ETH zürich

ETH Library

Quantitative Assessment of Resilience in Complex Systems

Doctoral Thesis

Author(s):
Tang, Junqing

Publication date:
2019

Permanent link:
https://doi.org/10.3929/ethz-b-000353417

Rights / license:
In Copyright - Non-Commercial Use Permitted

This page was generated automatically upon download from the ETH Zurich Research Collection.
For more information, please consult the Terms of use.

DISS.-NO. ETH 25935

QUANTITATIVE ASSESSMENT OF RESILIENCE IN COMPLEX SYSTEMS

A dissertation submitted to attain the degree of

DOCTOR OF SCIENCES of ETH ZÜRICH
(Dr. sc. ETH Zürich)

presented by

Junqing Tang

M.Sc., Imperial College London & University College London

born on 18 June 1991

citizen of China

accepted on the recommendation of

Prof. Dr. H.R Heinimann, examiner
Prof. Dr. L.C. Tang, co-examiner
Prof. Dr. N. Chen, co-examiner

2019

Junqing Tang: *Quantitative Assessment of Resilience in Complex Systems* ©2019

To my family

ABSTRACT

Complex systems, such as financial systems and infrastructure systems, are facing an increasing number of disruptions, either external (e.g., financial crisis and natural disasters) or internal (e.g., degradation, aging, and ill performance). Many previous works have dedicated to the question of how to measure the resilience in these complex systems. To date, system resilience can be assessed in various ways, i.e., qualitative or quantitative, summative or formative, and target-based or purpose-based. This thesis focuses on quantitative methods and makes contributions on filling research gaps and improving the up-to-date toolkits in three categories of resilience assessment tools, namely (1) Performance-based metrics; (2) Network-based approaches; And (3) Probability-based graphic models.

For performance-based metrics, critical system functions, such as tolerance thresholds for different level of degradation, are absent in the construction of these tools, and the metrics' applicability in complex performance is less developed. Therefore, Chapter 2 aims to develop a generic resilience metric for quantitative assessment based on system functions and test its strength in the complex performance of stock markets. The proposed metric satisfactorily characterized the markets' resilient behaviors and had comparative advantages throughout the analysis.

In network-based studies, one of the significant missing links in network resilience (specifically in temporal networks) is the relationship between the resilience of individual components (nodes or edges) and the dynamic interdependence of networks (dynamic changes in the topology of temporal networks). Thus, Chapter 3 and 4 was designed in a progressive manner where Chapter 3 acts as a pilot study, aiming to characterize individual resilience using complex network approach and explore the descriptive strength of multiple associated factors. Chapter 4 is a further study, aiming to develop a set of statistical models to identify individuals' resilient performance in a networked environment and perform in-depth analyses and forecasts. Taking London stock exchange as study objective, Chapter 3 found that the survivability resilience of individual stocks was correlated with node degree and node strength. This was further confirmed by Chapter 4, whose results showed that the survivability resilience could be described and approximated by degree-related centrality measures. In addition, the statistical models proposed in Chapter 4 offers an effective tool that can be used to predict different individual stock's resilient performance in the networked market.

Lastly, Chapter 5 proposes a hierarchical Bayesian network model with ontologically identified interdependence among resilience functions and system qualities. Based on current literature, the ontology-oriented Bayesian networks have been rarely applied to model system resilience, and the investigations on the dynamic resilience are still needed. Therefore, Chapter 5 aims to develop a probability-based graphic model to quantify the dynamic resilience. The chapter takes Beijing's road transportation system as a case study and studies the dynamic resilience of the system from 1997 to 2016 by fusing multi-source and heterogeneous urban data. The analysis found that Beijing's road system was not as resilient as expected, with the probability of being resilient between 50% and 70%. Moreover, the critical system qualities that mostly affect its dynamic resilience have been identified as well. The model proposed in this chapter is a promising tool for resilience assessments.

The main value of this thesis is to improve our understandings about how to effectively measure and quantify resilience in complex systems with complex performance, dynamic interdependence, massive system topology, and probability caused by uncertainties. The thesis enriches the state-of-art assessing methods in resilience research by exploring possible measures and methodologies in quantitative approaches. The specific findings of each chapter can be useful and heuristic for researchers, policy-makers, shareholders, and practitioners in the field. However, in the final chapter, the author has acknowledged some limitations and outlook of this thesis which can be addressed in future works.

ZUSAMMENFASSUNG

Eine zunehmende Anzahl von Gefahren bedroht komplexe Systeme, beispielsweise Finanz- und Infrastruktursysteme. Die Gefahren sind einerseits extern, die sich beispielsweise als Naturgefahren oder Finanzkrisen zeigen, und andererseits intern in Form von Alterung oder Degradierung, usw. Eine große Anzahl früherer Forschungsarbeiten ging der Frage nach, wie sich die Resilienz derartiger Systeme quantifizieren lässt. Dabei entstand eine ganze Palette von Ansätzen, die sich mit Spannungsfeldern charakterisieren lassen: qualitativ oder quantitativ, summarisch oder systematisch, zielorientiert oder pragmatisch. Die vorliegende Dissertation greift die Herausforderung der quantitativen Methoden zu Resilienz Charakterisierung auf und bezweckt, Methoden in drei Bereichen zu verbessern: (1) Skalare Metriken zur Charakterisierung der Systemleistungsfähigkeit, (2) Netzwerk-Metriken, und (3) probabilistische Metriken, basierend auf Netzwerkmodellen.

Die wesentliche Lücke bei den skalaren Resilienzmetriken liegt darin, dass die meisten Methoden kritische Systemfunktionen, die in komplexen Systemen essenziell sind, vernachlässigen, womit ihre Anwendbarkeit für komplexe Systeme beschränkt ist. Kapitel zwei dieser Dissertation entwickelte eine generische Resilienzmetrik, die auf Systemfunktionen aufbaut. Eine kritische Beurteilung der entwickelten Metrik geschah anhand eines großen Datenbestandes über das Verhalten von Firmen in Aktienmärkten. Es zeigte sich, dass die entwickelte Metrik geeignet ist, um die dynamische Entwicklung der Resilienz eines großen Firmennetzwerks dynamisch zu charakterisieren.

Die dynamische Wechselwirkung zwischen der Resilienz eines einzelnen Systemelements und der Resilienz eines Gesamtsystems ist kaum untersucht. Dies gilt insbesondere für Fälle, in denen sich die Netzwerke und ihre Topologie dynamisch verändern. Kapitel drei und vier nahmen diese Herausforderung auf mit dem Ziel, die Resilienz eines einzelnen Systemelements quantitativ zu beschreiben und mit den Methoden der komplexen Netzwerktheorie mit der Systemebene zu verbinden (Kapitel 3). Kapitel vier entwickelte mehrere statistische Modelle, um die Resilienz-Leistungsfähigkeit eines einzelnen Systemelements in einer vernetzten Umgebung zu charakterisieren. Die Anwendung der Methoden auf einen Datenbestand der Londoner Aktienbörse ergab, dass die Überlebensfähigkeit eines Systemelements (Firma, charakterisiert durch Aktienkurs) mit dem Vernetzungsgrad – gemessen als Anzahl Verbindungen mit anderen Knoten – und der Stärke dieser Verbindungen korreliert. Die Studie ergaben im Weiteren, dass auch die sogenannte Zentralität, d. h. die Bedeutung eines individuellen Systemelements für das Gesamtsystem, eine gute Approximation für die Charakterisierung der Resilienz erlaubt.

