff to determine the most critical section to be repaired first. The fundamental distinction between these two strategies lies in the amount of information used to make decisions and take actions in response to disruption.

In the random recovery strategy, each disrupted node is chosen randomly to be repaired. After the chosen node is repaired, another disrupted node is chosen at random. This recovery process continues until all disrupted nodes are recovered or the simulation reaches the end time. The time needed to recover one node is T_r . This strategy is illustrated in Figure 3. The second recovery strategy considers the impact of each disrupted node to the system performance before deciding the repair order. The impact of a disrupted node i is calculated by summing the output of the node i and all of the disabled nodes d_i as the result of its disruption (Equation 4). In other words, the disabled nodes d_i are also the descendants of node i . Subsequently, the information of the disrupted node’s impact is sent to the command centre or local coordinator. It takes T_{info} time step to complete the sending information process.

Since there are multiple ways in which informational links are structured and used, we decided to develop three different simulations of reporting lines configuration. The first is the *direct reporting* mode, where all of the nodes in the system report to the command centre directly. The second configuration is the *hierarchy reporting* mode, where each node reports

to its local coordinator. There is one local coordinator for each level. After it receives information from all disrupted nodes of its respective level, the local coordinator will send all of the information it has to the command centre, also in T_{info} time step. The third configuration is the *hybrid* mode, which has the same configuration as hierarchy reporting mode but a certain percentage of disrupted nodes are reporting directly to the command centre. These three reporting lines configurations are shown in Figure 4. It should be noted that for the local coordinator or command centre, the sending or receiving information process cannot be executed in parallel with another process. Thus, the local coordinator or command centre can only receive information from one unit at one time.

$$I_i = O_i + \sum_{j \in d_i} O_j^t \quad (4)$$

After the command centre receives all of the information directly from nodes or from local coordinators, it will make an optimum decision to determine the order to repair the disrupted nodes. The decision is based on the projected gain obtained when a disrupted node is repaired. The gain is calculated using

$$B_i = (T - t - T_R(P_i + 1)) I_i \quad (5)$$

where t is current time and P_i is the number of disrupted nodes in the upstream levels which provide service to node i directly or indirectly. In this scenario, a disrupted node is counted in P_i if its disruption will cause the node i to be disabled.

Figure 4. *Direct*: All disrupted nodes report to command centre directly; *Hierarchy*: All disrupted nodes report to their respective local coordinator. Each local coordinator will wait until it receives information from all disrupted nodes of its respective level before it reports to command centre; *Hybrid*: mixed of direct and hierarchy reporting mode.

Figure 5 illustrates the informed recovery strategy using a simple example where we assume that $T = 100, T_{info} = 1, T_R = 10$ and each unit has the same output $O = 1$. In this case, the disrupted nodes are node 2, node 3, and node 6. For the case of direct reporting mode, the command centre will receive information from all disrupted nodes at $t = 3$ since each unit takes $T_{info} = 1$ time step to report to the command centre. The information received by the

command centre is the impact value of each node. Node 2 has 7 direct and indirect dependent nodes, thus having an impact $I_2 = 1 + 7(1) = 8$, while node 3 and node 6 have impact values of 4 and 1, respectively. And then, the gain for each node is calculated by the command centre. Repairing node 2, 3, and 6 will gain $B_2 = (100 - 3 - 10(0 + 1))8 = 696$, $B_3 = (100 - 3 - 10(0 + 1))4 = 348$, and $B_6 = (100 - 3 - 10(1 + 1))1 = 77$. Therefore, the repair order will be node 2, node 3, and then node 6. Since the time to repair a node is 10 time steps, the system will get fully recovered at $t = 33$.

Figure 5. An example of informed recovery strategy with direct reporting mode where $T=100$, $T_{info} = 1$, $T_R = 10$, and output of each node is 1. (1) Node 2, 3, and 6 are disrupted. (2) Command centre receives impact information from all disrupted nodes at $t=3$. (3) The gain of each node is calculated using Equation 5. Node 2 has the highest priority thus chosen to be repaired first. (4) Node 2 is recovered at $t=13$. Node 3 is the next node to be repaired. (5) Node 3 is recovered. Node 6 is the last disrupted node. (6) Node 6 is repaired, system is completely recovered.

The recovery strategies and reporting line configuration for the simulations can be summarized in the following table:

Table 1. Recovery strategies and reporting line configuration used for the simulations.

		Reporting Lines Configuration		
		Direct Reporting	Hierarchy Reporting	Hybrid Reporting
Recovery Strategies	Random Recovery	<i>Random</i>		
	Informed Recovery	<i>Informed-Direct</i>	<i>Informed-Hierarchy</i>	<i>Informed-Hybrid</i>

3.3 Results and Discussion

This study starts by examining the effects of the parameters involved in our model, i.e. disruption severity D , recovery cost C , additional links probability p , number of levels α , system size N , and communication duration T_{info} . After that, we simulate how different reporting modes of informed recovery strategies affect the system resilience.

Effects of Disruption Severity (D)

The first simulations examine the effects of disrupted node percentage (D) to the system performance. In each simulation, we generated a network composed of 500 nodes in four levels ($\alpha = 4$): $N_1 = 16, N_2 = 43, N_3 = 118, N_4 = 322$. This configuration of four levels with exponential growth of nodes number are based on the model developed by Ganin et al (2016). Level 1 is the highest level and level 4 is the lowest level, meaning there will not be any incoming link to any node in level 1 and outgoing link from any node in level 4 since a node cannot provide service to the same or higher level nodes. In generating the network,

each node from level 2 and lower will establish one link randomly with a higher-level node. There is a probability p that the node can have additional links. The links are directional and always flow from higher-level nodes to the lower-level nodes. For example, a node from level 3 may have a link from a level 1 node and two links from level 2 nodes. We set the probability of having additional dependency links as $p = 0.02$. Each simulation is started by generating the output value for each node randomly between 0.01 to 1. Afterwards, a disruption event is generated, causing D percent of nodes in each level to be disrupted which consequently disable all of their dependent nodes. The recovery time T_R and sending information duration T_{info} are set to $0.01 TC$ and $0.001 TC$, respectively. For simplicity, recovery cost is assumed to be 0 in this part of simulations and will be taken into account in the next parts of simulations.

We started by simulating the random recovery strategy for initial damage D as equals to 5%, 10%, and 20%. For each disruption level, we averaged the results over 1000 simulations. Figure 7 shows the performance of this strategy. This result shows the impact of initial damage to the system, where a 20% initial damage can cause a drop in system performance to be as low as 0.2. In this strategy, disrupted nodes are recovered in random order.

The comparison between the performance of random and informed (direct reporting mode) recovery strategy with $D = 15\%$ is shown in Figure 6. This series of simulations demonstrates that informed recovery strategy is better compared to random strategy since it takes into account the output and impact value of each node before determining the order to repair the disrupted nodes. The process of receiving information is reflected during the early phase of the informed strategy where the performance does not increase since no disrupted node gets repaired. After that, the performance hikes significantly after it starts repairing nodes by prioritizing the highest gain nodes to be repaired first.

Figure 7. Performance of random recovery strategy for disruption percentage of 5%, 10%, and 20%. This result shows the impact of initial damage to the system. Initial damage of 20% can cause the drop of system performance to be as low as 0.2 and cannot reach full recovery.

Figure 6. Performance comparison between the informed recovery strategy (direct reporting mode) and random recovery strategy with D equals to 15%. The process of receiving information is reflected during the early phase of the informed strategy where the performance is not increasing. Then, the performance jumps significantly after it starts repairing nodes by prioritizing the highest gain nodes to be repaired first.

Effects of Recovery Cost (C)

In these simulations, the system has the same configurations as the previous section with an addition of recovery cost parameter. The output production rate T_o is set to $0.02T_c$. The system has initial resources for node recovery by 5% of total nodes, meaning that the system is ensured to not experience delayed recovery if a disrupted event is only causing 5% or less disrupted nodes. Disruption beyond this value may require the system to wait for more resources from the system output, thus slowing the recovery process.

Each active unit produces output between 0.01 to 1 which will be used as recovery resources during disruption. The simulation results in Figure 8 compare simulations of random recovery strategy for recovery cost C equals 25 and 200. As expected, the 5% disruption event gives the same results regardless of the cost since the system has the initial 5% resource redundancy. The recovery cost takes effect when the disruption is more severe than the resource redundancy such as shown in Figure 8 (bottom) for $D = 15\%$. The recovery rate during the initial period is similar for both recovery cost simulations. After the initial resources are used up, the high recovery cost simulations recover much slower as compared to the lower recovery cost simulation.

Using the informed-direct recovery strategy, there is no significant difference between the simulation results with recovery cost 10 and 200 for $D = 15\%$ (Figure 9, top). This is related to characteristics of the system configuration where the operation of many units on lower level depend on few higher level units. As the results, repairing a few critical nodes using the 5% initial resource is enough to improve the system performance drastically which in turn allow the system to produce more output as the resource for recovery. The performance

difference is more distinguishable for higher disruption severity such as shown in Figure 9 (bottom, $D = 30\%$).

Figure 8. Comparison between recovery cost equals to 10 (blue) and 200 (orange) in random recovery strategy for (top) $D = 5\%$ and (bottom) $D = 15\%$.

Figure 9. Simulation results of informed-direct strategy for $D = 15\%$ (Top) and $D = 30\%$ (bottom). There is no significant difference between simulations with recovery cost 50 (blue) and 300 (orange) with $D = 15\%$ because the characteristics of the system configuration in which the operation of many units on lower level depend on few higher level units. As the results, repairing few critical nodes using the 5% initial resource is enough to improve the system performance drastically. The performance is more distinguishable for disruption scenario $D = 30\%$.

The plot of resilience as the function of recovery cost between random and direct-informed recovery strategies for $D = 15\%$ in Figure 10 summarises the difference between both strategies. The random recovery strategy is shown to be affected by the recovery cost above

certain threshold (starting from $C = 100$) while the performance of the informed strategy does not affected at all. High recovery cost generally causes a slower recovery process because the system needs to produce enough resources before being able to repair its unit.

Figure 10. Plot of resilience as the function of recovery cost between random (blue) and direct-informed (orange) recovery strategies for $D = 15\%$. The random recovery strategy is shown to be affected by the recovery cost above certain threshold while the performance of the informed strategy does not affected at all.

Effects of Additional Dependency Links Probability (p)

The increase of p increases of initial disruption severity. In other words, higher dependency makes the system less robust since a small disruption especially on higher level units may cause massive cascading disruption on lower level units. As shown in Figure 11, both random and informed recovery strategies undergo the same pattern. The parameters used in the simulations are as follow: $N = 500$, $\alpha = 4$, $D = 15\%$, $C = 25$, $T_R = 0.01TC$, $T_{info} = 0.001TC$, and $T_o = 0.02TC$.

Figure 11. Simulations with additional dependency probability p equals to 0.01 (blue), 0.02 (orange), and 0.04 (green) for random (top) and direct-informed (bottom) recovery strategies. Increase in p values will cause greater initial disruption severity because higher p means that the system is more dependent from each other.

Effects of Number of Levels (α)

The simulations for this section use these following parameters: $N = 500$, $D = 15\%$, $C = 200$, $T_R = 0.01TC$, $T_{info} = 0.001TC$, and $T_o = 0.02TC$. We set $N_1 = 134$, $N_2 = 366$ for simulations with $\alpha = 2$, and $N_1 = 45$, $N_2 = 122$, $N_3 = 333$ for simulations with $\alpha = 3$. This numbers are set to follow the exponential growth of units to lower levels. The results for

random and direct-informed recovery strategy are shown in Figure 12. We observed a similar pattern as in the increase of p where the systems with higher number of levels experience greater initial performance drop. This is because systems with more levels have more units that depend on units from higher levels. In other words, less hierarchical structure leads the system to be more robust to disruption events since it is less probable to have ‘hub’ units which connect to many lower level units.

Figure 12. Simulation results for random (top) and informed (bottom) recovery strategies. The simulation results show the same pattern in which the increase of number of levels will make the system to be less robust to disruption.

Effects of Number of Units (N)

In these simulations, we set the parameter of additional links probability as 0 to reduce the structural disadvantage of systems with higher number of total units. The reason is that for the same probability p , the lower level units in the bigger system have more dependency links than the smaller system. The results in Figure 13 show the simulation results of random recovery strategy with following parameters: $p = 0, C = 25, D = 30\%, \alpha = 4$. Even though the disruption event causes the same degree of performance reduction (around 65% for all simulations), the performance of the system with a higher number of units recovers slower than the smaller system. That is caused by the fact that the recovery of each unit requires T_R timestep regardless of the system size, thus repairing 5% disrupted units in a bigger system takes longer time as compared to smaller systems.

Figure 13. Simulation results of random recovery strategy for different number of total units. The performance of system with higher number of units recovers slower than the smaller system because the recovery of each unit requires T_R timestep regardless of the system size.

On the other hand, informed recovery strategy is highly affected by the system size. As shown in Figure 14, larger systems need more time for recovery and also respond slower since more units need to send information to the local coordinators or command centre before making the decision to repair disrupted units.

Figure 14. Simulation results of direct-informed recovery strategy for different number of total units. Larger systems need more time for recovery and also response slower since more units need to send information to the local coordinators or command centre

In order to observe its relation with recovery cost parameter, we set the T_{info} to 0, meaning that there is no delay caused by information reporting. The simulation results in Figure 15 for recovery cost $C = 25, 200$, and 400 show that the larger systems ($N = 1000$ and $N = 1500$) are not significantly affected by the recovery cost parameter while the recovery speed of smaller system ($N = 500$ and $N = 750$) is negatively affected by the increase of recovery cost.

Figure 15. Simulation results of direct-informed recovery strategy for recovery cost equals to (a) 25, (b) 200, and (c) 400. Larger systems ($N = 1000$ and $N = 1500$) are not significantly affected by the recovery cost parameter while the rate of recovery of smaller system has negative correlation with recovery cost.

Effect of Communication Duration (T_{info})

This parameter affects the performance of informed recovery strategy in a straightforward manner. The simulation results in Figure 16 show that the longer communication duration will extend the delay of recovery action. The parameters used in the simulations are as follow: $N = 500$, $\alpha = 4$, $D = 15\%$, $p = 0.02$, $C = 200$, $T_R = 0.01TC$, and $T_o = 0.02TC$.

Figure 16. Simulation results of informed recovery strategy with various T_{info} values. Longer communication duration will extend the delay of recovery action.

Our results have shown that high number of disrupted units and long communication duration can slow the performance of informed recovery strategy significantly. This problem can be tackled by increasing the number of communication channels through informational structure configuration which will be explored and discussed in the next section.

Effects of Informational Structures

For a large-scale disruption, the high number of disrupted nodes that need to report to the command centre may cause a bottleneck effect, slowing the decision to start the recovery process. For example, Preece et al. (2013) identify the potential of bottleneck effect at the

information system of the UK's emergency call centre in case of large-scale disaster. On an individual level, the time pressuring situation, complex, and high information intensity environment can result in cognitive overload due to the mental capacity, which is known as bounded rationality (Lindblom, 1968; Simon, 1990).

Regarding the bottleneck issue, the reporting line in the system can be reconfigured to adopt a hierarchical structure. This structure is common in disaster management which utilizes incident management structure as the command centre to coordinate ambulances, hospitals, police, and fire departments (Perry, 2003). Another example also includes the tiered-structure systems in medical surge capacity management where the medical response and resource allocation are distributed based on the disaster severity which can be a local, state, inter-state, or national level (Barbera et al., 2007). Our results in Figure 17 demonstrates the advantage in applying hierarchical reporting mode compared to informed-direct strategies. We run the simulations using the following parameters: $N = 1000$, $p = 0.01$, $\alpha = 4$, $D = 15\%$, $C = 200$, $T_R = 0.01TC$, and $T_o = 0.02TC$. As demonstrated in the previous simulations, large N and T_{info} reduce the resilience of informed recovery strategy significantly, even lower than the performance of random strategy when T_{info} above a certain value.