Resilienz ist ein Verbundkonzept, das auch von bekannten Konzepten der Zuverlässigkeitstheorie abhängt. Kapitel fünf nahm die Herausforderung auf, den Beitrag verschiedenster Systemeigenschaften zur systemischen Resilienz mit einem ontologischen Modell zu beschreiben. Es zeigte sich, dass derartige Ontologie-Ansätze im Resilienz Bereich noch wenig entwickelt sind. Dabei ging es darum, das Ontologie-Netzwerk mit einem probabilistischen Graphenmodell (Bayes-Netzwerk) derart zu beschreiben, dass sich die dynamische Veränderung der System Resilienz charakterisieren lässt. Das Transportsystem von Beijing diente dazu, die dynamische Resilienz zwischen 1997 und 2016 zu untersuchen und zu charakterisieren. Einerseits zeigte sich, dass die Resilienz – gemessen mit probabilistischen Grössen – lediglich zwischen 0.5 und 0.7 lag, und

andererseits ließen sich Systemeigenschaften identifizieren, welche für die Resilienz des Gesamtsystems kritisch sind.

Die vorliegende Dissertation leistet einen Beitrag, um die Resilienz von komplexen Systemen besser verstehen und charakterisieren zu können, wobei sich Systemeigenschaften wie Topologie, dynamische Abhängigkeiten und Unsicherheiten explizit berücksichtigen lassen. Die Arbeiten basieren auf mehreren quantitativen Werkzeugen, die eine systematische Analyse und Charakterisierung ermöglichen. Die Ergebnisse der Arbeit sind sowohl für die Forschung, als auch für Infrastruktur-Praktiker und Entscheidungsträger relevant. Die Dissertation schließt mit einer Synthese, in der auch offene Fragen und Herausforderungen dargestellt sind.

ACKNOWLEDGEMENTS

It is impossible to express all my sincere gratitude for my supervisor, friends, collaborators, and my beloved ones. Without the continuous support and encouragement from them, this work would not have been possible.

I would like to thank

- Prof. Dr. Hans Heinimann, Director of Future Resilience Systems (FRS) and Full Professor of Department of Environmental Systems Science at ETH Zürich, for giving me the opportunity to work in his group, for his patience and guidance, and for always believing in me. I greatly appreciate the freedom he allowed me in pursuing ideas.
- Prof. Dr. Loon Ching Tang, Principal investigator of FRS and Director of Temasek Defence Systems Institute in National University of Singapore (NUS), and Prof. Dr. Nan Chen, Principal investigator of FRS and Faculty of Department of Industrial Systems Engineering and Management in NUS, for their help on my manuscripts and examinations. I also want to thank them for being the co-examiners.
- Dr. Layla Khoja, for collaborating on research projects, and for her support and encouragement as a Postdoctoral mentor through my Ph.D. study.
- Mr. Aaron Ang, our project manager in FRS, for his continuous support and coordination of public affairs and academic activities.
- All my fellow Ph.D. students and Postdocs in FRS, for their close friendship and companionship.
- All the anonymous reviewers and editors, for criticizing, improving, and accepting my papers.

Most of all, I am indebted to my parents for all their love and constant support in my life. I also thank my soulmate, Lulu Liu, for her love, trust, dedication, and all the wonderful moments we had together.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

1

INTRODUCTION

Persistence and resilience only come from having been given the chance to work through difficult problems.

— Gever Tulley

1.1 A BRIEF HISTORY OF "RESILIENCE"

The development of the word "resilience" is time-honored and diverse. With a Latin root, "resilire," that means to "leap back and rebound," the word was originally documented in law and literature and can be traced to approximately AD 35 [1]. However, it was not until the 19th Century that it was mentioned as an engineering concept, in the field of mechanics, with Thomas Young (1773-1829) [2] outlining the concept of resilience in his book "A Course of Lectures on Natural Philosophy and the Mechanical Arts", as follows:

"...The action which resists pressure is called strength, and that which resists impulse may properly be termed resilience. ...The resilience is jointly proportional to its strength and its toughness, ..." [2].

Since then, the concept had been promoted in the field of mechanics by Scottish engineer William J. M. Rankine (1820-1872) as "Resilience of a solid" [3] and by Timoshenko [4] as the "Modulus of resilience." In 1973, Holling [5] firstly brought this term to prominence from a perspective of systems science in ecology [1]. It also started to appear in psychology and social science as a distinct developmental line [6] before spreading significantly to other fields. Currently, resilience is a flourishing topic in multiple areas [7, 8]. Fig. 1.1 presents a schematic diagram illustrating the etymological study of "resilience."

During its renaissance, the term has become increasingly emphasized on its feature of ubiquity and capability of post-event reaction in the disruption. Because of this, many communities began to discuss the concept as an effective measure to achieve goals of risk reduction and strategic management [9]. Despite its ubiquitous use in the literature, few can agree on what system resilience is because of its wide variety of perceptions and interpretations of essential functions and attributes across disciplines [10, 11]. Also, the definition per se has a strong evolving characteristic. The following Fig. 1.2 depicts a timeline of key milestones in its definition.

Hosseini, Barker & Ramirez-Marquez [8] completed a comprehensive review in 2016. They reviewed a large amount of literature and summarized the following commonalities and highlights in the resilience definitions.

*This chapter is partially based on the book chapter published by Springer. *Tang, J.*, 2018. Assessment of resilience in urban complex systems. Encyclopaedia of the UN Sustainable Development Goals. Industry, Innovation and Infrastructure. Edited by Walter Leal Filho et al., Springer.*

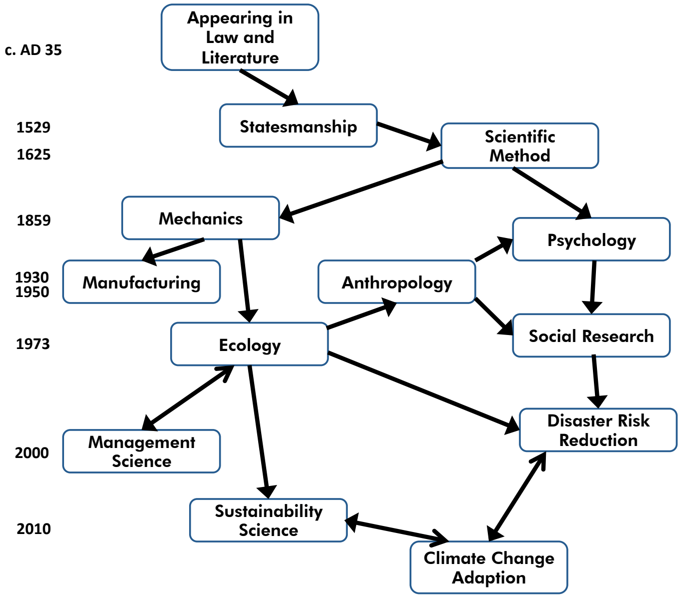


Figure 1.1: An Etymological study of the term "resilience", recreated from [1].

- Although mechanisms to achieve resilience are not always specified, many definitions focus on the capability of a system to "absorb," "adapt," and "recover."
- For some particular systems, reliability, and anti-vulnerability are often used interchangeably with the term "resilience."
- Some definitions suggest that resilience has multi-dimensional characteristics and they reveal the importance of time-dependent and shock-dependent features.
- The criticalities of pre- and post-event capabilities are sometimes recognized in preparedness and recovery, but other definitions do not usually consider pre-event capabilities.

Despite the controversy over the exact definition of resilience, this term is normally used to describe the ability of a system to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events [12]. The concept has been used as a novel lens to explore new ways of addressing development issues in increasingly complex urban systems.