Figure 17. Resilience curve of random (blue) and informed recovery strategies (orange = Direct mode, green = Hierarchy mode). In this scenario, informed-hierarchy performs better than informed-direct strategy. However, large N and T_{info} reduce the resilience of both informed recovery strategies significantly, even lower than the performance of random strategy when T_{info} above certain value.

While the hierarchical structure is the most practical and widely adopted, we also investigated the hybrid reporting mode. This mode is a mix of direct and hierarchical structures. We can assume that this is the case when the command centre will not only follow the standard rules of the hierarchical structure by waiting for reports from the local coordinator but it also proactively seeks information directly by itself. In a specific scenario, this type of information flow can be applied. For example, when a disaster happens in a certain area, the rapid health assessment (RHA) teams are sent to the location to assess the condition and to measure the medical logistics needed for that area. The RHA teams can be provided by the local or national government. These combined resources accelerate the information gathering for the central facility to make the best decisions regarding medical resources allocation to the affected areas. In establishing the reporting lines configuration of

hybrid mode, we used a parameter h as the probability that a disrupted node will report to the local coordinator, not directly to the command centre. Figure 18 shows the resilience of the informed-hybrid recovery strategy for various levels of probability h . The optimum value of the parameter for this network is 0.6, meaning that the probability of a disrupted node reports to the local coordinator is 60 %. Using this value, we compare the resilience curves of all of the recovery strategies in Figure 19 to show how system resilience can be improved by configuring the informational structure.

Figure 18. Hybrid mode is a mix of direct and hierarchical structures. A parameter h is used as the probability that a node will report to the local coordinator if disrupted. The plot shows the resilience as a function of T_{info} for different values of h . The optimum value of the parameter for this network is 0.6, meaning that the probability of a disrupted node reports to the local coordinator is 60 %.

In practice, our model emphasizes the importance of flexibility of informational relations between entities in sociotechnical systems. This flexibility allows adaptation at organizational level during a crisis, which can be embodied through different modes of reporting lines configurations. For example, the simulation results can be used to guide stakeholders to plan and design the systems to be able to adapt the information flow in the systems based on

various disruption severity, such as using direct reporting mode for low disruption severity to minimize the cost of manpower, and then change to hierarchical reporting mode for a rapid and efficient information processing in case of moderate to high disruption severity, or directing resources to partially bypass the hierarchical structure for an even faster information collection during large-scale disruptions.

Figure 19. Resilience curves of all recovery strategies. These results show how a system resilience can be improved by configuring the informational structure.

Furthermore, the results of our model and simulations were meant to capture the complex interaction in sociotechnical systems while incorporating the core attributes of sociotechnical resilience. We model the sociomaterial structures as the network of operational (sociotechnical) units representing human operators and the machine, along with the dependencies of services between those units. Each unit also has output value to represent the demands to be served in its respective area. Furthermore, we model informational relations as reporting lines configuration, which allows the units to report the impact of their disruption to the local coordinator or command centre. The decision in a form of recovery order is based

on the information of the impact of disruption. The anticipatory practices are embodied in the recovery strategy employed by the command centre. In this model, we demonstrated how information networks play an impactful effect on the systems' capability to respond to a crisis. While adaptation capability is not implemented in the simulations, our model provides insights into how adaptation can be taken in real-world settings through information network reconfiguration at organizational level based on the existing sociomaterial structure and the scale of the crisis.

3.4 Conclusions

Sociotechnical system is not simply an aggregation of social and technical aspects, but it is hybrid in nature. This is the underlying feature of sociotechnical resilience. In this study, a conceptual model has been proposed to lay a stronger foundation to translate the abstract concept of sociotechnical resilience into practical forms. As explained throughout the paper, our research introduced a novel way of modelling sociotechnical resilience as a hybrid phenomenon reflected in network-based interactions which emphasized the role of informational flows in the recovery process of sociotechnical systems. The model allows the adjustment of various configurations of informational relations, rendering it to be useful when stakeholders wish to enhance infrastructure resilience. This is achieved through a computational modelling that informs the design process of a better sociotechnical structure, information-sharing networks, and recovery strategies.

By taking into account the behaviour of complex sociotechnical systems, we incorporated the attributes of sociotechnical resilience namely informational relations, sociomaterial structures, and anticipatory practices. Our model shows the interplay between these resilience factors through a multi-level directed acyclic graph, reporting lines configurations, and

recovery strategies. The practical implication of our model is to guide stakeholders in efficiently and effectively planning their resources to be used in response to a crisis. For example, a direct reporting structure can be applied for a small-scale disruption. An action can even be taken immediately for a very small disruption as shown in the random recovery scenario. For a larger scale of disruption, the reporting lines should be reconfigured to a hierarchical structure to prevent a bottleneck, thus increasing information processing for command centres. The system performance can be further improved in case of large-scale disruption by having a flexible procedure where the command centre utilizes its manpower resources to proactively receive or seek information on the impact of each disrupted unit.

It should be noted that our model is applicable under three conditions. First, the system has to be hybrid where the operation does not take place in a purely technical realm such as an electrical circuit or mechanical device, but it has to involve organizational interactions in which information and coordination are shared and negotiated. Consequently, the model may have some aspects of unpredictability because it deals with organizational behavior. This is reflected especially in the random recovery scenario. At the same time, as simulated in the informed recovery scenario, we showed that the degree of unpredictability can be minimized through information and coordination that can only be provided by human operators and managers, not only from sensors or automatic machines. The second condition is that the system must have dynamic properties such as the demands of the population it has to serve in its operational area. It entails that these properties change from time to time. Further study can incorporate the interactions between local coordinators from multiple networks to capture the complexity of the large-scale interdependent sociotechnical systems.

Chapter 4

The Case Study: Jakarta as a Vulnerable City

This chapter aims to describe the case study for our modeling of sociotechnical resilience and the reasons why this study focuses on the healthcare system. In the first section of this chapter, the definitions of disaster and risk are briefly elaborated to highlight the complex nature and its multi-dimensional causes and impacts. In the next section, the general description of the city of Jakarta is presented, and its urban growth developments are discussed. The emerging infrastructure issues as the results of the existing economic, social, political, and geographical conditions, as well as the risk disaster in the city are addressed in the following sections. Lastly, the healthcare system and disaster management, along with its potential problems are identified to lay the background and problem for the next chapter to apply the concept of sociotechnical resilience and computational modeling into practice.

4.1 Disaster and Risk Defined

According to Turner and Pidgeon (1997), the term ‘disaster’ cannot be universally defined because it depends on the discipline that is using the term. The Oxford Dictionary of English provides the definition as a sudden accident or a natural catastrophe that causes great damage or loss of life. In organizational studies, Weick (1988) described disaster as a low probability with high consequence events that pose a threat to the most primary goals of an organization. Shrivastava et al. (1988) extend the definition as sociotechnical disaster, which is an event that causes extensive physical damages and social disruption that affect multiple stakeholders through complex technological, organizational, and social processes. A broader definition of disaster was defined by Parker (1992) as an uncommon man-made or natural event, which temporarily overwhelms the response capacity of groups of individuals and natural

environments leading to massive damage, economic loss, disruption, injury, and/or loss of life. The World Health Organization (WHO) defines disaster as a sudden ecological event with sufficient magnitude to require external aid (Noji, 1997). Hogan and Burstein (2007) further elaborated this definition for disaster medicine to include the terms of mass casualties and medical system. Along with the definition from WHO, they added that disaster occurs when the emergency department cannot provide care for sudden influx of patients during a certain time period without external assistance, or when an imbalance occurs between the availability of medical care or medical resources and casualties within a community .

The Federal Emergency Management Agency (FEMA) of the United States proposes four stages of disaster life cycle as shown in Figure 20. First is preparedness: plans and preparations made before emergency occurs, e.g. establishing response protocol or evacuation plan, stocking resources, etc. This stage may also involve a cycle of processes of planning, training, exercise/drill, and evaluation. Second is emergency response, actions taken during an emergency to save lives or prevent further damage. Third is recovery, actions taken after an emergency to return the system back to normal state. Fourth is mitigation, activities to reduce the chance or damaging effects. Since these stages are continuous, the learning or adaptation can take place in the system especially during the mitigation and preparedness stages by taking into account the experiences during the response and recovery stages.

Figure 20. Disaster life cycle.

Managing disaster revolves around the concept of risk. Risk reflects the possibility and the damage intensity of a disaster. As summarized by Brooks (2003), the definition of risk in natural hazards literature is probabilistic in nature because it is related to the probability of the occurrence of a hazard that can trigger a disaster, considering the likelihood of the consequences of the hazard. The consequences likelihood is referred to the concept of social vulnerability. The ‘social’ term was used to separate it with the concept of biophysical vulnerability where the definition may overlap with natural hazards. This term then has the equal definition with vulnerability as defined by Cutter (2003), which is the potential for loss of an individual or a group based on the hazard. Social vulnerability is the inherent characteristics of a system that has the potential for harm. It is independent of the probability of the occurrence of a disaster itself (Sarewitz et al., 2003). In another perspective, vulnerability can also be viewed as the characteristics and the situation of a person or group

that influence their capacity to cope, anticipate, resist, and recover from the shock of a natural hazard (Wisner et al., 2004).

International Strategy for Disaster Reduction (ISDR) formalized the concept of risk as the probability of harmful consequences such as deaths, injuries, environmental damages, disrupted economic activities or livelihoods, and loss of properties as the results of interactions between natural/human-induced hazards and vulnerability (Asian, 2002). It can be stated as follows:

$$\textit{risk} = \textit{hazard} \times \textit{vulnerability} \quad (6)$$

Hazards as the first component of risk are mainly divided into the natural and the technological. Three main origins of natural hazards include hydro-meteorological hazards (such as blizzards, cyclones, floods, drought, avalanches, permafrost, wind, etc), geological hazards (e.g. earthquakes, tsunamis, volcanic activity, landslides, liquefaction), and biological hazards (epidemic diseases outbreak), while technological hazards include nuclear and radioactivity, industrial pollution, dam failure, toxic waste, and technological, transport, or industrial accidents. The second component of risk, vulnerability, represents the state of physical factors (such as population density, building materials, remoteness of settlement), social factors (e.g. educational level, peace/security, systems of governance, religion/customs/traditional values, ideological beliefs, access to human rights, and political/organizational systems), economic factors (including debt, insurance, access to credit and loan, access to socio-economic infrastructures, and diversity of economic activities), and environmental condition (access to clean air and water, biodiversity, soil quality) of the individual or groups.

4.2. Jakarta

Jakarta is the capital of the Republic of Indonesia. It is located in the western part of Java island, situated at low, flat alluvial plains in the north coast of the island. The area is crossed by Ciliwung and Cisadane rivers, as well as many other short rivers all the way into the Jakarta bay. The area of Jakarta covers 650.4 square kilometers with a population estimated more than 10 million people, thus having population density around 15,000 people per square kilometers. Based on the data from the Statistics Bureau of Indonesia, the population of Jakarta has steadily been growing from 4,579,303 in 1971 to 9,607,787 people at the last census in 2010 (*BPS Provinsi DKI Jakarta*, 2019). Jakarta is a humid and tropical city with temperatures averaging between 24°C and 34°C. There are two main seasons in Jakarta, the hot dry season which is from March to September as the results of wind influenced by the Australian continent, and the rainy season as the results of wind from Java Sea and South China Sea.

In terms of administration, Jakarta bears a special metropolitan district status which equals to a province. Hence, it is headed by an elected governor as the chief executive. The governor is assisted by regional secretary, executive staff, city directorates, bureaus, and agencies. There are five administrative municipalities in Jakarta: West, North, East, South, and Central Jakarta, each of them is administered by a mayor appointed by the governor. There is only one regency (*kabupaten*) in Jakarta, that is the Thousand Islands (*kepulauan seribu*), a group of 105 small islands located on the Java Sea. The legislative branch is called the Jakarta Regional People's Representative Council (DPRD DKI Jakarta) and consists of 106 elected members. Furthermore, as the capital city where the national government is located. Jakarta hosts the main offices of executive branch which including president, vice presidents, and its cabinet, the legislative branch which is composed of People's Representative Council (DPR) and Regional Representative Council (DPD), and the judicial branch which consists of

Indonesian Supreme Court, Constitutional Court, and Judicial Commission, as well as other state institutions, state-owned enterprises, central bank, public service board, and other state or local-owned entities.

The history of Jakarta as a port and urban area dates back to the 12th century when the city was known as Sunda Kalapa. At that time, “it was a principal harbor for traders from coastal Arabia, India and China, as well as from nearby Malacca and other Southeast Asian trade centers” (Cybriwsky & Ford, 2001). The city also traded with the first Europeans, Portuguese, in 1511. Later, the city was named *Jayakarta* in 1527 and then changed by the Dutch to *Batavia* in 1619. The city served as the Asian trading headquarters of the largest multinational company of the Dutch colonial era, the *Vereenigde Oostindische Compagnie* (VOC), which was later dissolved and nationalized by the Dutch Republic. When the city fell to Japan, it was renamed Jakarta during World War II in 1942. Until 1910, Jakarta mainly only consisted of the old town, Merdeka Square (which is built by the Dutch as the settlements for Europeans and colonial administration), Tanjung Priok (a harbor which is built in 1870), and other suburban areas. Since then, there is no significant city development as the results of the lack of financial supports until Indonesia obtained its independence and officially became the capital of independent Indonesia in 1949 (Silver, 2007).

Despite having a Concept Plan of 1952 and Outline Plan of 1957, the development of the city was barely implemented properly, causing urban sprawling to surrounding towns such as Bogor, Tangerang, and Bekasi. According to Pratiwo and Nas (2005), the poor implementation of the plan was mainly influenced by the powerbrokers of the city. For instance, the first president, Soekarno, who envisioned Jakarta to be the modern city through symbolic and mega projects such as 132 meter high National Monument with 32 kg of gold

on top of the building, Senayan sport facilities for 1962 Asian Games, Istiqlal Mosque, Parliament Building, shopping centre, hotels, parks, resorts, etc. Later the development was continued by President Soeharto during his 'New Order' regime by building highways, high-rise buildings, luxurious estates, electric railway, Taman Mini Indonesia theme park, international airports, and industrial areas to attract investors. Other powerbrokers such as governor, ministers, businessman, and real estate entrepreneurs also played substantial roles in Jakarta's city development. As a result, Jakarta was partly shaped by the interests and vision of these elites, which unfortunately were not always in the best interests for the city and the people since many urban challenges remained unsolved for many years. According to the review of Jakarta's vulnerability and current risks by Salim and Firman (2011), the challenges Jakarta are facing are population and economic pressure, traffic congestion, climate change, and environmental issues.

4.3. City and Infrastructure Issues of Jakarta

The lack of vigorous planning and poor implementation of infrastructure development as well as the deeply-rooted corruption practice has caused various problems in Jakarta. Furthermore, the issues are complex and at some level, intertwined with each other, requiring comprehensive approaches to untangle and solve those multidimensional problems. The main challenges for the city include:

- Rapid population growth

After independence, Jakarta became a magnet for people from all over Indonesia since it offered more jobs and economic opportunities compared to other regions. Ali Sadikin, the Jakarta Governor who served during 1966 to 1977 had attempted to make a policy to limit the population only to those who had residence permits. However, the enforcement was ineffective, thus failing to curb rapid urbanization (Firman, 1999). Population had

increased drastically from around 600,000 in 1945 to 4.5 million in 1970 (Sedyawati et al., 1986). The population keeps growing until it reached 10.5 million in 2019 (*BPS Provinsi DKI Jakarta*, 2019).

- Traffic congestion

As the increase of population and economy are not followed by an expansion in the transportation infrastructure, heavy traffic congestion cannot be avoided. In Jakarta, this condition is exacerbated by more than 1–1.5 million daily commuters from the surrounding cities who work in Jakarta (Rahmatulloh, 2018). Based on the traffic data from navigation technology and software company TomTom, Jakarta ranks 7th in the world in 2018 in terms of traffic congestion. The congestion level of Jakarta city reaches 53%, meaning that in average, a driver experiences extra travel time by 53% compared to the travel time during uncongested conditions. The root problem arose from unimplemented visionary ideas of Master Plan 1965-1985 to construct a rail-based rapid transit system by 1980 (Salim & Firman, 2011). The construction of Jakarta's Mass Rapid Transit (MRT) system was finally completed and commenced operation in March 2019. Currently, the public transportation systems in Jakarta include bus rapid transit (busway system), commuter rail which also serves Bogor, Depok, Tangerang, and Bekasi, and Jakarta MRT. Yet, it is still inadequate to serve the growing needs of the population and to solve traffic congestion problems.

- Flooding and Environmental Issues

Jakarta is situated in a low and flat alluvial plain where it is crossed by large and small rivers. Some of the areas are even lower than the sea level. This condition renders Jakarta prone to floods. The first occurrence of flood in Jakarta was recorded in 1670 (de Haan,

1922). The condition became worse as the floods became annual events. The worst flood happened in 2007, affecting 500,000 people and causing 1066 people treated in hospitals for diarrhoea and 329 for dengue fever (Aldrian, 2008). Apart from the topographical disadvantage and a lack of flood management infrastructure, the flooding is also caused by other factors such as the degradation of water catchment areas. This is mainly caused by excessive constructions of buildings and resorts for local tourists, especially in the mountainous area (called 'Puncak') which are located in the south of Jakarta. Another cause of flooding is land-use change in which open space and green parks were converted into housing and commercial properties. Furthermore, illegal settlements in the riverbanks which are exacerbated by the littering behaviour of the people are making the rivers narrower and shallower. In relation to climate change, the rise of sea-level also poses a real threat in the future. Using the TOPEX/Poseidon satellite data that measure the surface topography of oceans, Takagi et al. (2016) estimated the sea level rise at a rate of 0.7 cm per year. Exacerbated by the land subsidence which is predicted around 11.3 cm per year in North Jakarta (Djaja et al., 2004), the projection using hydrodynamics model shows that up to 110.5 km² area of Jakarta can be submerged by seawater inundation in 2050 (Takagi et al., 2016).

- Water Management Problem

The root problem of Jakarta's water supply is the contract signed in 1997 between the government and private sectors (Harsono, 2003). As a result, low income households have very limited access to clean water. Majority of the customers of the water service providers are middle and lower-middle class people. Another alternative of water supply is the use of groundwater, which accounts for around 40% of the urban water demand in Jakarta (Ardelia et al., 2015). However, the quality of groundwater varies largely

depending on the location and depth. The quality of shallow water is getting worse over the years, mainly caused by households and industries irresponsible waste dumping, and poor sewerage system which only serves less than two percent of the Jakarta area. A survey on shallow wells in Jakarta shows that 84% of the samples were contaminated by *E. coli* bacteria (Kooy et al., 2018). Another research shows that seawater intrusion has reached 10 to 15 km from the coastline, rendering the shallow groundwater useless. Deep groundwater has a higher quality but it is much more expensive than the shallow source. Furthermore, the excessive use of groundwater is also strongly linked to the occurrences of land subsidence (Nur et al., 2001; Abidin et al., 2011).

As discussed above, the infrastructure problems in Jakarta are complex and intertwined. The rapid population growth, coupled with economic growth causes increased mobility demands, which in turn lead to traffic congestion since the public transportation infrastructure is not ready to cope with the demand. On the other hand, the existing flood problem is exacerbated by illegal settlements in riverbanks and private properties development in the upper water catchment areas. Poor water supply infrastructures force a large portion of population to rely excessively on groundwater. This causes more land subsidence in Jakarta, worsening the flood risk even further. On top of the existing urban problem and its vulnerabilities, Jakarta is also under various threat of disasters. The following section elaborates the 9 disaster types in Jakarta based on historical data and government documents.

4.4 Disaster Risk in Jakarta

The references for the disaster risk in Jakarta for this thesis will be based on the datasets from the regulations of National Disaster Management Agency (BNPB, 2012), Government of Indonesia (GoI, 2007a), and the 2013-2017 Jakarta Disaster Management Plan (BPBD,

2013). Disaster is defined as an event or a sequence of events which threaten and disrupt society, caused by either natural or non-natural factors, resulting in the loss of properties and lives, environmental destruction, and psychological impact (GoI, 2007a). The definition of risk is also defined in a similar way as defined by ISDR which is the cost and the probability of loss of lives, economic damages, caused by hazard in a certain area during a certain period of time. The disaster risk assessment of these documents was based on the scores of hazard (H), vulnerability (V), and capacity (C) on region or province, which is calculated using equation (7). This difference of how risk is calculated compared to the one from ISDR comes from the definition of vulnerability. The definition of vulnerability in these documents does not include the ‘positive’ perspective such as defined by Wisner et al. (2004), even though it also considers the physical, social, economic, and environmental factors. Instead, the definition of vulnerability was split into vulnerability and capacity. The capacity in this case is defined as the potential of individuals, families, and society to prevent, mitigate, respond, or recover from a disaster. Whereas, according to the definition of vulnerability from ISDR, capacity is still viewed as part of vulnerability.

$$R = H \times \frac{V}{C} \quad (7)$$

Capacity as the third component of risk assessment is related to the national and local government regulation, availability of data and studies, early warning systems, education and training, mitigation, and preparedness. Capacity was measured based on the indicators from *Hyogo Framework for Actions* (UNISDR, 2005). In practice, the calculation of hazards (H), vulnerability (V), and capacity (C) are based on index levels which are grouped into Level 1, Level 2, and Level 3 for low, medium, and high category, respectively.

Based on historical data, there are nine types of natural and man-made disasters in Jakarta.

1. Flood

Flooding in Jakarta are essentially caused by these following factors:

- Heavy rainfall
- High volume water from upstream causing overflow of Ciliwung River and other smaller rivers
- Lack of drainage systems and catchment areas
- Heavy sedimentation and piles of trash in the Ciliwung River
- Sea level rise caused by global warming
- Geographical condition where 40% (about 26,000 hectare) of Jakarta city is under sea level.

It is estimated that floods in Jakarta can affect 3.85 million lives and potentially cause economic damage of around 75 million USD as well as environmental damage of 32,382 hectare. According to the hazard map shown in Figure 21 (BPBD, 2018), the flood prone areas cover most of the city, especially north and south part of Jakarta as these areas are easily affected by coastal flooding and water overflow from the upstream rivers in Bogor and West Java. Even though the infrastructures, information systems, and training are improving, the littering habit, growing population, and downgraded catchment areas hinder the level of capacity to respond to flooding.

Figure 21. Flood risk in Jakarta

2. Building and Residential Fire

The main cause of this type of disaster is an electrical short circuit mostly due to the lack of understanding and awareness of safe use of electronics as well as inability to install electrical protection devices at home. Long dry seasons and human errors such as fire from gas stove explosions and cigarettes are also the contributing factors of building and residential fire. For some areas in the city, high-density settlements with non-permanent or semi-permanent houses in a very narrow alley exacerbate this type of disaster since they cause fire to spread quickly while hindering fire trucks from getting to the site.

The risk of fire disaster is relatively even in the whole city. For example, the frequency of fire occurrences during January – September in 2014 as shown in Figure 22 indicates

that most areas have low to medium intensity (BPBD, 2014). However, along with the population density way above 1000 people/km² and potentially affecting more than 7.5 million lives and causing more than 1000 billion rupiahs of economic loss, the disaster risk of Building and Residential Fire falls into HIGH level category.

Figure 22. Frequency of fire incidents in Jakarta

3. Epidemic and outbreak

There are 17 diseases that potentially cause extraordinary events (abbreviated as KLB in Indonesia). KLB, which stands for “Kejadian Luar Biasa” is an official status from Indonesian government to indicate that an epidemic or an outbreak of disease is happening in a certain region. These diseases are cholera, plague, malaria, dengue, measles, polio, pertussis, rabies, Avian Influenza H5N1, anthrax, hepatitis, H1N1, meningitis, yellow fever, chikungunya, leptospirosis, and HIV. However, the hazard risk of epidemic and outbreak in Jakarta is not significant. Only a few times when a

notable KLB is declared and most of the cases can be taken care of by the local healthcare facilities (BPBD, 2013). Four diseases which are considered as the most threatening and highly probable in Indonesia are malaria, dengue, measles, and HIV/AIDS. Overall, the risk disaster of epidemic and outbreak falls into MEDIUM category after taking into account the other factors such as high-density population, socio-economic status, and areas affected.

4. Social conflict

Social conflict is physical interactions involving violence between two or more groups of people causing safety issues or stability of the nation. For example, terrorist attacks, student brawls, beating and thuggery, mass riots, clashes between groups or protesters and security forces. According to the data from Global Terrorism Database, there are 58 bombing incidents in Jakarta between 1978 – 2017 (GTD, 2017). Additionally, the fact that Jakarta has an average of 152 conflicts each year and potentially affecting more than 8 million people, as well as other factors such as high-density population, socio-economic status, and number of gangsters, confirms that the risk of social conflict in Jakarta is very high.

5. Technological failure

The presence of transportation infrastructures such as commuter rail, LRT, and MRT, gas pipelines, industrial facilities in and around Jakarta, and being the center of business activities can be the contributing factors to the level of this hazard. Considering the vulnerability level of Jakarta, risk of technological failure in the city falls to high level category.

6. *Tornado*

This phenomenon has a higher probability to happen during the transition season between dry season and rainy monsoon season. During the period from 2010 – 2019, there were 21 occurrences of tornadoes in Jakarta (*Data Informasi Bencana Indonesia*, 2019). This event can lead to the destruction of houses, billboards, and trees. Considering the overall trend of tornado occurrences, its impacts, and the vulnerability of Jakarta city, the risk of tornado falls into a high category.

7. *Earthquake*

The peak ground acceleration (PGA) value in determining the level of earthquake hazard is measured by the value of peak ground acceleration having 2% chance of being exceeded in 50 years. According to the earthquake hazard map of DKI Jakarta as shown in Figure 23 (Irsyam et al., 2015), the range of PGA values from North Jakarta to South Jakarta is 0.33 to 0.39 g. The contour map was developed using probability seismic hazard assessment based on active seismic sources 250 km radius from Jakarta city and attenuation functions. Therefore, the hazard level of this disaster falls into the medium category.

Figure 23. PGA value contour in Jakarta for 2500 years return period.

8. *Extreme tidal waves and abrasion*

Monsoons and global warming are the main factors in causing strong winds and waves. Furthermore, without mangrove vegetation and coral reef, the waves may cause coastal erosion. This hazard is particularly threatening people living in coastal areas such as North Jakarta and Kepulauan Seribu. During the period of 2006-2009, there were 18,003 people affected, 167 people injured, 4300 people evacuated, and 17 houses were heavily damaged (BPBD, 2013). Considering the area and population affected by this hazard, the disaster risk of extreme tidal waves and abrasion falls into high category.

9. *Landslide*

When the document of Disaster Management Plan of Jakarta (2013) was published, there were only one occurrence of landslide in Jakarta recorded in 2006. Therefore, no data and official analysis for this hazard from BPBD DKI Jakarta, the provincial/local

disaster management agency in the Special Capital Region of Jakarta. However, according to the real-time data from the National Disaster Management Agency (*Data Informasi Bencana Indonesia*, 2019), the frequency of this disaster has increased since 2016 (shown in Figure 24) and most likely to happen in South Jakarta and East Jakarta where a lot of residential areas are located around riverside or cliff.

Figure 24. Landslide occurrences in Jakarta during 2010 - 2019.

Based on the analysis from Disaster Management Plan of Jakarta (2013) by using the Hyogo Framework, the capacity level of Jakarta is low. By taking into account the population density as well as the characteristics of Jakarta as the national capital and business center of Indonesia, BPBD DKI Jakarta classified the risk of all types of disaster as HIGH category. For that reason, all types of disaster have the same priority for disaster risk reduction investments.

However, according to the evaluation report of Governor Regulation Document no.143 Year 2015 pertaining to disaster management plan in Jakarta (Jannah & Rahman, 2016), it is necessary to set a proper priority in capacity development for disaster management.

Prioritizing all types of disaster causing difficulty in setting and achieving the performance targets with limited resources. Therefore, it was decided to set the priorities for disaster risk reduction based on the probability of occurrence and its impacts. Table 2 shows the classification for the level of impacts and occurrence probability. Furthermore, Table 3 shows the impact and probability levels for each disaster. Finally, the priority ranking was shown in Table 4. Landslide was included in the table after considering that its intensity of occurrences was increasing during the last few years. Based on these results, building and residential fire has the highest priority, followed by earthquake, flood, social conflict, epidemic and outbreak, tornado, landslide, and technological failure that have medium priority level. Extreme tidal waves and abrasion has the lowest priority.

Table 2. Classification for the impact level and probability level of disaster in Jakarta.

Impacts Level	Probability Level
5 = 80-99 % of damaged area	5 = Certain (80-99% to happen in the next year)
4 = 60-80 % of damaged area	4 = 60-80 % to happen next year, or once in the next 10 years
3 = 40-60 % of damaged area	3 = 40-60 % to happen next year, or once in the next 100 years
2 = 20-40 % of damaged area	2 = 20-40 % to happen in the next 100 years
1 = Less than 20 % of damaged area	1 = Less than 20 % to happen in the next 100 years

Table 3. Impact level and Probability level of each hazard in Jakarta.

Hazards	Probability Level	Impact Level	Remarks
Earthquake	2	3	- Megathrust prediction in Indian Ocean (south of Java Island) - Epicentre is in the ocean (lesser impact to Jakarta)
Flood	4	3	- High probability but better structural mitigation has successfully reduce the flood prone areas
Extreme Tidal Waves and Abrasion	3	1	- Higher probability to happen in December - Breakwater construction in coastal area has reduced the impact significantly

Tornado	4	3	- High probability to happen each year (La-Nina and El-Nino events) - Mostly damaging houses and destroying trees or billboards
Building and Residential Fire	5	3	- Occur almost on a daily basis
Epidemic and Outbreak	4	3	- Health education for the society still needs to be improved - East Jakarta almost declared KLB for dengue in 2016 - Better healthcare systems and health insurance systems to prevent epidemic and outbreak
Technological Failure	3	3	- High number of factories especially in North Jakarta and East Jakarta
Social Conflict	3	2	- Political year may increase the probability of the social conflict

Table 4. Priority ranking of each hazards for capacity development in Jakarta.

Impact Level	5					
	4					
	3	Earthquake	Technological Failure	Flood, Tornado, Epidemic and Outbreak	Building and Residential Fire	
	2		Social Conflict, Landslide			
	1		Extreme Tidal Waves and Abrasion			
	1	2	3	4	5	
Probability Level						

High
 Medium
 Low

4.5 Jakarta Healthcare System

This research concerns on sudden onset with acute impact events. This is the type of disaster that happens in a very short duration, causing an immediate damage to people, building, or environment. For example, the occurrence of earthquakes causing collapses of buildings, or

terrorist bombing in mass gathering locations. While there is no mass casualty disaster ever recorded in the history of Jakarta, the potential of the events to occur still clearly exists in this city. Therefore, the healthcare system in Jakarta becomes an important factor of the city resilience to withstand mass casualty disasters.