Even though the concept of resilience would probably continue to evolve, researchers have acknowledged that the assessment of resilience is important because it enables them to refine their objectives and clarify general understanding about the complexity of the systems [13, 14]. Most importantly, the assessment of resilience could be an effective way to achieve better management in complex urban systems. Therefore, many frameworks, models, and approaches have been developed and attempted to tackle problems such as its quantification models.

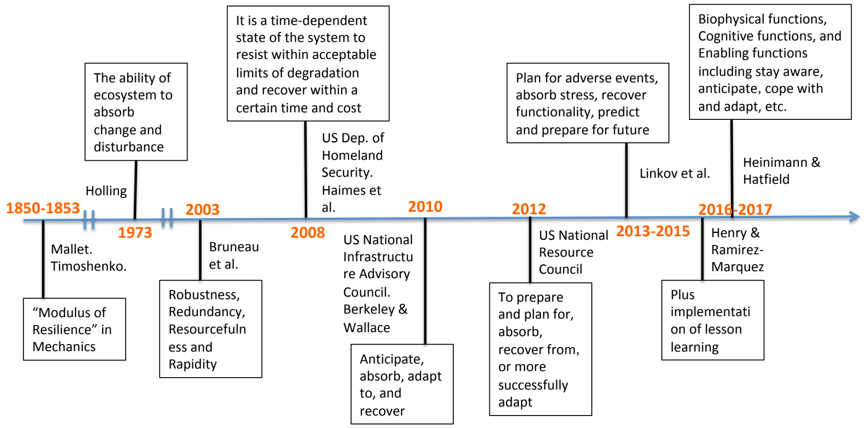


FIGURE 1.2: Critical milestones in defining the system resilience

1.2 STATE-OF-ART KNOWLEDGE OF RESILIENCE ASSESSMENT

Resilience can be assessed in various ways, i.e., qualitative vs. quantitative; summative vs. formative; or target-based ('for whom') vs. purpose-based ('why') [15]. In this thesis, we use the perspectives of quantitative and qualitative. The quantitative methods are further categorized into deterministic and probabilistic models [8], either of which provides a uniform scale for measuring resilient performance and comparing it across different scenarios. The methodological pluralism on resilience assessments ranges from low-dimensional metrics to multi-dimensional approaches such as Bayesian-based and simulation-based tools. Here, we briefly revise several main streams of resilience assessments by starting with qualitative approaches.

1.2.1 *Qualitative assessment toolkits*

Qualitative tools commonly involve a large portion of expert knowledge and shareholder engagement. For example, Arbon *et al.* [16] has proposed a question-oriented toolkit for assessing the disaster resilience of societies. The scorecard comprises 22 assessment questions about the general performance of a community, such as “Does the community actually meet requirements for disaster readiness?” and “What proportion of the population with skills useful in emergency response (e.g., first aid skills, safe food handling) can be mobilized if needed?” 10 to 15 community-selected members of the committee then assign scores (1-5) to each answer. If a disagreement occurs, the lower, rather than the higher, is recorded. Community resilience is then evaluated according to a final, aggregate score that is computed by summing the total scores for all questions. The merits of this toolkit are three-fold: 1) it is workable for assessing resilience qualitatively and engaging the community in planning for future actions; 2) the process of assessment can produce a “cycle of quality improvement" for local authorities; and 3) the results are available online, with a user-friendly interface, so that participants have easy access.

Among similar qualitative tools that are based on the same principle is the two-dimensional "Resilience Matrix" established by Linkov *et al.* [17]. The first dimension divides the attributes of a system into physical, informational, cognitive, and social levels. Afterward, the second dimension assesses each level against four resilience functions – prepare, absorb, recover, and adapt. This results in a 4-by-4 matrix table, in which each cell contains operations and key points for assessing purpose. Experts from the focal system can then use the matrix to evaluate the system, based on the questions and points in each cell, finally reaching a comprehensive assessment of system resilience. The strength of this tool is its simplicity and rapidity. As explained [17, 18], "the resilience matrix is not a comprehensive guide, but instead could be used to identify and link system measures to the design and operation of complex systems."

Despite the advantages of these two approaches (scorecard and matrix), Heinimann & Hatfield [19] have argued that the structure of the system, interdependence of system components, and coupling strength between system complexity and granularity cannot be captured by such tools, which could cause planners to overlook upper-level system straits such as region shift and self-organization behaviors.

1.2.2 *Performance-based metrics*

This is a very popular tier of resilience quantification tools. Such metrics normally rely upon the aggregated system performance with a time-series character. The most representative work is the capture of performance loss due to external disruptions proposed by Bruneau *et al.* [20]. They have pioneered the most well known "Resilience-Triangle" metric, or "Resilience cycle", in earthquake engineering communities. Its "4R" framework – Robustness, Redundancy, Resourcefulness, and Rapidity – depicts a system's resilience loss as the difference between the performance area confined under the 100% functionality level and the area confined by the actual performance level. Fig. 1.3 demonstrates a typical "Resilience-Triangle" in a system's time-series performance. Successful implementation of this metric requires that one identify the beginning and the end of the "triangle." This deterministic, time-dependent metric has inspired many other "performance-based" resilience metrics, such as that of [21–23].

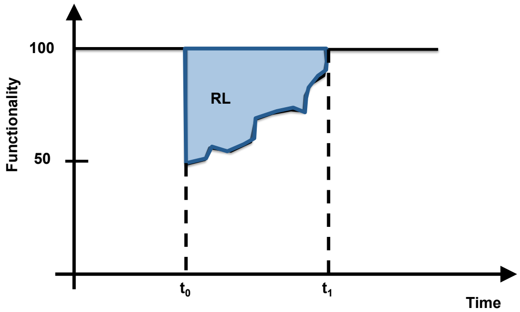


FIGURE 1.3: Resilience-Triangle in a typical resilience cycle, recreated from [20].

Another type of performance-based metrics are models developed from the reliability and risk reduction communities, which leverage a multi-state, multi-phase approach. Unlike "Resilience-Triangle" metrics, models from this class are prominent in characterizing resilience according to not only the macroscopic system performance but also the multiple system states along the temporal dimension. For instance, Ayyub [24] has examined two phases – Failure and Recovery – after an unexpected disruption. The former phase includes brittle, ductile, and graceful cases while the latter considers six cases: 1) expeditious recovery to better-than-new, 2) expeditious recovery to as-good-as-new, 3) expeditious recovery to better-than-old, 4) expeditious recovery to as-good-as-old, 5) recovery to as-good-as-old, and (6) recovery to worse-than-old. As shown in Fig. 1.4, this multi-state model considers the natural effects of aging, the role of time, the possibility of adaptive recovery performance, and the stochastic property of a system, all of which provide a comprehensive analysis of system performance [24, 25].

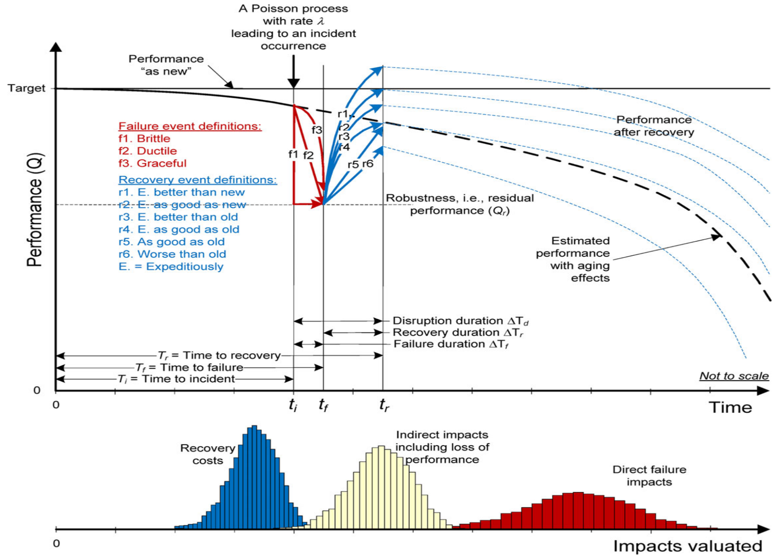


FIGURE 1.4: Multiple states of a resilience cycle, adopted from [24].

Although performance-based metrics and their derivatives are quick and straightforward means to obtain first-hand impressions on a system's resilient behavior, some critical system functions, such as thresholds for withstanding the different level of degradation, are absent in the construction of these tools. Moreover, the applicability of these metrics in more complex performance, such as consecutive time-varying cycles, is needed for further investigations.

1.2.3 *Network-based approaches*

Unlike metrics that rely upon integrated and overall performance, the network approaches are more microscopic and structure-oriented (focus on the topology of networked systems). Identification of the "scale-free" and "small-world" characteristics in many real-world complex networks in the late 1990s promoted the study of complex network theory [26, 27]. Quickly adopted for systems research, those network models served as good examples for investigating connected systems in which nodes represent physical components such as the power stations in a power network, the junctions in a road network, or the individual participants in a social network, while the links indicate dependence among nodes. This theory provides a comprehensive basis for evaluating some of the generic properties hidden beneath the complexity of a system's topology, e.g., robustness and resilience [28] (see Fig. 1.5). In particular, research on Percolation Theory [29] has advanced our understandings about the resilience of networks when deliberate attacks or random failures of nodes and links are applied. An incomplete list of representative works includes: [30–34]. The merits of network-based approaches include the following. First, when compared with performance-based metrics, more details about structures can be studied in a time-dependent system. Second, this conceptualized representation of actual structures is an effective way to perform advanced simulations and detailed investigations. Finally, network-based metrics are more mathematically rigorous than those from the previous tier, thereby allowing for many in-depth upper-level inferences and deductions.

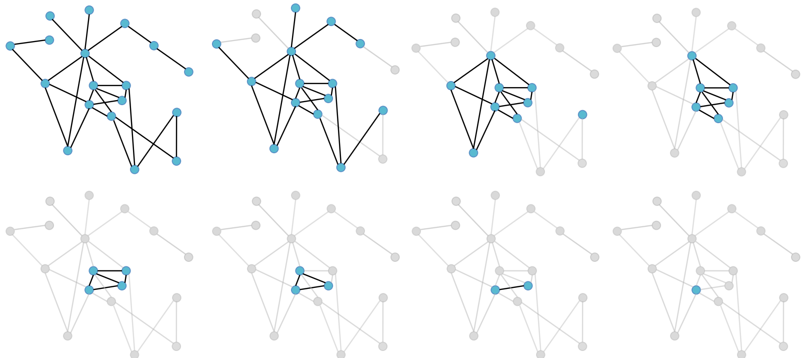


FIGURE 1.5: An illustration of percolation process in a network topology

A branch of the network-based approach is from infrastructure communities, such as transportation systems, water supply systems, and power systems. Networked infrastructure systems are expected to not only maintain their topological robustness but, most importantly, to provide essential service flows. In the transportation context, the systems are still abstracted as graph networks. However, edge weights are often associated with this approach, representing one more dimension from the realistic situation such as travel time, cost, or travel distance [35]. Also, the travel demand and route choice problems are taken into account as well. The travel demand is modeled with respect to trip generation and attraction, as well as destination and mode choices [36]. On the other hand, route choice problem is modeled using network equilibrium by assignment and loading [37]. This combined method between purely network topology and service flow has been well developed in the transportation community and widely accepted as more realistic.

Despite these advantages, however, the robustness and resilience addressed in network percolation are mostly macroscopic. One of the significant missing links in network resilience (specifically in temporal networks) is the relationship between the resilience of individual component (the behavior of nodes or edges themselves, not the overall resilience of the network topology) and the dynamic interdependence of networks (dynamic changes in the topology of temporal networks). Filling this missing link would be valuable for understanding those systems with a temporally interdependent environment, such as eco-systems, where species interact with other species dynamically, and financial market systems which the dynamic changes in the network influence individual participant's resilient behavior.

1.2.4 *Probability-based graphic models*

One emerging stream of resilience assessment is based on advanced probabilistic network models, i.e., Bayesian networks (BN). Unlike complex network models, this type utilizes variable conditional dependence to form a directed acyclic graph that is built upon the Bayesian Theorem [38]. There, nodes do not represent physical components of the system but are instead system variables to depict their probabilistic dependence [39]. Based on various frameworks, users can establish a BN to assess resilience in terms of probable loss and recovery. Resilience can be set as a "leaf node," where quantitative assessment can be achieved from probabilistic inference from the "root nodes," which generally are variables influencing the system performance. These popular tools have a strong foundation in Bayesian statistics and are often data-oriented. For example, Hosseini & Barker [40] implemented this technique to evaluate the resilience of an inland waterway port. They proposed a BN model to quantify port system resilience as a function of many system qualities using historical data collected from multiple variables.

The interdependence of variables in BN can be determined by expert knowledge or learned from massive observation data. One promising way, but less applied, to determine interdependence among variables in BN is by applying ontology studies. A good example comes from the ontology study on various system qualities and capabilities, such as reliability, maintainability, reparability, affordability, and, most importantly, general system resilience [41]. There, the goal is to assess the resilience by providing a common framework for reasoning the ontological dependence of resilience with other system properties because they often are used interchangeably, which creates confusion and misconceptions. Such research begins by identifying a hierarchical top-level system of "-ilities", including 1) Mission effectiveness, e.g., physical and cyber-capability of a system; 2) Resource utilization, such as sustainability and cost; 3) Robustness and protection, including security, safety, reliability, availability, and survivability; 4) Flexibility and composability, including modifiability, adaptability, and interoperability; and 5) Composite resilience. After investigating the means-to-end relationship and hierarchical definitions of those "-ilities," Boehm [42, 43] has proposed an ontological structure to "decompose" system resilience and provide a way to assess it (see Fig. 1.6). Most importantly, ontological studies enhance and clarify the interpretation of a tricky concept by not trying to find a one-size-fits-all definition, instead relying upon a systematic roadmap approach.

The Bayesian-network models (BNM) are well known for their powerful strength on prediction. Also, because of its probabilistic essence, the BN-based approaches are excellent in explaining the uncertain features and detailed propagation analysis in the resilience assessment process. Despite

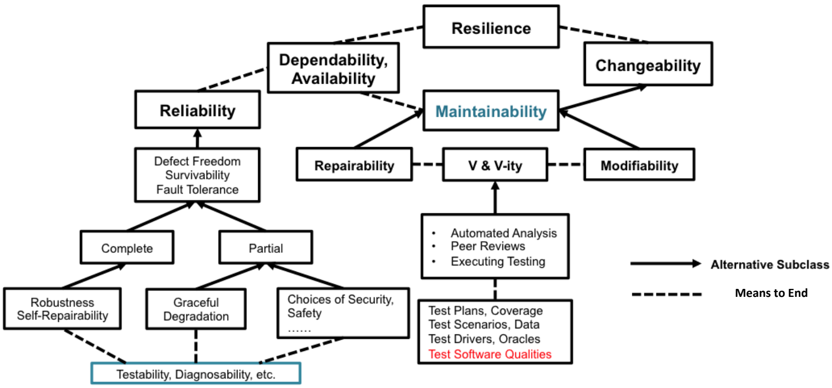


FIGURE 1.6: Role of resilience in ontological structure of system "-ilities", adopted from [42].

its merits and popularity, these tools lay on a strong assumption that full knowledge of the distribution or conditional probability tables is provided, or at least gain from the expert knowledge, which bring uncertainty to the model itself. Moreover, these models are generally case-specific, and their validity is limited by the availability of the data, which means that the interpretation of resilience within the same system can vary from case to case. In literature, the ontology-based BN have been less applied to model system resilience for infrastructure such as road transportation systems.