In Indonesia, medical emergency service is mainly provided by community health centers (Puskesmas) and private or public hospitals. Figure 25 shows the structure of the healthcare system in Indonesia. Following the government decentralization in 1999, the healthcare system was also decentralized to provincial and district levels, under the supervision of provincial and district government. However, private hospitals and other private healthcare providers are almost autonomous entities since they do not report to another entity. They are only controlled through technical regulations under the Ministry of Health, provincial health office, and district health office. According to the data from the Ministry of Health (2018), there are 321 community health centers, 143 general hospitals, and 60 specialist hospitals in Jakarta. Table 5 shows the number of beds, GPs, specialists, and nurses as well as its ratio per 1000 population using the estimation of 10,467,629 total population of Jakarta in 2018.

Table 5. Total number of medical resources and its ratio per 1000 population in Jakarta.

Medical Resources	Total Number	Ratio (/1000 populatoin)
Beds	24,352	2.33
General Practitioners	18,905	1.81
Specialists	5,732	0.55
Nurses	33,484	3.20

Figure 25. Structure of healthcare organization in Indonesia (Mahendradhata et al., 2017).

From the perspective of disaster medicine, the number of medical resources is generally not the main issue during a disaster in a city. The more critical factor in enhancing the capacity of the healthcare system is the capability to efficiently manage and allocate medical resources. Maldistribution of medical resources is a more common problem in this scenario (Auf der Heide, 2002). Therefore, the disaster and medical emergency management are the key elements in determining the resilience capacity to respond to disaster instead of the aggregate number of medical resources. The following section elaborates the disaster management in Indonesia and its coordination with the healthcare system during a disaster.

4.6 Disaster Response in Indonesia

The disaster management in Indonesia is supervised by National Disaster Management Agency (BNPB, stands for Badan Nasional Penanggulangan Bencana) and the local disaster

management agency for province, city, or regency level (BPBD, stands for Badan Penanggulangan Bencana Daerah). Their main functions are planning, organizing, preparing, executing, as well as monitoring and evaluating the disaster management processes along with other government agencies and NGOs. According to the law no 21 year 2008 (GoI, 2008), there are three iterative steps for disaster management in disaster prone areas, which are pre-disaster (preparedness, early warning system, mitigation), emergency response, and post-disaster (rehabilitation and reconstruction).

When a disaster happens, BNPB or BPBD will send a rapid assessment team to determine the severity of disaster and the emergency status. BNPB is responsible for national level of emergency status, while BPBD is responsible for provincial or city/regency level of emergency status. If a local government does not have enough capacity to respond to a disaster, BPBD can request aid from its counterparts from other region. After the emergency status has been determined, BNPB or BPBD will establish the incident command systems to enable effective and efficient disaster response by integrating human resources, equipment, facilities, and logistics, as well as allowing coordination with other government agencies or institutions. The main objectives of the command systems are to rescue and evacuate affected people, to provide basic needs, to protect vulnerable and disabled people, and to recover critical facilities or infrastructures quickly.

BPBD DKI Jakarta is the disaster management agency in Jakarta province. This agency coordinates with Provincial Health Office of Jakarta (Dinkes DKI Jakarta, stands for Dinas Kesehatan DKI Jakarta) to provide emergency medical services (GoI, 2014). Therefore, Dinkes DKI Jakarta and the city/district health offices are directly in charge of managing community health centre (Puskesmas) to respond a disaster in Jakarta. In the city-level disaster, BPBD will coordinate its counterparts from other regions. In total, there are 6 public

health offices under Dinkes DKI Jakarta serving 6 areas: Seribu Island, West Jakarta, South Jakarta, East Jakarta, North Jakarta, and Central Jakarta.

Similar to BNPB or BPBD, provincial and city/regency Dinkes also have disaster management guidelines in terms of emergency health services during pre-disaster, emergency response, and post-disaster phase (GoI, 2007b). Some of the emergency response activities for the head of provincial health office, director of provincial hospital, the head of city/regency health office, and the director of city/regency hospital are shown in Table 6. Similar to the nature of the healthcare organization described in Figure 25, the interactions between the health organization entities are mainly through coordination to prepare for the surge of medical demands. On the other hand, community health centers have a clear reporting line in which they can request medicine or medical staff from city/district health office (Depkes, 2007).

Table 6. Highlighted activities of head of provincial health office, director of provincial hospital, the head of city/regency health office, and the director of city/regency hospital during a disaster.

Actors	Highlighted Activities
Head of Provincial Health Office	<ul style="list-style-type: none"> - Coordinating with incident command systems of BPBD - Coordinating with provincial hospitals to prepare for referred patients from refugee camps or disaster sites. - Coordinating with teaching hospitals from outside of the province to request aid or to accept referred patients - Coordinating with head of city/regency health office for medical resource allocation - Mobilizing medical staff to help the disaster area
Director of Provincial Hospital	<ul style="list-style-type: none"> - Coordinating with city/regency hospitals to optimize referral system - Requesting medicine and other equipment if needed - Sending medical staff and equipment to disaster site if needed
Head of City/Regency Health Office	<ul style="list-style-type: none"> - Coordinating with incident command systems of BPBD - Coordinating with hospitals and community health center to prepare for referred patients from disaster

	site or refugee camp - Contacting community health center to send doctors, nurses, medicine, and needed equipment to disaster site - If the city/regency has insufficient capacity to respond to the disaster, the person-in-charge of emergency medicine services will be the head of provincial health office
Director of City/Regency Hospital	- Preparing the hospital to receive patients from disaster site or refugee camp - Contacting the provincial hospital for the possibility of referring patients - Sending medical staff and equipment to disaster site if needed

In practice, hospitals can also request for assistance from the health office in case of emergency. However, it is not formally regulated by the government. Meanwhile, hospitals are not allowed to reject patients during disaster (GoI, 2009). This condition will become an issue when a hospital does not have enough medical resources to treat the victims, thus causing significant delay in providing emergency medical service. To make it worse, a hospital also cannot control the inflow of victims since the majority of them usually come to the hospital using private vehicles, provided by themselves or volunteers (Auf der Heide, 2002). In case of a large-scale disaster, we argue that the current practice where the medical resource management is only implemented through incident command systems or reactive coordination is not enough to efficiently treat mass disaster casualties. Additional efforts have to be made to complement the current practice, for example adjusting the coordination structures and strategy based on the severity of the disaster event.

4.7 Chapter Summary

Disasters can be caused by natural or man-made hazards, and can result in the loss of lives, economy loss, and damage to environment. Disaster risk is assessed based on hazards,

vulnerability, and capacity levels. This chapter describes the vulnerabilities and disaster risk of Jakarta city in general, and elaborates on its healthcare system and disaster risk management. As the national capital and center of business, Jakarta still has many infrastructure issues as a result of poor city development and population pressure. Besides the flooding problem, Jakarta also has other hazards that can potentially cause large-scale disasters such as earthquake and terrorist bombings. This makes the healthcare system an extremely important factor in the city's resilience. According to our study, we identified two main issues in the Jakarta healthcare system in responding to the surge of patients. First, there is no clear regulation for the hospitals to make requests to the local health office in case they are short of medical resources. At the same time, the majority of the victims are carried to the hospitals by private vehicles, thus it is not possible to direct them to other hospitals before they arrive. Furthermore, without proper coordination procedures and technologies to facilitate information sharing, the incident command system is prone to the bottleneck effect, especially in a case of large-scale disaster. This may delay the coordination between entities significantly. What has been described here serves as the basis of our argument to develop a model of healthcare systems in Jakarta and simulate the disaster response during a disaster event as presented in the following chapter.

Chapter 5

Optimizing Disaster Response Strategies in Healthcare Systems

This chapter aims to apply the principles of sociotechnical resilience and the conceptual model presented in Chapter 3 in a real-world situation. As described in Chapter 4, the healthcare system in Jakarta is used as a case study to build our model and simulations. The first section of this chapter describes the development of disaster medicine and the practice of emergency medicine. The second section elaborates on the methodology including data collection, model description, system performance and resilience formula, and disaster response strategies. The results and discussions are presented in the third section of this chapter. The fourth section concludes by highlighting key points of this research.

5.1 Introduction

5.1.1 Disaster Medicine

Throughout history, the role of emergency medicine has been clearly understood as the frontline in saving lives and treating injuries during a war or disaster, which are known as military medicine and disaster medicine. These two are closely related disciplines in emergency medicine. It is often mentioned that the practices in disaster medicine are the results of the adaptation of the military model for medical responses in civilian context (Dara et al., 2005; Iserson & Moskop, 2007). The military experience and strategy have inspired the way to provide efficient response to mass victims in a dire situation.

However, a clear distinction between the situation in war and disaster are the characteristics of the victims. While the majority of the casualties in a battlefield are young and fit soldiers,

a disaster can inflict various types of people including children, elderly, infant, malnutrition, disabled, etc. Furthermore, the preparedness and response systems are also different between these two conditions. In war, the number of involved people and possible types of injuries can be determined and used to prepare the medical teams while it is not the case for disaster. There are no medical practitioners who get ready in the morning knowing that they will treat disaster patients at hospital. The random nature of disaster makes it less likely to prepare such a protocol. Usually, the emergency medical responder around the disaster event will be forced to take the role. Therefore, disaster medicine is systems-oriented in terms of its implementations as it is necessary for those who practice in emergency health services to have a basic working knowledge in disaster medicine and disaster management (Ciottonne, 2016).

Based on the nature and severity of a disaster, as well as the phase of disaster life cycle, the provision of health care service may involve various areas of medical expertise such as public health, orthopedic, surgery, toxicology, psychiatric, primary care, and infectious diseases (Hogan & Burstein, 2007).f. Compared to other disasters, earthquakes are the only natural disaster that has a higher demand for orthopedic, plastic surgery, and general surgeon because of large numbers of traumatic injuries as the results of building damage (Ramirez & Peek-Asa, 2005; Bartholdson & von Schreeb, 2018). Infectious diseases specialists are suitable for handling major outbreaks, especially during the recovery phase of a disaster (Ragnar Norrby, 2005; Watson et al., 2007). Psychiatrists also have an important role in the aftermath of disaster for managing the victims' emotional distress (Kinston & Rosser, 1974; Norwood et al., 2000). Generally, the most important medical staff after a disaster are nurses with the ability to treat wounds and general practitioners with the skills to treat communicable and

non-communicable diseases, as well as performing basic surgeries (Bartholdson & von Schreeb, 2018).

The treatment of casualties in a disaster is not only being done in hospital. Pre-hospital care after a disaster can also be provided by the emergency medical service (EMS), which is defined as a comprehensive system consisting of well-coordinated personnel, facilities, and equipment providing health and safety services to victims of acute illness or injury in an effective and timely manner (Moore, 1999). The roles of EMS are primarily to triage, provide early treatment, and transporting casualties to hospital. Generally, there are two philosophies for this pre-hospital care, namely Franco-German and Anglo-American models (Arnold, 1999; Dick, 2003). The former model focuses on bringing the 'hospital' to patients, meaning that the medical teams arriving in the field will prioritize treatment of the victims at the site of incident. The latter model refers to the 'scoop and run' philosophy, which focuses on sending casualties to hospitals rapidly. However, in practice, the EMS systems in a country can be either mix or modified version of these models (Page et al., 2013; Haddadi et al., 2017).

The traditional mass casualty management scheme in the field is shown in Figure 26 (Hogan & Burstein, 2007). Initially, all victims from the incident site and its vicinity are going through the triage process where they are getting first treatment and tagged with a certain color representing their level of injury. Black color is used for deceased or people with zero probability of survivability as the results of having extensive injuries, red color means that the patient is in life-threatening injuries with clear abnormal vital signs, yellow color suggests that the patient potentially has life-threatening injuries but no abnormal vital signs were observed, and green color means that the patient still able to walk and can verbalize their

issue as well as maintain their own breath (Glarum et al., 2009). After that, the red and yellow tagged patients will be transported by ambulances and other available vehicles to hospitals for further treatment.

Figure 26. Mass casualty management: triaging and transporting victims to health facilities.

There is a critical issue when a disaster happens in a rural area. Local health facilities or hospitals in rural areas generally have less capacity, medical personnel, resources, and funding (Rudman et al., 2004; Hoard et al., 2005). External aid such as volunteers and organized medical teams will be required to respond to such disasters. For example, large-scale disasters such as the Aceh tsunami in 2004 (Telford & Cosgrave, 2007), the Haiti earthquake in 2010 (Margesson & Taft-Morales, 2010; Zook et al., 2010), the Tohoku earthquake in 2011 (Norio et al., 2011; Holguín-Veras et al., 2014), and many more have involved international humanitarian relief and foreign medical team for the affected countries.

On the other hand, hospitals or other public health facilities will be relied on heavily rather than the first medical responders during a disaster in the city because they are most likely to be around the vicinity of the disaster site. The ambulance or any prehospital care are less significant as most casualties will be brought to nearest hospitals by private vehicles. In this case, the triage and first medical treatments are provided by the hospitals instead. The record of Oklahoma bombing which caused 167 deaths and around 592 injured people (Mallonee et al., 1996) shows that there were 139 casualties transported to hospitals by ambulance while more than 300 were transported by private vehicles, buses, or vans (Maningas et al., 1997). The data in St. Luke's Hospital during Tokyo Sarin attack which affected more than 5000 people shows that only 10% of 640 patients arrived at the Emergency Department (ED) by ambulance, 5% by fire department minivan, while the rest arrived by the assistance of nonmedical motorists (Okumura et al., 1996). During the San Francisco earthquake (Loma Prieta earthquake), only 23% out of 830 earthquake-related patients arrived at the hospital by ambulance (Tierney, 1991).

This trend also indicates that when a disaster takes place in a city, the EMS systems may not be able to effectively control the destination of patients to hospitals because they are usually transported by the bystanders around the site or by themselves. This condition will cause a maldistribution of patients to the hospitals because they are usually transported to the nearby hospitals in the vicinity. On average, the majority of patients will arrive within the first 90 minutes of the disaster (der Heide, 2006). During this period, the surge capacity will become the key component of the hospitals and public health facilities in saving the casualties.

In order to provide guidelines for hospitals to prepare an emergency situation, WHO issued a hospital emergency response checklist to assist hospital administrators and emergency managers to respond all types of disaster effectively (WHO, 2011). The document is structured around nine key components of emergency management principles: Command and control, communication, safety and security, triage, surge capacity, continuity of essential services, human resources, logistics and supply management, and post-disaster recovery. Surge capacity as one of the key components is generally defined as the ability to manage sudden increase of demand for clinical care through resource management and allocation (Hick et al., 2004; Barbisch et al., 2010). The resources include hospital beds, medical doctors, nurses, ambulances, medicine and equipment, as well as non-medical staff.

5.1.2 Modeling and Optimization of Healthcare Systems

Most of the works on modeling and optimization of emergency logistics for disaster are dominated by study for facility location, relief distribution, and casualty transportation (Caunhye et al., 2012). For examples, shelter location-allocation model for flood evacuation planning to minimize the total evacuation time and to determine the evacuation route using genetic algorithm (Kongsomsaksakul et al., 2005), location-allocation planning of stockpiles and temporary distribution facilities for effective disaster mitigation to minimize the delay of assistance during disaster emergency (Paul & Hariharan, 2012; Khayal et al., 2015; Sharma et al., 2019), resource allocation optimization after earthquake disasters (Fiedrich et al., 2000), evacuation modeling and optimization for disaster relief operation (Barbarosoğlu et al., 2002; Yi & Özdamar, 2007), and many more.