1.2.5 *Simulation-based tools*

Agent-based modeling is another popular technique for assessing resilience. Unlike other approaches that focus on the top-down, overall performance of the system, this technique provides a platform for several interacting, autonomous, and adaptive "agents" that create a detailed, bottom-up simulation paradigm [44] and can examine collective behavior, such as failure, recovery, and overall resilience. The behavioral rules of those agents must be pre-set and well-defined before the simulation can be done in a step-by-step fashion that is updated along the way [45]. Brudermann, Hofer & Yamagata [44] have applied that technique for diverse projects, including a study of short-term resilience in reducing the risks of urban disasters that focuses on acute external shocks and immediate responses of urban systems. Their research group has also looked at sustainable planning that involves a discussion about implementing the concept of resilience in the long-term development of communities and cities. The agent-based system has an overwhelming advantage because it can connect the behavior-effect relationship between the microscopic and macroscopic levels [46].

Because agents are useful for describing bottom-up collective features, this simulation method has also been applied in one of the emerging approaches of modeling infrastructure resilience, that is the System of Systems (SoS) analysis, which seeks interconnections between multiple systems with various complexity [48] (also known as network of networks in network science). SoS

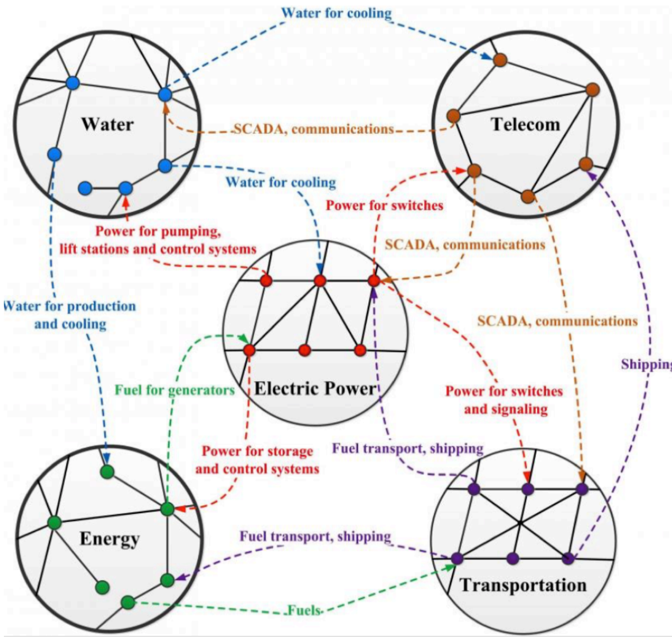


FIGURE 1.7: An illustration of a SoS structure of five infrastructure systems, adopted from [47].

model can be seen as a multi-layer large-scale concurrent network whose components are complex systems themselves [49] (see Fig. 1.7). A SoS model usually has an operating organization, a user subsystem, a SCADA system, and an engineered system [50]. Gorod, Sauser & Boardman [51] have summarized three main properties of a SoS, including (1) decentralized control, (2) network-centric structure, and (3) emergence and unpredictable behavior. Performing simulations on this complex structure can well capture the emerging phenomenon in system performance and study the interactions among different subsystems, which provide a step forward in understanding the resilience of complex systems.

Regardless of their benefits, however, agent-based simulation tools have several shortcomings, e.g., irreconcilable stochastic features caused by incomplete details for agent rules to accurately produce real-world behavior, and the need for complementary Monte Carlo simulations to compensate randomness and uncertainty.

1.3 RESEARCH CHALLENGES AND APPROACHES

1.3.1 *Research challenges and chapter aims*

After comprehensively reviewing the main streams of resilience assessment methods, it is evident that each group of tools has its own merits and shortcomings. In this thesis, we attempt to address four general challenges in three main streams (one for performance-based metrics, two for network-based approaches, and the last one for probability-based graphic models). These four challenges are summarized as follows.

1. **How to measure resilience in complex system performance, such as consecutive resilience cycles, with a generic metric built upon system's elemental functions?**
2. **How can we characterize an individual's resilient behavior in a swarm environment using the complex network approach?**
3. **After characterization, how can we identify and predict resilient individuals in such complex networked systems?**
4. **How can we use probability-based graphic models to depict dynamic resilience and study the influence of system qualities?**

These four challenges are addressed and tackled in the following four chapters in turn. According to these four challenges and specific designs of individual chapters, the following sub-divided research aims and contributions are designed and anticipated for the chapters, as shown in Table 1.1

1.3.2 *Technical approach and structure*

To tackle these four research challenges, this thesis is organized as follows: In the following Chapter 2, a generic functions-based metric is proposed and tested in consecutive resilience cycles. The construction process of this metric is based on ontologically defining thresholds from the system's fault-tolerance capabilities and fundamental functions. In the meantime, the metric is compared with three well-documented metrics in complex stock market performance.

In Chapter 3, we demonstrate a pilot study in modeling individual resilience in signed temporal networks. Taking the London stock market as the case study, we construct a networked correlation-based system and study the survivability resilience of its components. Further, the associated basic network measures, with a proposed network measure as a new factor, are statistically explored to find the most descriptive factors that may affect the characterization of the stock's survivability resilience.

Based on the investigation in Chapter 3, Chapter 4 further explores individuals' resilience in a networked system environment with more sophisticated approaches and different objectives. In this chapter, the long-term temporal evolution of the London stock market is investigated and a set of probabilistic models are constructed based on the dynamic interdependence to quantitatively identify the survivability resilience of all individual stocks that have ever been listed in the market. Finally, we explore the predictive strength of this set of statistical models.

Chapter 2	1. To propose a novel and relatively better performance-based metric, from a systems perspective and quantify consecutive resilient responses in stock markets, which consider the effects of a system's capability of fault tolerance.
	2. To investigate the stochastic characters of time-varying resilient behaviors in a volatile market performance and draw inferences about the market resilience and the effects of the investors' psychological tolerance.
Chapter 3	1.To construct stock markets as weighted temporal networks with signed edges and study their properties based on a long-term observation.
	2.To characterize stock resilience through the statistical model using network measures and explore their descriptive strength in the model.
Chapter 4	1. To explore the correlation-based interdependence of the entire London exchange market by constructing weighted, signed and temporal networks and to understand the long-term dynamic evolution of their topological features.
	2.With the understandings of the long-term historical evolution process, to characterize the survivability resilience of stocks through a set of statistical probability models (using interdependence and network measures as variables) and test their predictability.
Chapter 5	1.To propose a BNM for quantifying the resilience of Beijing's road transportation system with multiple qualities from a systems perspective.
	2.To perform analyses of influence and sensitivity on sub-level qualities and study the overall trend of the dynamic resilience of Beijing's road transportation system in the past two decades.

Table 1.1: Summary of the objectives in the main-body chapters.

In Chapter 5, we propose a BNM based on resilience framework and ontology interdependence among 10 system qualities to probabilistically assess the resilience of the road transportation system in Beijing from 1997 to 2016. We test the model with a multi-source dataset collected from various sectors. The system qualities are examined by analysis of sensitivity and influence. Interesting temporal patterns of system resilience are observed and investigated through this chapter.

Finally, the main findings from Chapters 2 to 5 are summarized in the final chapter. The limitations and open questions of the thesis and several future directions in the quantitative assessment of resilience in complex systems are also presented.

2

ASSESSING CONSECUTIVE RESILIENCE CYCLES IN COMPLEX PERFORMANCE

I often say that when you can measure what you are speaking about, and express it in numbers, you know something about it; but when you cannot express it in numbers, your knowledge is of a meager and unsatisfactory kind.

— William Thomson, 1st Baron Kelvin

2.1 CHAPTER OUTLINE

In this chapter, we quantitatively examined consecutive resilience cycles in the time-varying performance of stock markets. After ontologically defining elemental functions and fault-tolerance thresholds, we proposed and tested a function-based metric for quantifying resilience in complex market performance. In the meantime, the metric was compared with three well-established metrics. This chapter deals with the first challenge: How to measure resilience in complex system performance, such as consecutive resilience cycles, with a generic metric built upon the system's elemental functions?

2.2 INTRODUCTION AND BACKGROUND

Due to the rapid growth in interest among policymakers, practitioners, and academics over the past years, the cognitive and technical analysis of resilience permeates many research disciplines. Abundant frameworks and approaches have been proposed [52] to understand and evaluate this emerging risk-related property via quantitative or qualitative approaches [18, 53–55].

To date, quantitative assessments of resilience can be roughly categorized as general performance-based measures or structure-based models [8]. Metrics for general measures based on system-level performance are commonly developed as deterministic and probabilistic. This type of metrics usually requires full knowledge of a system's time-series performance profile for subsequent analysis. In this chapter, the focus is on deterministic performance-based metrics.

As described in the previous chapter, Bruneau *et al.* [20] have proposed a quantitative metric to assess the "Resilience-Triangle" in a system's time-series performance [53, 56]. In particular, if one considers that the performance of a system decreases after an external shock but recovers after a certain length of time, then a very straightforward proxy for a system's resilience loss is the decline in performance, which is defined by: (1) failure process (measured from the level of performance immediately before the shock to the lowest performance after the shock), (2) the recovery process (from the lowest performance to the post-event performance after the recovery), and (3) total time

*This chapter is based on the paper published on *Physica A.*: Tang, J*, and Heinimann, HR., Khoja, L., 2019. Quantitative evaluation of consecutive resilience cycles in stock market performance: A systems-oriented approach. **Physica A: Statistical Mechanics and its Applications.**

between the shock and the end of the post-event recovery. A single successive process of this "failure and recovery" is also referred to as one "resilience cycle." Because stock markets can be viewed as systems, we would like to propose a new approach which adopts this systems-oriented perspective to measure the resilience of consecutive cycles in market performance.

2.3 RELATED WORKS

2.3.1 *Resilience in financial systems*

Stock markets can be seen as complex evolving systems that constantly undergo uncertain and unexpected disturbance and risks [57], causing frequent, volatile, and dynamic market responses. Therefore, performance evaluations concerning factor analysis are not uncommon in stock market research. For instance, the relationship between CEO ownership and stock market performance [58] and the relationship between political risks and market equity returns [59] have been examined. Other factors also include Monetary policy, environmental issues [60], and even the outcome of the US presidential election [61]. However, evaluating resilient performance in stock markets is missing in these studies.

Apart from those factor-related studies on general market performance, some has focused on the stability and resilience of the markets. For example, Leal & Napoletano [62] studied the stability and resilience of low- and high-frequency trading using agent-based models. They found that regulatory policies can tackle volatility and flash crashes in market performance. Bookstaber, Foley & Tivnan [63] studied the impact of decision cycles on overall market resilience and the stochastic features of prices. Erragragui *et al.* [64] investigated the effects of ethics in improving stock market resilience with instability. Drakos [65] studied the diffusion mechanism of terrorist shocks to third countries' stock market responses.

Moreover, there is a research stream in assessing stock market resilience using methods of network science. In this vein, the complex market environment is often represented as networks to study interesting traits, such as market structure and resilience [57], individual stock's survivability resilience [66, 67], and models for better managing networked markets [68]. This different vision of stock market analysis offers novel insights into intractable questions, such as explaining why stock markets crash [69] and the temporal evolutionary process of financial systems [70]. To our knowledge, the studies of stock market resilience using systems perspectives are mainly focusing on such "network proxy," systems-oriented approaches still need to be further developed.

In the broader community of economics system studies, Rose [71] has attempted to define several important dimensions of economic resilience to disasters and has established a solid foundation for understanding economic resilience. Furthermore, Rose [7] has proposed a static resilience metric to define system resilience as the ratio of the avoided downturn in overall output and its maximum theoretical downturn. The difficulty in implementing this metric is that the estimation of the expected post-event system performance is usually unknown [8]. Even so, this metric has been adapted by others for measuring macroscopic economic resilience [72]. Other excellent and well-acknowledged contributions in the area of economic resilience have also been made by Duval, Elmeskov & Vogel [73], Simmie & Martin [74], Martin [75], and Hill *et al.* [76]. However, most of them are merely qualitative and policy-driven.

2.3.2 *Resilience assessment in complex performance*

Complex system performance, such as multi-cycle (i.e., systems undergo multiple disturbance so that the performance profile has multiple failure-recovery cycles) and adaptive (growing behaviors) performance, have been increasingly studied in recent years. For example, Zobel & Khansa [77] have presented an approach to characterize multi-event disaster resilience based on the "Resilience-Triangle." Their work has helped improve our understanding of multi-disaster performance in a heavily populated area that could suffer from possible landslides and flooding caused by an earthquake. Tran *et al.* [78] have also examined multi-cycle resilience in a networked information exchange system, performing successive node removal events on the topology of the network and evaluating the performance of such time-series deterioration. Other researchers [14, 79] have addressed the issue of case-specific adaptive performance in disaster resilience through the use of different frameworks and various metrics. Readers can further refer to an incomplete list of similar studies, which includes [80–84]

2.3.3 *Problem definition and contributions*

However, among those recent works, three missing links can be identified. First, most of the established metrics or indicators consider only time-dependent performance attributes, excluding possible system quality attributes, such as fault tolerance. Second, a comparison study among popular quantitative metrics is also needed to test their measuring strengths. Finally, the exploration of the dynamic features of consecutive resilience cycles in time-series market performance has been largely overlooked.

The main contributions of this chapter are summarized as:

1. To propose a novel and relatively better performance-based metric, from a systems perspective, to quantify consecutive resilient responses in stock markets, which considers the effects of a system's capability of fault tolerance.

2. To investigate the stochastic characters of time-varying resilient behaviors in volatile market performance and draws inferences about market resilience as well as investors' psychological effects.

2.4 FUNCTION-BASED RESILIENCE FRAMEWORK

Recent research by Heinimann & Hatfield [50] framed and defined resilience in terms of transferable system functions, following the "Structure-System" paradigm of systems engineering and providing a more comprehensive multi-dimensional consideration (Fig. 2.1). There, biophysical functions should include resistance, re-stabilization of critical functionality, rebuilding and reconfiguration of that functionality. From the perspective of a socio-technical system, cognitive resilience must feature awareness, anticipation, remembrance of useful action, learning, and adapting. Resilience can then be incorporated into property work, with the goal of coping with and preventing degradation. In this chapter, we adopted this comprehensive framework to quantify system's resilience and its dynamics. In doing so, a pragmatic way of start is to focus on biophysical functions [50].