In terms of modeling medical response in urban areas, not many studies have been done especially for a large-scale disaster scenario. Su and Shih (2003) model the emergency

medical services (EMS) system using computer simulation to explore alternatives of EMS and hospitals cooperation to achieve lesser call waiting probability. Silva and Pinto (2010) used discrete-event simulation and optimization procedures to model and evaluate the response time of the EMS system of the city of Belo Horizonte. Janosikova (2009) developed a mathematical model to optimize hospital network design to serve insurance companies to determine which hospitals should be closed or opened as well as to allocate customers to the open hospitals. Maria (2012) proposes an index to measure the efficiency of predefined hospital networks for mass casualty disasters using data envelopment analysis and regression analysis.

Our research aims to examine the resilience of various coordination structures and strategies of healthcare systems during a large-scale disaster. We apply the principles of sociotechnical resilience and the conceptual model presented in Chapter 3. The next section elaborates the methodology including the data collections and detailed descriptions of the model we developed.

5.2 Methodology

The case study for our model was applied to Jakarta, Indonesia. There are two main reasons to choose this city. First, Jakarta is a national capital with a high population density of about 15,300 people/km², rendering the city to be vulnerable in terms of health emergencies. Improvement in surge capacity is essential in reducing its vulnerability. Second, the regulations on disaster management and national agency are still relatively new. The national disaster management agency was formed in 2007 while the local disaster management agencies were established afterwards. The coordination strategy is still working around the

concept of centralized systems without being supported by advanced information technology systems.

In our research, we developed a model to evaluate disaster response strategies that takes the account of the organizational structures of healthcare systems during a large-scale disaster. As mentioned in Chapter 4, our research focuses on a sudden onset with high impact disaster, e.g. earthquake or terrorist bombing, because the healthcare system in this city may not be prepared to deal with this type of disaster. While other types of disaster such as epidemic or outbreak that has slow onset characteristic are important and relevant in studying the resilience of Jakarta healthcare systems, these factors are not explicitly modelled in this chapter. Besides the reason of simplicity, slow onset disaster is not modelled since it does not get much benefits from rapid and efficient coordination strategies that are investigated in our study.

The general workflow of this research is shown in Figure 27. Data inputs include hospital data, disaster locations, and travel time data between locations. The hospital data consists of the number of available beds, beds occupancy rate (BOR), and coordinate location of each hospital. The disaster sites represent the risk of the disaster in the region. Since there are no occurrences of mass casualty disasters in Jakarta based on historical data, we picked random locations all over the city as the hypothetical scenarios of mass casualty by terrorist bombing or collapsing buildings by earthquake. The disaster locations are used to generate disaster events during the simulations. The travel time data determines the time it takes for a victim to travel from hospital to hospital or disaster site to hospital. Recovery strategy involves various coordination structures in reporting the number of untreated victims and instructing hospitals that still have available capacity to help overcrowded hospitals.

Figure 27. General workflow of modelling and simulations for healthcare resilience evaluation.

5.2.1 Data Collection

In order to apply the methodology proposed in the previous section, the data on the hospitals as well as the potential disaster locations are required. The data of hospitals in Jakarta were obtained from the Ministry of Health of the Republic of Indonesia while the disaster locations were chosen randomly over the whole area of the city.

- Hospitals

The data set contains information of 195 hospitals. The relevant features for our model cover the hospital name, grade, type, address, total number of beds from all these types: VVIP, VIP, I, II, III, ICU, PICU, NICU, HCU, ICCU, Operation, Emergency, Isolation, and Nursery), and Bed Occupancy Rate (BOR). To simplify our model, we filter out the grade D and ungraded hospitals as well as specialist hospitals. The main reason for this exclusion is that they have a low number of available beds thus not having noticeable contribution to the system performance while slowing the simulations. Several hospitals from these categories are also missing some information such as the numbers of beds and BOR. There are 75 hospitals in total for our model. Furthermore, we used the Google API

service to obtain the longitude and latitude of each hospital using the hospital address information.

- Disaster Location

We chose 16 locations randomly over the whole area of Jakarta city. These locations include department stores, apartments, train stations, stadiums, and airports. The location information consists of longitude and latitude.

- Travel Time

The expected travel time by car between hospitals and between disaster location and hospitals were obtained using Google API. The data contain the best guess of travel time on a certain date based on Google's database. We obtained data on Wednesday, 28th August 2019 at 6 AM, 10 AM, 2 PM, 6 PM, and 10 PM. Figure 28 shows a sample of our data: the travel time in seconds between Gandaria Heights Apartment to National Central General Hospital Cipto Mangunkusumo during the time of the day. The travel time mostly gets worse during the peak hour at 6 PM. Therefore, we choose the travel time at 6 PM for our simulations to reflect the worst-case scenario in the road during chaos.

Figure 28. Travel time between Gandaria Heights Apartment to RSUPN Dr. Cipto Mangunkusumo

5.2.2 Model Description

Each node represents a hospital with a certain amount of resources. The resources encompass the available beds in hospital during a disaster. In our model, we calculate the number of available beds for each hospital i in a set of hospitals H using equation 8, where B_i is the total number of beds, and BOR_i (bed occupancy rate) is the average occupancy of beds in a year. The extra 25% of total beds is based on the study by Hick et al. (2004) where 20% to 30% of additional beds can be mobilized during emergency by early discharge of stable patients as well as the use of hospital space such as lobby, therapy areas, hallways, conference facility, and waiting rooms.

$$b_i = B_i (1.25 - BOR_i), \quad i \in H \quad (8)$$

For each disaster site r , a V_r number of victims is generated. All hospitals within $d_r + \delta$ minutes of travel time from the disaster site are considered as responding hospitals, meaning that these hospitals will experience a surge of injured people coming as the result of the disaster. The variables d_r and δ are the travel time between the disaster site r to the nearest

hospital and tolerance of travel time, respectively. We assumed that the victims will be distributed evenly between the responding hospitals a_r . The number of people coming to the responding hospital i which is caused by disaster site r is calculated using equation 9. The time for the people to reach the hospital is based on the data of travel time by car between the disaster site and the hospital. Figure 29 illustrates the disaster site and responding hospitals.

$$v_i^r = \frac{V_r}{|a_r|}, \quad i \in a_r \quad (9)$$

Figure 29. Nearest hospital to mass casualty site and another hospital within the vicinity are responding to the mass casualty incident. All victims are coming to these hospitals (purple markers).

When the victims arrive at a hospital, doctors or nurses will start triaging and stabilizing heavy injured victims. Each victim is put on 1 bed after the treatment. If the total number of victims that arrive is more than the available beds of the hospital, the hospital manager will contact Provincial Health Office (PHO) to ask for help and give information about the number of untreated victims as the results of insufficiency hospital beds. PHO then contacts other nearest hospitals to obtain information about their available beds and prepare for victims transfer. Once the health office finds a hospital with available beds, it will notify the overcrowded hospital to send the untreated victims based the number of the available beds. The health office keeps doing this process until it is enough to accommodate all untreated victims. In our model, it takes T_{info} timestep for each communication action. Other parties cannot interrupt communication that is happening and have to wait until it is finished. We call this type of coordination structure as *PHO mode*. This model represents the current

practice in Jakarta as a special region which only has a PHO that is responsible for the health crisis in the city. Figure 30 illustrates the example of victim transfer strategy of *PHO mode* with $T_{info} = 60$ s.

Moreover, we also developed other coordination structures beside the *PHO mode* to examine how different informational structure and strategy affect system performance. First additional mode we developed is called *CH+PHO mode*. When there is a disaster, the overcrowded hospital contacts the nearest central hospital (CH) to coordinate for the victims transfer. If all CHs run out of available beds, the overcrowded hospital will contact PHO to ask for help. The standard procedure by referring to the nearest hospital will be implemented. In our model, we chose Central General Hospital Fatmawati (RSUP Fatmawati), Central General Hospital Persahabatan (RSUP Persahabatan), and National Central General Hospital Cipto Mangunkusumo (RSUPN Cipto Mangunkusumo) which are the only hospitals owned by Ministry of Health in Jakarta as our Central Hospitals. This strategy is shown in Figure 31.

Figure 30. PHO mode strategy in transferring victims to nearby hospitals that still have available beds. In this example, at $t = 0$, a disaster that causes 200 victims takes place near hospital 1. The victims are brought by ambulances and nearby volunteers to hospital 1 that has 100 available beds. The travel time from disaster site to hospital 1 is d . At $t = d$, hospital 1 has 100 untreated victims and need to transfer them to other hospitals. It contacts PHO to ask for help. The communication duration (T_{info}) in this example is assumed to be 60s. After receiving the request detail at $t = d + 60s$, PHO contacts the first nearest hospital of hospital 1 to get information on available beds. At $t = d + 120s$, after knowing that hospital 2 has 50 available beds, PHO notifies (dashed-green line) hospital 1 to send 50 victims to hospital 2. Meanwhile, PHO continues to contact other nearest hospitals since hospital 1 still has the remaining 30 untreated victims. At $t = d + 180s$, 30 untreated victims are transferred to hospital 3. At $t = d + 720s$, the victims that were sent at $t = d + 120s$ arrive at hospital 2. Lastly, 30 remaining untreated victims reach hospital 3 at $t = d + 1080s$.

Figure 31. CH+PHO mode strategy. In this example, at $t = 0$, a disaster that causes 250 victims takes place near hospital 1. The victims are brought by ambulances and nearby volunteers to hospital 1 that has 50 available beds. The travel time from disaster site to hospital 1 is d . At time $t = d$, hospital 1 has 200 untreated victims. In this scenario, hospital 1 will firstly contact nearest CH. At $t = d + 60\text{s}$, after coordinating with CH, hospital 1 sends their untreated victims according to the number of available beds in CH. Since there is no more available bed in CH, hospital 1 contacts PHO to ask for help. PHO contacts hospital 2 and then notifies hospital 1 to send their remaining untreated victims to hospital 2 at $t = d + 180\text{s}$. All victims reach hospital 2 and hospital 3 (CH) at $t = d + 780\text{s}$ and $t = d + 1260\text{s}$, respectively.

Second additional coordination strategy we developed involve District Health Office (DHO) as well as PHO. There are 5 DHOs for each city: West, East, South, North, and Central Jakarta. In the current practice, DHOs in Jakarta focus on improving health facilities and public health. They are not responsible for managing hospitals during a disaster. This model assumes that these DHOs are involved in disaster response. In this *DHO+PHO mode*, DHO can only interact with hospitals in its administrative area. However, if the DHO cannot find any hospital with available beds in its area, it will contact PHO for help since PHO has authority of all hospitals in the city. This coordination structure is shown in Figure 32.

Figure 32. Victims transfer strategy of DHO+PHO mode. In this example, a disaster that causes 200 victims takes place near hospital 1 at $t = 0$. The victims are brought by ambulances and nearby volunteers to hospital 1 that has 100 available beds. The travel time from disaster site to hospital 1 is d . at $t = d$, hospital 1 has 100 untreated victims thus it contacts DHO 1 that is responsible for the area. At $t = d + 60s$, after receiving the report from hospital 1, DHO 1 contacts hospital 2 to coordinate for the victims transfer. When $t = d + 120s$, DHO 1 notifies hospital 1 to start sending 50 of its untreated victims to hospital 2 while DHO 1 contacts PHO to ask for help since there is no other hospital with available beds under its administrative area. PHO contacts hospital 3, the nearest hospital outside the area of DHO 1. Hospital 1 sends its remaining untreated victims to hospital 3 at $t = d + 240s$. Finally, all untreated victims are admitted and assigned to beds at $t = 1190s$.

Disaster event E is characterized by severity parameter V and the number of disaster sites D . Severity V determines the number of victims generated on each disaster site. For each E , we run S number of simulations. For example, if a disaster event E is set to have $V = 1000$ and $D = 4$, there will be 4 disaster sites chosen randomly from the set of 16 disaster locations in each simulation where each site generates 1000 victims. In order to measure the performance of each coordination mode, for a given disaster event E , we defined the system performance at time t in each simulation as

$$p_t^E = \frac{\sum_{i \in H} z_t^i}{\sum_{i \in H} z_t^i + u_t^i} \quad (8)$$

where u_t^i and z_t^i are the number of untreated victims and treated victims in the hospital i at time t , respectively. Untreated victims are the victims that reach the nearest hospital from the disaster site and have not been assigned to a bed.

It is impossible to evaluate the resilience for all possible disaster event E . Disaster that causes 1000 victims in one place has a different nature with a disaster that causes 100 victims in 10 various places even though it has 1000 victims in total. Therefore, the resilience in our model can only be evaluated for a certain E and is defined as

$$R^E = \frac{1}{ST} \sum_{k=1}^S \sum_{t=1}^T p_t^{E,k} \quad (9)$$

where T is simulation duration.

Table 7. Parameters, Sets, and Variables

V	Number of victims generated from each disaster site
D	Number of disaster sites generated in each simulation
E	Disaster event
S	Number of simulations
T	Simulation duration
T_{info}	Communication duration.
δ	Travel time tolerance
H	Set of hospitals
a_r	Set of responding hospitals to a disaster site r
v_i^r	Number of victims arriving at hospital i caused by disaster site r
u_t^i	Number of untreated victims at hospital i at time t
z_t^i	Number of treated victims at hospital i at time t
b_i	Number of available beds in hospital i , where $i \in H$
B_i	Total number of beds in hospital i , where $i \in H$
BOR_i	Bed occupancy rate of hospital i , where $i \in H$
d_r	Travel time radius from a disaster site r to the nearest hospital
p_t^E	System performance at time t given a disaster event E
R^E	Resilience of the system given a disaster event E

5.3 Results and discussion

The 75 hospitals and 16 disaster locations for our model and simulations are shown in Figure 33. The green markers and the red markers represent hospitals and disaster locations, respectively. Figure 34 shows hospitals as nodes (instead of marker icons) where the size of each node is based on its available beds. The contour plot represents the level of resources in the area.

Figure 34. Hospitals (green marker) and disaster locations (red marker) in Jakarta.

Figure 33. Hospitals represented by green nodes. The size and contour plot indicate the amount of resource

Figure 35 shows the simulation results of disaster event with low severity $V = 100$ and $D = 4$. Top (red), mid (green), and bottom (blue) plots show the total number of untreated victims u , total treated victims (z), and system performance (p). In this simulation, the performance is almost fully stable since the disaster severity is low. In case of severe disaster event with $V = 1000$ and $D = 4$ (Figure 36), the performance falls considerably since the available beds of hospitals around the disaster sites are not enough for all victims. After some time, the performance p then starts to increase when victims are arriving at the nearby hospitals. We set the following parameters for all simulations in this study: $S = 1000$, $\delta = 300s$, and $T = 7200s$. The tolerance time δ is set to 5 minutes since volunteers tend to take victims to the nearest hospitals and other hospitals around the same travel time.

Figure 35. Simulation results of disaster event with low severity $V = 100$ and $D = 4$. Top (red), mid (green), and bottom (blue) plots show the total number of untreated victims u , total treated victims (z), and system performance (p). In this simulation, the performance is almost fully stable since the disaster severity is low.

Figure 36. Simulation results of disaster event with high severity $V = 1000$ and $D = 4$. Top (red), mid (green), and bottom (blue) plots show the total number of untreated victims u , total treated victims (z), and system performance (p). The performance falls considerably since the available beds of hospitals around the disaster sites are not enough for all victims. After some time, the performance p then starts to increase when victims are arriving at the nearby hospitals.