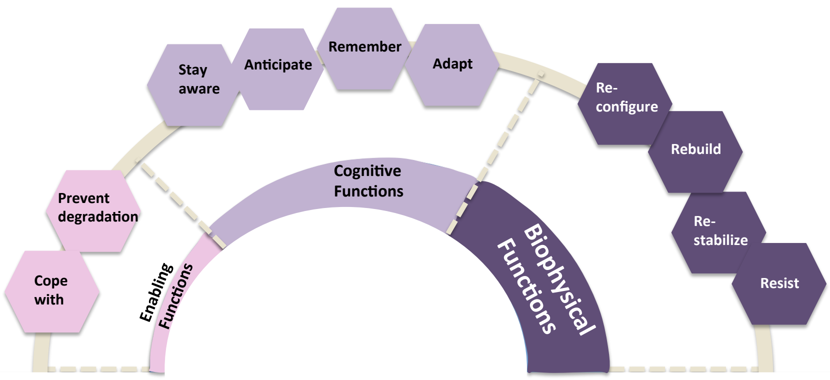


FIGURE 2.1: Reconstructed resilience framework with functions [50].

Biophysical functions provide an aggregated characterization of a single "resilience cycle" in typical system performance. This particular shape can be triggered by a shock (either external or internal), followed by immediate absorption and post-event reaction by the system that includes the abilities to restore and adapt [85]. The framework assigns these responsive capabilities as broader concepts, e.g., the capability to resist, re-stabilize, rebuild and re-configure, which then questions our understanding of a system's behavior as:

- *Resist*: How is the system's ability to resist the negative effect of the shock on its performance? This function acts as an aggregated outcome of a system's overall ability to resist and should include all sources of resisting efforts, such as the ability to be robust, ability to actively prevent disturbance, and ability to maintain stability, etc.

- *Re-stabilize*: Can the system respond to a shock by stabilizing its performance, and how much effort is needed to regain or maintain this post-event stability? This function describes the system's ability to stabilize the level of functionality so that the adverse effects caused by disturbances would not fatally compromise the system.

- *Rebuild*: Once the performance is stabilized and total collapse prevented, how can the system rebuild its performance after the shock? This function is essential because there would be minimal room to discuss resilience if the systems do not acquire the ability to rebuild its performance.

- *Re-configure*: After surviving the shock, how can the system's overall performance be re-organized and updated? In this way, the adaptive behavior would be possible, and the overall system would be more resilient than before.

Here, we term these biophysical functions as elemental functions (resistance, re-stabilization, rebuilding, and re-configuration) because they are the key characteristics of a system's resilient response during a disruption event. From the perspective of system performance, they crystallize the system states from "pre-event" via "during-event" to "post-event" according to the original framework.

2.5 TOLERANCE THRESHOLDS

Primarily described as a generic system character, fault tolerance – enables a system to continue its operation with acceptable performance in the event of compromising some of its components [86] – also plays an indispensable role in guarantee system resilience. Here, we define two static attributes that contribute to a system's tolerance capability, robustness range (RR) and elasticity threshold (ET) [22]. These attributes represent two levels of threshold on how tolerant the system could be in terms of failure or functionality compromise and are sculptured by system design and its internal architecture.

First level: RR acts as the first level of tolerance, where the compromise is not fatal. As described, this attribute can be seen as the "system's ability to maintain its functionality within an acceptable range of degradation [87]". Therefore, as long as the functionality maintains within the RR, the performance is considered normal. More importantly, this idea could be generic across various types of systems. Three examples are pertinent here: (1) Water distribution systems have high- and low-pressure boundaries that must not be exceeded in order to maintain acceptable functionality [88]; (2) Blood pressure also has upper and lower boundaries between which any monitored results are considered as normal readings; and (3) Investors incorporate an intuitive "safe" range in stock market indexes to perceive attentive losses and gains [89, 90].

Second level: Similar to the concept of elasticity in the field of material mechanics, we believe that a lower threshold, ET, should also be set to denote shifts in a system's state. Some social and engineering systems are known to have "phase transition" shifts [91], where system states change from one particular "normal" phase to another "abnormal" one. Some substantial examples include: (1) A large-scale network has a critical point of tolerance against topological attacks, where removal of nodes at that critical point would cause a dramatic collapse in overall connectivity [92]. (2) Studies of the traffic flow theory have demonstrated the existence of "phase transition" in flow states, in which density continuously increase, the self-organizing ability and free-flow state begin to deteriorate and then shift to a congested state [93]. (3) In stock markets, the performance of either individual stocks or the overall market experiences well-documented regime shifts during major financial crushes [94].

Fig. 2.2 illustrates an ontological relationship between these two thresholds and the elemental functions established in the previous section. The tolerance thresholds influence the elemental functions of a system and, consequently, its resilience. Therefore, those thresholds should be incorporated into the process of measuring resilient responses.

2.6 METRIC CONSTRUCTION

This section presents the quantification of functions and thresholds to form the proposed metric. Firstly, some general assumptions are necessary: (1) Assume that a shock happens at time t_{pre} with the level of performance (LoP) at $P(t_{pre})$, the point at which the downturn/failure process starts (red area in Fig. 2.3), and the system's LoP begins to decrease. At time t_{event}, the LoP would reach its minimum level at $P(t_{event})$, which then initiates the upturn/recovery segment (green area in Fig. 2.3). The recovery would eventually complete at time t_{post} with a post-event performance of $P(t_{post})$; And (2) Discussion on shock features, such as sources, intensities, forms, etc., are not

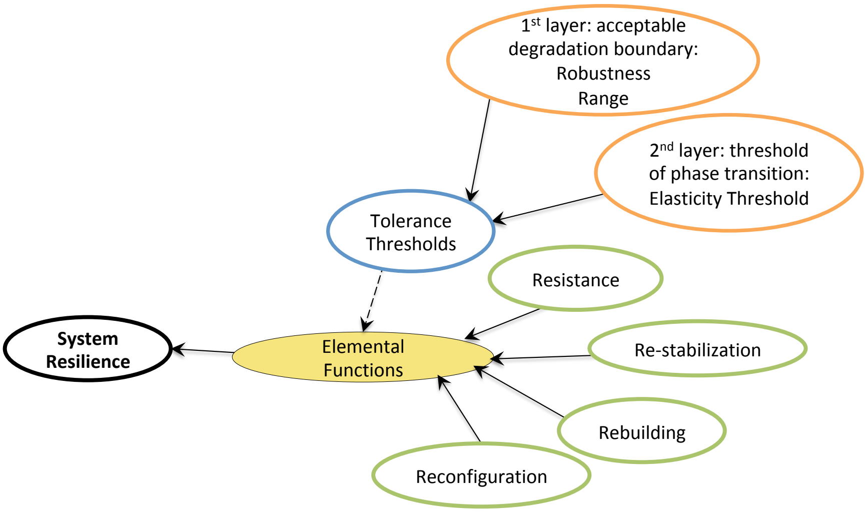


FIGURE 2.2: System resilience decomposed as fault tolerance and elemental functions. Notes: black arrows indicate ontological interdependence or causal relationships; dotted arrow, interactive effect between tolerance thresholds and elemental functions.

in the scope of this chapter, we simply symbolized "shocks" as a general outcome of stimuli and disturbance that could reflect on the overall performance in a broader sense.