The simulation results in Figure 37 shows the performance comparison between the *PHO* and *CH+PHO mode* during a disaster event with $V = 1000$ and $D = 4$. The performance improvement in *CH+PHO mode* results from a better communication strategy since it has fewer number of interactions between PHO and hospitals during a large-scale disaster event. However, in case of low severity disaster ($V = 250$ and $D = 4$) such as shown in Figure 38, the standard approach performs better because the gain from finding closer hospitals is higher than the gain from having fewer communication interactions.

Figure 37. The performance comparison between the PHO and CH+PHO mode during a disaster event with $V = 1000$ and $D = 4$. The performance improvement in CH+PHO mode results from a better communication strategy since it has fewer number of interactions between PHO and hospitals during a large-scale disaster event.

Figure 38. The performance comparison between the PHO and CH+PHO mode during a disaster event with $V = 250$ and $D = 4$. The PHO mode performs better because the gain from finding closer hospitals is higher than the gain from having fewer communication interactions.

The main problem of the coordination structure such as in *PHO mode* is the bottleneck effect. Increasing the communication channels will help to reduce the issue. The strategy of *DHO+PHO mode* performs significantly better than *PHO mode* during a severe disaster event such as shown in Figure 39 where $V = 1500$, $D = 4$, and $T_{info} = 90s$. However, the *DHO+PHO mode* does not perform better during a smaller scale of disaster event because of limited options in finding nearby hospitals or having a longer chain of communication. The results in Figure 40 shows the comparison between those modes for $V = 1500$ and $D = 1$.

Figure 39. By reducing the bottleneck of information flow, the strategy of *DHO+PHO mode* performs significantly better than *PHO mode* during a severe disaster event where $V = 1500$, $D = 4$, and $T_{info} = 90s$.

Figure 40. The DHO+PHO mode does not perform better during a smaller scale of disaster event with $V = 1500$ and $D = 1$ because of limited options in finding nearby hospitals or having a longer chain of communication.

Figure 41 shows a different perspective on the performance of each response strategy through the plot between resilience and communication duration. The *PHO mode* is highly affected by T_{info} parameter during large-scale disaster. The simulations are based on a disaster event E with $V = 1500$ and $D = 4$. The results suggest that *DHO mode* is more suitable to be applied during a large-scale disaster if the time for information sharing and coordination is slow. However, the cost to produce the regulation and the training to prepare the human resource for disaster response may be high. Alternatively, another approach such as *CH+PHO mode* that only needs minimal effort to be applied still shows a slight improvement of resilience. This strategy only needs to appoint big capacity hospitals as the central hospitals to accommodate the first wave of victims. On the other hand, if the communication duration only takes a very short time ($T_{info} < 30s$), the application of different coordination

structures is no longer beneficial. This may be the case when all hospitals are connected through a real-time information update and resource sharing system.

Figure 41. The plot of resilience as the function of communication duration. The PHO mode is highly affected by T_{info} parameter during large-scale disaster. The simulations are based on a disaster event E with $V = 1500$ and $D = 4$. The results suggest that DHO mode is more suitable to be applied during a large-scale disaster if the time for information sharing and coordination is slow. On the other hand, if the communication duration only takes a very short time ($T_{info} < 30s$), the application of different coordination structures is not beneficial anymore.

Reflecting back to the theoretical concept of our framework, the model is built based on the concept of sociotechnical resilience. This theoretical framework places an emphasis on the notion of transformability which consists of three fundamental components, namely sociomaterial structures, informational relations, and anticipatory practices. From a practical perspective, the hospitals along with its location and resources level, disaster management agencies, as well as other government bodies related to healthcare systems are parts of the sociomaterial structures. These components are the actors and environment which exists in the current time. It is a given state to the system. The next component, informational

relations, represents the designed information flow during a crisis, determining how information is shared between entities in the systems. The hierarchical reporting systems and the coordinator role of PHO and DHO are the examples of informational relations. It governs how information regarding victims is shared between disaster management agencies and pre-hospitals entities (such as ambulances, first responders, police, and fire departments), and how information about resources level is shared between hospitals, health office, local government, and ministry of health. Anticipatory practices as the last component are embodied in the preparedness and response protocol of the healthcare systems. For instances, establishing hospital disaster plan and integrated disaster training as preparedness actions, or in a form of response protocol such as hospitals calling their off-duty medical staff to help during mass casualty disaster, ambulances taking critical victims to hospital, local government requesting aid from regional or national level disaster management agencies, or health office and Incident Command Systems (ICS) allocating resources and coordinating pre-hospital and hospital entities.

This study explores various strategies of the healthcare system in responding to large-scale disasters in Jakarta. The practical application of the model we developed is to give recommendation for the local government in formulating disaster response policy based on the nature of disaster. For example, a smaller scale of disaster that causes low number of victims in only a few areas is very effective to be responded to through centralized methods such as *PHO mode* since this approach is very efficient in utilizing information and resources. However, during a larger scale of disaster, the command center may be overwhelmed since many overcrowded hospitals need coordination for victims transfer at the same time. Simple procedures such as *CH+PHO mode* can be applied to reduce the frequency of communication for coordination in finding hospitals with available beds. In

order to further improve the system resilience towards the large-scale disaster, *DHO+PHO mode* can be implemented to reduce the bottleneck effect significantly. Alternatively, the government may invest in the information system technology in healthcare to improve the coordination time through real-time medical resources update.

5.4 Conclusions

Healthcare is a sociotechnical system that requires sociotechnical approach to enhance its resilience. Our study focuses on modeling the disaster response given the components of sociotechnical resilience such as the institutional network, physical system and its resources, as well as the recovery strategies. Using the empirical data, we simulated large-scale disaster in Jakarta and its healthcare capability in saving lives. The system performance is measured based on how many victims can be saved as early as possible. The flexibility of our model allows the user to examine various disaster scenarios and recovery protocols, thus helping stakeholders in formulating efficient response strategies given their available resources during large-scale disaster in urban cities.

Chapter 6

Conclusions

This research addresses the challenge in modeling sociotechnical resilience while taking into account the hybrid nature of the sociotechnical systems. In this regard, a conceptual model that consists of a networked system embedded with a decision-maker agent was developed. The model adopts the structure of multi-level directed acyclic graph and employs the operational resilience paradigm through the concept of functionality function to capture the temporal dimension of system performance. In this model, we investigated two recovery scenarios to represent unprepared and prepared responses during a crisis. Furthermore, three different informational flow configurations were employed to evaluate the resilience capacity of the system for various levels of disruption severity. This model highlights the importance of system flexibility to allow structural reconfiguration at the organizational level during a large-scale disruption which can be achieved through planning and policy design.

Subsequently, the concept of sociotechnical resilience was implemented into a real system. The healthcare system in the city of Jakarta was used as the case study to demonstrate the application of model and simulation to enhance the medical emergency capacity of the system through sociotechnical resilience approach. The concept of various coordination structures and strategies was proposed in this study to improve the response of healthcare organizations to a disaster event in a city through a faster decision making and victims transfer. In practice, the model can help stakeholders in designing policy and strategies to enhance the system capacity to withstand a disaster.

This dissertation focuses on the development of the concept of resilience in sociotechnical systems by showing how the interplay between technical and organizational structures,

informational relations, as well as recovery strategies are shaping the capability of sociotechnical systems to respond to crisis. The chapters are constructed to present the theoretical framework, conceptual model, and the practical application of the concept. The results confirm the importance of disaster response planning and institutional flexibility to prepare the system to be able to make and execute optimum decisions such as allocating resources or repairing components and to allow structural reconfiguration when it is necessary.

Therefore, this research shows that besides the factor of redundancy, resource management is also an important factor in system resilience. It demands all levels of stakeholders and decision makers to formulate effective disaster response based on disaster severity, system capacity, and organizational structure. Furthermore, the preparedness must also include the regulation for institutional reconfiguration during a crisis. This is because critical infrastructure itself is a social construct. It is essentially designed to support the society and its economic activities. Being able to withstand disruptions and recover from a shock are different objectives for the system which may require different organizational structure to allow optimum disaster response.

There are several limitations of this research that should be highlighted. The developed conceptual model is only applicable under two conditions. First, the system has to be hybrid, meaning that the operation does not only take place in a purely technical realm where it is predictable using the chemical, electrical, or mechanical laws, but it also has to involve organizational interactions where information and coordination are shared and negotiated. Therefore, the system will have unpredictability factors since it deals with social and organizational behavior. In our simulation, this is reflected especially in the random recovery

scenario. At the same time, as simulated in the informed recovery scenario, the degree of unpredictability can be minimized through information and coordination between human operators and managers, not only from sensors or automatic machines. The second condition is that the system must have dynamic properties such as the demands of the population it has to serve in its operational area. It represents the impact or value which is changing from time to time. Further study can incorporate the interactions between local coordinators from multiple networks to capture the complexity of the large-scale interdependent sociotechnical systems.

The limitations for the model of hospital and its resources are due to the availability of hospital data and disaster risk assessment. Since the government data only relies on self-reporting from the hospitals, there are a lot of missing information such as the number of specialists, nurses, beds, BOR, and even GPs. Therefore, the current model only focuses on the inpatient treatment based on the available beds. By having a complete data set, further study can take into account the bed types and specialist doctors that depends on the nature of disaster. For example, earthquakes usually lead to trauma injuries that require surgeon, orthopedic, and anesthesia specialists in an operation room to treat a patient, thus able to make the model more realistic. In order to make the model more applicable, a detailed data of disaster risk can be used in future works to generate a potential number of victims in the area. For example, using the data of seismic vulnerability of high-rise buildings and its expected inhabitant number to estimate the number of victims in a certain area as the results of an earthquake. By doing so, the framework would be able to help the policymakers and stakeholders to prepare for a large-scale disaster in a more holistic approach which incorporates the improvement in technical resources and institutional relations.

References

- Abidin, H. Z., Andreas, H., Gumilar, I., Fukuda, Y., Pohan, Y. E., & Deguchi, T. (2011). Land subsidence of Jakarta (Indonesia) and its relation with urban development. *Natural Hazards*, 59(3), 1753.
- Adjetei-Bahun, K., Birregah, B., Châtelet, E., & Planchet, J.-L. (2016). A model to quantify the resilience of mass railway transportation systems. *Reliability Engineering & System Safety*, 153, 1–14.
- Agogino, A., & Tumer, K. (2007). Evolving distributed agents for managing air traffic. *Proceedings of the 9th Annual Conference on Genetic and Evolutionary Computation*, 1888–1895.
- Aldrian, E. (2008). Dominant factors of Jakarta's three largest floods. *Jurnal Hidrosfir Indonesia*, 3(3).
- Almoghatawi, Y., Barker, K., & Albert, L. A. (2019). Resilience-driven restoration model for interdependent infrastructure networks. *Reliability Engineering & System Safety*, 185, 12–23.
- Amir, S., & Juraku, K. (2014). Undermining disaster: Engineering and epistemological bias in the Fukushima nuclear crisis. *Engineering Studies*, 6(3), 210–226.
- Amir, S., & Kant, V. (2018). Sociotechnical resilience: A preliminary concept. *Risk Analysis*, 38(1), 8–16.
- Andersson, G., Donalek, P., Farmer, R., Hatziaargyriou, N., Kamwa, I., Kundur, P., Martins, N., Paserba, J., Pourbeik, P., & Sanchez-Gasca, J. (2005). Causes of the 2003 major grid blackouts in North America and Europe, and recommended means to improve system dynamic performance. *IEEE Transactions on Power Systems*, 20(4), 1922–1928.
- Appleby, L. (2013). Connecting the last mile: The role of communications in the Great East Japan Earthquake. *London: Internews Europe*.
- Ardelia, M. N., Harsasto, P., & Retno, N. (2015). Analisis Akses Masyarakat DKI Jakarta Terhadap Air Bersih Pasca Privatisasi Air Tahun 2009-2014. *Journal of Politic and Government Studies*, 5(4), 51–60.
- Arnold, J. L. (1999). International emergency medicine and the recent development of emergency medicine worldwide. *Annals of Emergency Medicine*, 33(1), 97–103.
- Asian, D. R. C. (2002). *Living with risk. A global review of disaster reduction initiatives. Preliminary version*. United Nations.
- Auf der Heide, E. (2002). Principles of hospital disaster planning. *Disaster Medicine. Philadelphia: Lippincott Williams and Wilkins*, 57–89.
- Aven, T. (2016). Risk assessment and risk management: Review of recent advances on their foundation. *European Journal of Operational Research*, 253(1), 1–13.
- Aven, T., & Renn, O. (2009). The role of quantitative risk assessments for characterizing risk and uncertainty and delineating appropriate risk management options, with special emphasis on terrorism risk. *Risk Analysis: An International Journal*, 29(4), 587–600.
- Barbarosoğlu, G., Özdamar, L., & Cevik, A. (2002). An interactive approach for hierarchical analysis of helicopter logistics in disaster relief operations. *European Journal of Operational Research*, 140(1), 118–133.

- Barbera, J. A., Macintyre, A. G., Knebel, A., & Trabert, E. (2007). *Medical surge capacity and capability: A management system for integrating medical and health resources during large-scale emergencies*. US Department of Health and Human Services.
- Barbisch, D., Haik, I., Tessone, A., & Hanfling, D. (2010). Surge capacity. *Koenig and Schultz's Disaster Medicine: Comprehensive Principles and Practices*, 133.
- Bartholdson, S., & von Schreeb, J. (2018). Natural disasters and injuries: What does a surgeon need to know? *Current Trauma Reports*, 4(2), 103–108.
- Baxter, G., & Sommerville, I. (2011). Socio-technical systems: From design methods to systems engineering. *Interacting with Computers*, 23(1), 4–17.
- Below, R., & Wallemacq, P. (2018). Annual disaster statistical review 2017. *CRED, Centre for Research on the Epidemiology of Disasters: Brussels, Belgium*.
- Benner, L. (1975). Accident investigations: Multilinear events sequencing methods. *Journal of Safety Research*, 7(2), 67–73.
- Bierly III, P. E., & Spender, J.-C. (1995). Culture and high reliability organizations: The case of the nuclear submarine. *Journal of Management*, 21(4), 639–656.
- Bijker, W. E., Hughes, T. P., & Pinch, T. J. (1987). *The social construction of technological systems: New directions in the sociology and history of technology*. MIT press.
- Bijker, W. E., & Law, J. (1994). *Shaping technology/building society: Studies in sociotechnical change*. MIT press.
- Bjerge, B., Clark, N., Fisker, P., & Raju, E. (2016). Technology and information sharing in disaster relief. *PloS One*, 11(9), e0161783.
- Blom, H. A., Stroeve, S. H., & de Jong, H. H. (2006). Safety risk assessment by Monte Carlo simulation of complex safety critical operations. In *Developments in risk-based approaches to safety* (pp. 47–67). Springer.
- BNPB. (2012). *Law Number 2 Year 2012 on General Guidelines For Disaster Risk Analysis*.
- Bocchini, P., Frangopol, D. M., Ummenhofer, T., & Zinke, T. (2014). Resilience and sustainability of civil infrastructure: Toward a unified approach. *Journal of Infrastructure Systems*, 20(2), 04014004.
- Bourrier, M. (1996). Organizing maintenance work at two American nuclear power plants. *Journal of Contingencies and Crisis Management*, 4(2), 104–112.
- Bowonder, B., & Linstone, H. A. (1987). Notes on the Bhopal accident: Risk analysis and multiple perspectives. *Technological Forecasting and Social Change*, 32(2), 183–202.
- BPBD. (2013). *Rencana Penanggulangan Bencana Provinsi DKI Jakarta Tahun 2013-2017*. https://bpbd.jakarta.go.id/assets/attachment/study/RPB_DKI_Jakarta_Final.pdf
- BPBD. (2014). *Peta Tingkat Kerawanan Kebakaran di DKI Jakarta Bulan Januari-September 2014*. https://bpbd.jakarta.go.id/assets/attachment/fire_maps/Peta_Tingkat_Kerawanan_Kebakaran_sd_September_2014.pdf
- BPBD. (2018). *Peta Kawasan Rawan Banjir DKI Jakarta*. https://bpbd.jakarta.go.id/assets/attachment/document/PETA_KAWASAN_RAWAN.pdf
- BPS Provinsi DKI Jakarta. (2019). <https://jakarta.bps.go.id/>

- Brooks, N. (2003). Vulnerability, risk and adaptation: A conceptual framework. *Tyndall Centre for Climate Change Research Working Paper*, 38(38), 1–16.
- Brunkard, J., Namulanda, G., & Ratard, R. (2008). Hurricane katrina deaths, louisiana, 2005. *Disaster Medicine and Public Health Preparedness*, 2(4), 215–223.
- Bull Torres, M. (2012). *An Index To Measure Efficiency Of Hospital Networks For Mass Casualty Disasters*.
- Cai, C., Jahangiri, P., Thomas, A. G., Zhao, H., Aliprantis, D. C., & Tesfatsion, L. (2011). Agent-based simulation of distribution systems with high penetration of photovoltaic generation. *2011 IEEE Power and Energy Society General Meeting*, 1–7.
- Carayon, P. (2006). Human factors of complex sociotechnical systems. *Applied Ergonomics*, 37(4), 525–535.
- Caunhye, A. M., Nie, X., & Pokharel, S. (2012). Optimization models in emergency logistics: A literature review. *Socio-Economic Planning Sciences*, 46(1), 4–13.
- Cavallaro, M., Asprone, D., Latora, V., Manfredi, G., & Nicosia, V. (2014). Assessment of urban ecosystem resilience through hybrid social–physical complex networks. *Computer-Aided Civil and Infrastructure Engineering*, 29(8), 608–625.
- Cerè, G., Rezgui, Y., & Zhao, W. (2017). Critical review of existing built environment resilience frameworks: Directions for future research. *International Journal of Disaster Risk Reduction*, 25, 173–189.
- Cimellaro, G. P. (2016). Urban resilience for emergency response and recovery. *Switzerland: Springer [DOI: 10.1007/978-3-319-30656-8]*.
- Cimellaro, G. P., Reinhorn, A. M., & Bruneau, M. (2010). Framework for analytical quantification of disaster resilience. *Engineering Structures*, 32(11), 3639–3649.
- Ciottone, G. R. (2016). Introduction to disaster medicine. *Ciottone's Disaster Medicine*, 2.
- Comfort, L. K., Sungu, Y., Johnson, D., & Dunn, M. (2001). Complex systems in crisis: Anticipation and resilience in dynamic environments. *Journal of Contingencies and Crisis Management*, 9(3), 144–158.
- Congress, U. S. (2001). The 9/11 Commission Report. *National Commission on Terrorist Attacks Upon the United States*. [Http://Www. House. Gov/Shays/News/2004/July/911Report2. Pdf](http://www.house.gov/shays/news/2004/july/911report2.pdf).
- Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. *Social Science Quarterly*, 84(2), 242–261.
- Cybriwsky, R., & Ford, L. R. (2001). City profile: Jakarta. *Cities*, 18(3), 199–210.
- Dahlberg, R., Johannessen-Henry, C. T., Raju, E., & Tulsiani, S. (2015). Resilience in disaster research: Three versions. *Civil Engineering and Environmental Systems*, 32(1–2), 44–54.
- Dara, S. I., Ashton, R. W., Farmer, J. C., & Carlton, P. K. (2005). Worldwide disaster medical response: An historical perspective. *Critical Care Medicine*, 33(1), S2–S6.
- Data Informasi Bencana Indonesia. (2019). <https://bnpb.cloud/dibi/>
- Davidson, D. J. (2010). The applicability of the concept of resilience to social systems: Some sources of optimism and nagging doubts. *Society and Natural Resources*, 23(12), 1135–1149.
- de Haan, F. (1922). *Oud Batavia: Gedenkboek uitgegeven ter gelegenheid van het driehonderdjarig bestaan der stad in 1919* (Vol. 1). G. Kolff.

- Depkes. (2007). *Pedoman Teknis Penanggulangan Krisis Kesehatan Akibat Bencana*.
- der Heide, E. A. (2006). The importance of evidence-based disaster planning. *Annals of Emergency Medicine*, 47(1), 34–49.
- Dick, W. F. (2003). Anglo-American vs. Franco-German emergency medical services system. *Prehospital and Disaster Medicine*, 18(1), 29–37.
- Djaja, R., Rais, J., Abidin, H. Z., & Wedyanto, K. (2004). Land subsidence of Jakarta metropolitan area. *3rd FIG Regional Conference, Jakarta, Indonesia*, 3–7.
- Emery, F. E., & Trist, E. L. (1960). *Socio-technical systems. Management sciences, models and Techniques*. Churchman CW et al. Pergamon. London.
- Fiedrich, F., Gehbauer, F., & Rickers, U. (2000). Optimized resource allocation for emergency response after earthquake disasters. *Safety Science*, 35(1–3), 41–57.
- Firman, T. (1999). Indonesian cities under the “Krismon”: A great “urban crisis” in Southeast Asia. *Cities*, 16(2), 69–82.
- Flach, J. M., Carroll, J. S., Dainoff, M. J., & Hamilton, W. I. (2015). Striving for safety: Communicating and deciding in sociotechnical systems. *Ergonomics*, 58(4), 615–634.
- Foundations, C. (1997). *Protecting America's Infrastructures: The Report of the President's Commission on Critical Infrastructure Protection*. Washington, DC: The President's Commission on Critical Infrastructure Protection.
- Fraustino, J. D., Liu, B., & Jin, Y. (2012). *Social media use during disasters: A review of the knowledge base and gaps*.
- Frisch, D., & Baron, J. (1988). Ambiguity and rationality. *Journal of Behavioral Decision Making*, 1(3), 149–157.
- Galus, M. D. (2012). *Agent-based modeling and simulation of large scale electric mobility in power systems* [PhD Thesis]. ETH Zurich.
- Ganin, A. A., Massaro, E., Gutfraind, A., Steen, N., Keisler, J. M., Kott, A., Mangoubi, R., & Linkov, I. (2016). Operational resilience: Concepts, design and analysis. *Scientific Reports*, 6(1), 19540. <https://doi.org/10.1038/srep19540>
- Gittell, J. H., Cameron, K., Lim, S., & Rivas, V. (2006). Relationships, layoffs, and organizational resilience: Airline industry responses to September 11. *The Journal of Applied Behavioral Science*, 42(3), 300–329.
- Glarum, J., Birou, D., & Cetaruk, E. (2009). *Hospital Emergency Response Teams: Triage for Optimal Disaster Response*. Butterworth-Heinemann.
- GoI. (2007a). *Law Number 24 Year 2007 on Disaster Management*.
- GoI. (2007b). *Law Number 145 Year 2007 on Disaster Management Guidelines For Health*. <https://www.persi.or.id/images/regulasi/kepmenkes/kmk1452007.pdf>
- GoI. (2008). *Law Number 21 Year 2008 on Disaster Management*. https://www.bnpb.go.id/ppid/file/PP_No._21_Th_2008.pdf
- GoI. (2009). *Law No. 36 Year 2009 On Health*.
- GoI. (2014). *Law Number 39 Year 2014 on Division of Task For Public Officer In Disaster Management*. https://bpbd.jakarta.go.id/assets/attachment/rules/PERGUB_NO_39_TAHUN_2014.pdf
- Gordon, J. E. (1949). The epidemiology of accidents. *American Journal of Public Health and the Nations Health*, 39(4), 504–515.

- GTD. (2017). *GTD / Global Terrorism Database*. <https://www.start.umd.edu/gtd/>
- Guha-Sapir, D., Hoyois, P., Wallemacq, P., & Below, R. (2016). *Annual disaster statistical review 2016: The numbers and trends*. Brussels, Belgium: Centre for Research on the Epidemiology of Disasters.
- Guidotti, R., Chmielewski, H., Unnikrishnan, V., Gardoni, P., McAllister, T., & van de Lindt, J. (2016). Modeling the resilience of critical infrastructure: The role of network dependencies. *Sustainable and Resilient Infrastructure*, 1(3–4), 153–168.
- Haddadi, M., Sarvar, M., Soori, H., & Ainy, E. (2017). The Pattern of Pre-hospital Medical Service Delivery in Iran; a Cross Sectional Study. *Emergency*, 5(1).
- Harrison, C. G., & Williams, P. R. (2016). A systems approach to natural disaster resilience. *Simulation Modelling Practice and Theory*, 65, 11–31.
- Harsono, A. (2003). Water and politics in the fall of Suharto. *Center for Public Integrity* ([Http://Www. Icij. Org](http://www.icij.org)).
- Heinimann, H. R. (2016). A generic framework for resilience assessment. *An Edited Collection of Authored Pieces Comparing, Contrasting, and Integrating Risk and Resilience with an Emphasis on Ways to Measure Resilience*, 90.
- Heinrich, H. W. (1941). Industrial Accident Prevention. A Scientific Approach. *Industrial Accident Prevention. A Scientific Approach., Second Edition*.
- Hettinger, L. J., Kirlik, A., Goh, Y. M., & Buckle, P. (2015). Modelling and simulation of complex sociotechnical systems: Envisioning and analysing work environments. *Ergonomics*, 58(4), 600–614.
- Hick, J. L., Hanfling, D., Burstein, J. L., DeAtley, C., Barbisch, D., Bogdan, G. M., & Cantrill, S. (2004). Health care facility and community strategies for patient care surge capacity. *Annals of Emergency Medicine*, 44(3), 253–261.
<https://doi.org/10.1016/j.annemergmed.2004.04.011>
- Hoard, M., Homer, J., Manley, W., Furbee, P., Haque, A., & Helmkamp, J. (2005). Systems modeling in support of evidence-based disaster planning for rural areas. *International Journal of Hygiene and Environmental Health*, 208(1–2), 117–125.
- Hogan, D. E., & Burstein, J. L. (2007). *Disaster medicine*. Lippincott Williams & Wilkins.
- Holguín-Veras, J., Taniguchi, E., Jaller, M., Aros-Vera, F., Ferreira, F., & Thompson, R. G. (2014). The Tohoku disasters: Chief lessons concerning the post disaster humanitarian logistics response and policy implications. *Transportation Research Part A: Policy and Practice*, 69, 86–104.
- Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, 4(1), 1–23.
- Hollnagel, E. (2014). Resilience engineering and the built environment. *Building Research & Information*, 42(2), 221–228.
- Hollnagel, E., & Goteman, O. (2004). The functional resonance accident model. *Proceedings of Cognitive System Engineering in Process Plant, 2004*, 155–161.
- Hopkins, A. (2000). *Lessons from Longford: The Esso gas plant explosion*. CCH Australia limited.
- Irsyam, M., Hutabarat, D., Asrurifak, M., Imran, I., Widiyantoro, S., Hendriyawan, D., Sadisun, I., Hutapea, B., Firmanti, A., & Ridwan, M. (2015). Development of seismic

- risk microzonation maps of Jakarta city. In *Geotechnics for Catastrophic Flooding Events*. CRC Press.
- Iserson, K. V., & Moskop, J. C. (2007). Triage in medicine, part I: Concept, history, and types. *Annals of Emergency Medicine*, 49(3), 275–281.
- Jannah, N., & Rahman, S. (2016). *Laporan Kegiatan Tinjauan Ulang (Review) Dokumen Peraturan Gubernur No. 143 Tahun 2015 tentang Rencana Penanggulangan Bencana Provinsi DKI Jakarta 2014-2019*. <https://www.slideshare.net/ninil/laporan-review-rpb-dki-2016>
- Jánošíková, L. (2009). *Reduction of a hospital network as a multiple criteria optimisation problem*.
- Janssen, M. A., & Ostrom, E. (2006). *Resilience, vulnerability, and adaptation: A cross-cutting theme of the International Human Dimensions Programme on Global Environmental Change*. Citeseer.
- Kee, D., Jun, G. T., Waterson, P., & Haslam, R. (2017). A systemic analysis of South Korea Sewol ferry accident—Striking a balance between learning and accountability. *Applied Ergonomics*, 59, 504–516.
- Khayal, D., Pradhananga, R., Pokharel, S., & Mutlu, F. (2015). A model for planning locations of temporary distribution facilities for emergency response. *Socio-Economic Planning Sciences*, 52, 22–30.
- Kinston, W., & Rosser, R. (1974). Disaster: Effects on mental and physical state. *Journal of Psychosomatic Research*, 18(6), 437–456.
- Klein, R. J., Smit, M. J., Goosen, H., & Hulsbergen, C. H. (1998). Resilience and vulnerability: Coastal dynamics or Dutch dikes? *Geographical Journal*, 259–268.
- Knight, F. H. (1921). *Risk, uncertainty and profit* (Vol. 31). Houghton Mifflin.
- Koetse, M. J., & Rietveld, P. (2009). The impact of climate change and weather on transport: An overview of empirical findings. *Transportation Research Part D: Transport and Environment*, 14(3), 205–221.
- Kongsomsaksakul, S., Yang, C., & Chen, A. (2005). Shelter location-allocation model for flood evacuation planning. *Journal of the Eastern Asia Society for Transportation Studies*, 6, 4237–4252.
- Kooy, M., Walter, C. T., & Prabaharyaka, I. (2018). Inclusive development of urban water services in Jakarta: The role of groundwater. *Habitat International*, 73, 109–118.
- Kroes, P., Franssen, M., Poel, I. van de, & Ottens, M. (2006). Treating socio-technical systems as engineering systems: Some conceptual problems. *Systems Research and Behavioral Science: The Official Journal of the International Federation for Systems Research*, 23(6), 803–814.
- La Porte, T. R. (1988). *The United States air traffic control system: Increasing reliability in the midst of rapid growth*.
- Leonardi, P. M. (2012). Materiality, sociomateriality, and socio-technical systems: What do these terms mean? How are they different? Do we need them. *Materiality and Organizing: Social Interaction in a Technological World*, 25.
- Leveson, N. (2004). A new accident model for engineering safer systems. *Safety Science*, 42(4), 237–270.

- Leveson, N. G. (2011). Applying systems thinking to analyze and learn from events. *Safety Science*, 49(1), 55–64. <https://doi.org/10.1016/j.ssci.2009.12.021>
- Leveson, N. G., & Weiss, K. A. (2009). Software system safety. In *Safety Design for Space Systems* (pp. 475–505). Elsevier.
- Li, Z., Shahidehpour, M., Aminifar, F., Alabdulwahab, A., & Al-Turki, Y. (2017). Networked Microgrids for Enhancing the Power System Resilience. *Proceedings of the IEEE*, 105(7), 1289–1310. <https://doi.org/10.1109/JPROC.2017.2685558>
- Lindblom, C. E. (1968). *The policy-making process*. Prentice-Hall.
- Linkov, I., Bridges, T., Creutzig, F., Decker, J., Fox-Lent, C., Kröger, W., Lambert, J. H., Levermann, A., Montreuil, B., & Nathwani, J. (2014). Changing the resilience paradigm. *Nature Climate Change*, 4(6), 407–409.
- Lundberg, J., & Johansson, B. J. (2015). Systemic resilience model. *Reliability Engineering & System Safety*, 141, 22–32.
- Luthar, S. S., & Sexton, C. C. (2007). Maternal drug abuse versus maternal depression: Vulnerability and resilience among school-age and adolescent offspring. *Development and Psychopathology*, 19(1), 205.
- Macal, C. M., & North, M. J. (2005). Tutorial on agent-based modeling and simulation. *Proceedings of the Winter Simulation Conference, 2005.*, 14–pp.
- Mallonee, S., Shariat, S., Stennies, G., Waxweiler, R., Hogan, D., & Jordan, F. (1996). Physical injuries and fatalities resulting from the Oklahoma City bombing. *Jama*, 276(5), 382–387.
- Malone, T. W., & Crowston, K. (1990). What is coordination theory and how can it help design cooperative work systems? *Proceedings of the 1990 ACM Conference on Computer-Supported Cooperative Work*, 357–370.
- Maningas, P. A., Robison, M., & Mallonee, S. (1997). The EMS response to the Oklahoma City bombing. *Prehospital and Disaster Medicine*, 12(2), 9–14.
- Margesson, R., & Taft-Morales, M. (2010). *Haiti earthquake: Crisis and response*.
- Memarzadeh, M., & Pozzi, M. (2016). Integrated inspection scheduling and maintenance planning for infrastructure systems. *Computer-Aided Civil and Infrastructure Engineering*, 31(6), 403–415.
- Mensah, P., & Merkuryev, Y. (2014). Developing a resilient supply chain. *Procedia-Social and Behavioral Sciences*, 110, 309–319.
- Miller, J. H., & Page, S. E. (2009). *Complex adaptive systems: An introduction to computational models of social life*. Princeton university press.
- Moore, L. (1999). Measuring quality and effectiveness of prehospital EMS. *Prehospital Emergency Care*, 3(4), 325–331.
- Mumford, E. (2006). The story of socio-technical design: Reflections on its successes, failures and potential. *Information Systems Journal*, 16(4), 317–342.
- Mustapha, K., & Frayret, J.-M. (2016). Agent-based modeling and simulation software architecture for health care. *2016 6th International Conference on Simulation and Modeling Methodologies, Technologies and Applications (SIMULTECH)*, 1–12.
- Noji, E. K. (1997). *The public health consequences of disasters*. Oxford University Press, USA.

- Norio, O., Ye, T., Kajitani, Y., Shi, P., & Tatano, H. (2011). The 2011 eastern Japan great earthquake disaster: Overview and comments. *International Journal of Disaster Risk Science*, 2(1), 34–42.
- Norwood, A. E., Ursano, R. J., & Fullerton, C. S. (2000). Disaster psychiatry: Principles and practice. *Psychiatric Quarterly*, 71(3), 207–226.
- Nur, Y., Fazi, S., Wirjoatmodjo, N., & Han, Q. (2001). Towards wise coastal management practice in a tropical megacity—Jakarta. *Ocean & Coastal Management*, 44(5–6), 335–353.
- Ohno, T. (1988). *Toyota production system: Beyond large-scale production*. crc Press.
- Okumura, T., Takasu, N., Ishimatsu, S., Miyanoki, S., Mitsuhashi, A., Kumada, K., Tanaka, K., & Hinohara, S. (1996). Report on 640 victims of the Tokyo subway sarin attack. *Annals of Emergency Medicine*, 28(2), 129–135.
- Orlikowski, W. J. (2007). Sociomaterial Practices: Exploring Technology at Work. *Organization Studies*, 28(9), 1435–1448. <https://doi.org/10.1177/0170840607081138>
- Oughton, E. J., Usher, W., Tyler, P., & Hall, J. W. (2018). Infrastructure as a complex adaptive system. *Complexity*, 2018.
- Page, J., Vazquez, K. M., Sbat, M., & Yalcin, Z. D. (2013). *Analysis of emergency medical systems across the world*.
- Panteli, M., Trakas, D. N., Mancarella, P., & Hatziaargyriou, N. D. (2017). Power systems resilience assessment: Hardening and smart operational enhancement strategies. *Proceedings of the IEEE*, 105(7), 1202–1213.
- Park, J., Seager, T. P., Rao, P. S. C., Convertino, M., & Linkov, I. (2013). Integrating risk and resilience approaches to catastrophe management in engineering systems. *Risk Analysis*, 33(3), 356–367.
- Parker, D., & PARKER, D. (1992). The mismanagement of hazards. *Parker, DJ; Handmer, JW (Eds), Hazard Management and Emergency Planning: Perspectives on Britain*, 3–21.
- Paul, J. A., & Hariharan, G. (2012). Location-allocation planning of stockpiles for effective disaster mitigation. *Annals of Operations Research*, 196(1), 469–490.
- Perrow, C. (2011). *Normal accidents: Living with high risk technologies-Updated edition*. Princeton university press.
- Perry, R. W. (2003). Incident management systems in disaster management. *Disaster Prevention and Management: An International Journal*.
- Pidgeon, N. (1997). The limits to safety? Culture, politics, learning and man-made disasters. *Journal of Contingencies and Crisis Management*, 5(1), 1–14.
- Poli, R. (2010). The Many Aspects of Anticipation. *Foresight 2010*, 7–17.
- Pratiwo, M. R., & Nas, P. (2005). Jakarta: Conflicting directions. *Directors of Urban Change in Asia*. Routledge, London, 270.
- Preece, G., Shaw, D., & Hayashi, H. (2013). Using the Viable System Model (VSM) to structure information processing complexity in disaster response. *European Journal of Operational Research*, 224(1), 209–218. <https://doi.org/10.1016/j.ejor.2012.06.032>
- Ragnar Norrby, S. (2005). Infectious disease emergencies: Role of the infectious disease specialist. *Clinical Microbiology and Infection*, 11, 9–11.

- Rahmatulloh, R. (2018). DINAMIKA KEPENDUDUKAN DI IBUKOTA JAKARTA (Deskripsi Perkembangan Kuantitas, Kualitas dan Kesejahteraan Penduduk di DKI Jakarta). *Genta Mulia: Jurnal Ilmiah Pendidikan*, 8(2).
- Ramirez, M., & Peek-Asa, C. (2005). Epidemiology of traumatic injuries from earthquakes. *Epidemiologic Reviews*, 27(1), 47–55.
- Rasmussen, J. (1997). Risk management in a dynamic society: A modelling problem. *Safety Science*, 27(2), 183–213.
- Rasmussen, J., & Suedung, I. (2000). *Proactive risk management in a dynamic society*. Swedish Rescue Services Agency.
- Reason, J. (1990). The contribution of latent human failures to the breakdown of complex systems. *Philosophical Transactions of the Royal Society of London. B, Biological Sciences*, 327(1241), 475–484.
- Reason, J. (1997). *Managing the risks of organizational accidents*.
- Reed, D. A., Kapur, K. C., & Christie, R. D. (2009). Methodology for assessing the resilience of networked infrastructure. *IEEE Systems Journal*, 3(2), 174–180.
- Renn, O., & Graham, P. (2006). Risk governance: Towards an integrative approach, White Paper No. 1. *International Risk Governance Council, Geneva*.
- Rinaldi, S. M., Peerenboom, J. P., & Kelly, T. K. (2001). Identifying, understanding, and analyzing critical infrastructure interdependencies. *IEEE Control Systems Magazine*, 21(6), 11–25.
- Roberts, K. H., & Grabowski, M. (1999). Organizations, technology and structuring. *Managing Organizations: Current Issues*, 159.
- Robinson, C. P., Woodard, J. B., & Varnado, S. G. (1998). Critical infrastructure: Interlinked and vulnerable. *Issues in Science and Technology*, 15(1), 61–67.
- Rochlin, G. I., La Porte, T. R., & Roberts, K. H. (1998). From Our Autumn 1987 Issue...: The Self-Designing High-Reliability Organization: Aircraft Carrier Flight Operations at Sea. *Naval War College Review*, 51(3), 97–113.
- Rudman, W. B., Clarke, R. A., & Metzl, J. F. (2004). *Emergency responders: Drastically underfunded, dangerously unprepared*. Council on Foreign Relations Press.
- Salem, H., Attiya, G., & El-Fishawy, N. (2015). A survey of multi-agent based intelligent decision support system for medical classification problems. *International Journal of Computer Applications*, 123(10).
- Salim, W., & Firman, T. (2011). Governing the Jakarta city-region: History, challenges, risks, and strategies. *Planning Asian Cities: Risks and Resilience*, 241–259.
- Sarewitz, D., Pielke Jr, R., & Keykhah, M. (2003). Vulnerability and risk: Some thoughts from a political and policy perspective. *Risk Analysis: An International Journal*, 23(4), 805–810.
- Schoon, I. (2006). *Risk and resilience: Adaptations in changing times*. Cambridge University Press.
- Sedyawati, E., Rahardjo, S., Johan, I. M., & Manilet-Ohorella, G. A. (1986). *Sejarah Kota Jakarta 1950-1980*. Direktorat Jenderal Kebudayaan.
- Sharma, B., Ramkumar, M., Subramanian, N., & Malhotra, B. (2019). Dynamic temporary blood facility location-allocation during and post-disaster periods. *Annals of Operations Research*, 283(1), 705–736.

- Sharpanskykh, A., & Stroeve, S. H. (2011). An agent-based approach for structured modeling, analysis and improvement of safety culture. *Computational and Mathematical Organization Theory*, 17(1), 77–117.
- Sheffi, Y. (2005). The resilient enterprise: Overcoming vulnerability for competitive advantage. *MIT Press Books*, 1.
- Shrivastava, P., Mitroff, I. I., Miller, D., & Miclani, A. (1988). Understanding industrial crises [1]. *Journal of Management Studies*, 25(4), 285–303.
- Shrivastava, S., Sonpar, K., & Pazzaglia, F. (2009). Normal accident theory versus high reliability theory: A resolution and call for an open systems view of accidents. *Human Relations*, 62(9), 1357–1390.
- Silva, P. M. S., & Pinto, L. R. (2010). Emergency medical systems analysis by simulation and optimization. *Proceedings of the 2010 Winter Simulation Conference*, 2422–2432.
- Silver, C. (2007). *Planning the megacity: Jakarta in the twentieth century*. Routledge.
- Simon, H. A. (1990). Bounded Rationality. In J. Eatwell, M. Milgate, & P. Newman (Eds.), *Utility and Probability* (pp. 15–18). Palgrave Macmillan UK.
https://doi.org/10.1007/978-1-349-20568-4_5
- Stainsby, H., Taboada, M., & Luque, E. (2009). Towards an agent-based simulation of hospital emergency departments. *2009 IEEE International Conference on Services Computing*, 536–539.
- Su, S., & Shih, C.-L. (2003). Modeling an emergency medical services system using computer simulation. *International Journal of Medical Informatics*, 72(1–3), 57–72.
- Sutton, J., Spiro, E. S., Johnson, B., Fitzhugh, S., Gibson, B., & Butts, C. T. (2014). Warning tweets: Serial transmission of messages during the warning phase of a disaster event. *Information, Communication & Society*, 17(6), 765–787.
- Svenson, O. (1991). The accident evolution and barrier function (AEB) model applied to incident analysis in the processing industries. *Risk Analysis*, 11(3), 499–507.
- Tabibzadeh, M., & Meshkati, N. (2015). Applying the AcciMap methodology to investigate a major accident in offshore drilling: A systematic risk management framework for oil and gas industry. *SPE Western Regional Meeting*.
- Takagi, H., Esteban, M., Mikami, T., & Fujii, D. (2016). Projection of coastal floods in 2050 Jakarta. *Urban Climate*, 17, 135–145.
- Tasic, J., & Amir, S. (2016). Informational capital and disaster resilience: The case of Jalin Merapi. *Disaster Prevention and Management*.
- Tasic, J., Tantri, F., & Amir, S. (2019). Modelling multilevel interdependencies for resilience in complex organisation. *Complexity*, 2019.
- Taylor, P. J., Ni, P., Derudder, B., Hoyler, M., Huang, J., Lu, F., Pain, K., Witlox, F., Yang, X., & Bassens, D. (2009). The way we were: Command-and-control centres in the global space-economy on the eve of the 2008 geo-economic transition. *Environment and Planning A*, 41(1), 7–12.
- Telford, J., & Cosgrave, J. (2007). The international humanitarian system and the 2004 Indian Ocean earthquake and tsunamis. *Disasters*, 31(1), 1–28.
- Tierney, K. J. (1991). *Emergency medical care aspects of the Loma Prieta earthquake*.
- Trist, E. (1981). The evolution of socio-technical systems. *Occasional Paper*, 2(1981), 1981.

- Turner, B. A., & Pidgeon, N. F. (1997). *Man-made disasters*. Butterworth-Heinemann.
- Underwood, P., & Waterson, P. (2013). Accident analysis models and methods: Guidance for safety professionals. *Loughborough University*.
- UNISDR, U. (2005). Hyogo framework for action 2005–2015: Building the resilience of nations and communities to disasters. *Extract from the Final Report of the World Conference on Disaster Reduction (A/CONF. 206/6)*, 380.
- Van Dam, K. H. (2009). *Capturing socio-technical systems with agent-based modelling*.
- Vaughan, D. (1996). *The Challenger Launch Decision: Risky Technology, Culture, and Deviance at NASA*. University of Chicago Press.
- Vermaas, P., Kroes, P., van de Poel, I., Franssen, M., & Houkes, W. (2011). A philosophy of technology: From technical artefacts to sociotechnical systems. *Synthesis Lectures on Engineers, Technology, and Society*, 6(1), 1–134.
- Vespignani, A. (2012). Modelling dynamical processes in complex socio-technical systems. *Nature Physics*, 8(1), 32–39.
- Walker, B. H., Anderies, J. M., Kinzig, A. P., & Ryan, P. (2006). Exploring resilience in social-ecological systems through comparative studies and theory development: Introduction to the special issue. *Ecology and Society*, 11(1).
- Walker, B., Holling, C. S., Carpenter, S. R., & Kinzig, A. (2004). Resilience, adaptability and transformability in social–ecological systems. *Ecology and Society*, 9(2).
- Watson, J. T., Gayer, M., & Connolly, M. A. (2007). Epidemics after natural disasters. *Emerging Infectious Diseases*, 13(1), 1.
- Weick, K. E. (1988). Enacted sensemaking in crisis situations [1]. *Journal of Management Studies*, 25(4), 305–317.
- Weick, K. E. (1995). *Sensemaking in organizations* (Vol. 3). Sage.
- Weick, K. E., Sutcliffe, K., & Obstfeld, D. (2000). High reliability: The power of mindfulness. *Leader to Leader*, 17(07), 1–56.
- WHO. (2011). *Hospital emergency response checklist*. <https://www.who.int/publications-detail-redirect/hospital-emergency-response-checklist>
- Wisner, B., Blaikie, P. M., Blaikie, P., Cannon, T., & Davis, I. (2004). *At Risk: Natural Hazards, People's Vulnerability and Disasters*. Psychology Press.
- Wolfe, S. R. (2007). Supporting Air Traffic Flow Management with Agents. *AAAI Spring Symposium: Interaction Challenges for Intelligent Assistants*, 137–138.
- Woods, D. D. (2006). Resilience engineering: Redefining the culture of safety and risk management. *Human Factors and Ergonomics Society Bulletin*, 49(12), 1–3.
- Woods, D. D. (2015). Four concepts for resilience and the implications for the future of resilience engineering. *Reliability Engineering & System Safety*, 141, 5–9.
- Yi, W., & Özdamar, L. (2007). A dynamic logistics coordination model for evacuation and support in disaster response activities. *European Journal of Operational Research*, 179(3), 1177–1193.
- Zio, E., & Aven, T. (2013). Industrial disasters: Extreme events, extremely rare. Some reflections on the treatment of uncertainties in the assessment of the associated risks. *Process Safety and Environmental Protection*, 91(1–2), 31–45.

Zook, M., Graham, M., Shelton, T., & Gorman, S. (2010). Volunteered geographic information and crowdsourcing disaster relief: A case study of the Haitian earthquake. *World Medical & Health Policy*, 2(2), 7–33.