A multi-cycle hybrid performance (MCHP) contains a series of resilience cycles with a mixed combination of different types of post-event performance. The overall system-level performance of a stock market is often represented as a time-series evolving index, which can be seen as a concrete example of MCHP. Fig. 2.3 presents four possible post-event performance that can be widely observed in a typical resilience cycle [95]. They can be outlined as follows:

- *Collapse*: This type of $P(t_{post})$ is equivalent to "worst-case recovery" or "no recovery," which represents a situation in which a system's performance cannot organize any form of effective recovery after the shock. Here, notice that the term "Collapse" did not necessarily indicate physical damages, but rather served as a representation of "collapse of LoP";
- *Insufficient*: As is self-evident, this type of $P(t_{post})$ indicates a partial recovery when compared with $P(t_{pre})$, such that $P(t_{pre}) > P(t_{post})$;
- *Leveled*: This is the most widely studied paradigm in the field of resilience, and is used to describe the case at which performance loss is fully restored at $P(t_{post})$;
- *Adaptive*: Learning and adapting behaviors are pervasive in some highly evolving (e.g., complex adaptive and intelligent systems) or volatile systems (such as stock markets). Such systems often foster cases in which $P(t_{post})$ exceeds the level of $P(t_{pre})$ to promote growth in overall performance.

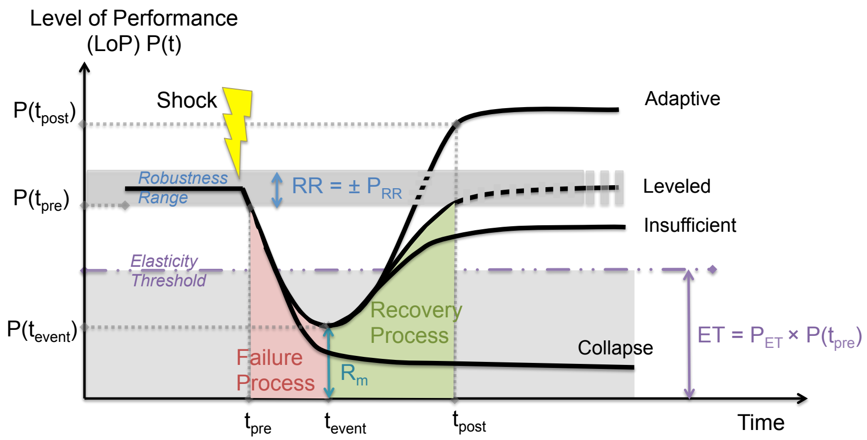


FIGURE 2.3: System behaviors associated with four types of recovery in a time-series performance.

2.6.1 *Characterization of tolerance thresholds*

Based on this outline of the possible post-event performance in a resilience cycle, the tolerance thresholds can then be defined as follows:

Robustness Range (RR): The wider the RR, the more resilient the performance. During the process of calculations, the range is computed as a percentage, P_{RR}, and is expressed as:

$$RR = \pm P_{RR} \tag{2.1}$$

Elasticity Threshold (ET): If LoP falls below the ET (when the phase transition occurs), then extra efforts may be needed to help the system re-gain its LoP. It can be expressed as a certain percentage, P_{ET}, of the $P(t_{pre})$ in a resilience cycle.

$$ET = P_{ET} \times P(t_{pre}) \tag{2.2}$$

2.6.2 *Quantification of elemental functions*

Once the tolerance thresholds were set, the elemental functions can be quantified accordingly as follows:

Resistance (R_m): Resistance should be a total measure of the capability to resist the negative impact caused by a disturbance with the capability to maintain the LoP immediately after that occurrence. It is an aggregated outcome of a system's overall ability to prevent negative effects of the shock, which could be approximated as the minimum LoP $P(t_{event})$ during the entire process from t_{pre} to t_{post} [96] plus the resistance effects contributed from the robustness range. This measure identifies the maximum impact of disruptive events, and use the remaining capacities as a proxy for the system's current ability to resist.

$$R_m = P(t_{event}) + RR \quad for \quad t \in [t_{pre}, t_{post}] \tag{2.3}$$

Re-stabilization (R_e): This function determines the need to regain stability when a phase transition occurs in performance. Intuitively, if the level drops below ET (assuming that the transition happens when LoP falls below ET), then the need for R_e would be considered large because more stability has been lost after disruptive events. Therefore, a high R_e should indicate low resilience and $1 - R_e$ would denote the remaining available stabilizing capacity. If the minimum point of LoP was above ET, it is assumed that its R_e shall be zero. Hence:

$$R_e = \frac{ET - P(t_{event})}{P(t_{pre}) - P(t_{event})} \quad if \quad ET > min[P(t)] \tag{2.4}$$

Rebuilding (R_d): The relative rapidity of the entire recovery process is considered a sensible measure for assessing and quantifying the rebuilding function in a resilience cycle. A quick recovery process means that the system is adequate to re-organize, rearrange, and re-establish. As defined by [96], let S_f and S_r represent the rapidity in downturn and upturn processes, respectively, then the rebuilding capability is measured as:

$$R_d = \frac{S_r}{S_f} \tag{2.5}$$

where,

$$S_f = \frac{P(t_{pre}) - P(t_{event})}{t_{event} - t_{pre}} \quad and \quad S_r = \frac{P(t_{post}) - P(t_{event})}{t_{post} - t_{event}} \tag{2.6}$$

Reconfiguration (R_s): This attribute is sometimes labeled as the "Recovery scenarios" [22] or "Recovery path" in previous studies [96]. Nevertheless, this term essentially characterizes various reconfiguration results after a recovery. It can be defined, straightforward, as follows:

$$R_s = \frac{P(t_{post}) - P(t_{event})}{P(t_{pre}) - P(t_{event})} \tag{2.7}$$

where, $P(t_{post}) - P(t_{event})$ is the LoP restoration during the recovery process and $P(t_{pre}) - P(t_{event})$ is the LoP loss in the failure process.

2.6.3 *Proposed metric for resilience indicator (RI)*

After defining and quantifying all of these elemental functions accordingly, we expressed the proposed metric for offering a resilience indicator (RI) in each resilience cycle as:

$$RI(t) = f(R_m, 1 - R_e, R_d, R_s) = R_m \times (1 - R_e) \times R_d \times R_s \tag{2.8}$$

The rationale of this function-based metric is explained in several steps. First, a multiplicative form was designed to avoid casual bias because the weight of each function is often unobtainable. Second, resilience should intuitively be proportional to the resistance capability, i.e., a larger

R_m would denote a larger RI. Third, in the case of recovery per unit time, S_r, is larger than the loss/failure per unit time, S_f, the system performance should exhibit resilient behavior due to a rapid rebuilding of the LoP. This would then lead to a larger RI value. Fourth, if minimum performance was below ET, then $(1 - R_e)$ represents the available capacity for stabilizing performance during the phase transition. Finally, R_s differentiates various post-event cases where the value for adaptive behavior would be larger than that calculated for other types of recovery, such that the following order occurred: "Adaptive" > "Leveled" > "Insufficient" > "Collapse."

The metric is supposed to be dimensionless (after normalization), and non-negative whose value will be zero in the following cases: (1) there is no recovery (i.e., a collapsed case), meaning that both S_r and R_s are zero and system performance either shows no resilience to cope with a shock or the LoP is stabilized at the lowest point and never re-bounce; (2) given that the lowest point of LoP reaches zero, i.e., R_m and $(1 - R_e)$ are zero. Meanwhile, it may only take a second to realize that this metric could be mathematically correct if and only if the downturn process existed, that is, the S_f is not zero so that R_d and R_s would each have a non-zero denominator.

2.6.4 *Selected metrics for comparison*

Three well-established resilience metrics are selected for comparison exercises. The selection criteria were based on their characteristics and popularity.

The first metric, R1, was the "Resilience-Triangle" metric proposed by [20] as described in the Section 1. It depicts the total loss of system resilience based on the difference in area between 100% functionality and the actual performance $Q(t)$. Because it is characterized by the triangular area of performance loss, its value should always be greater than zero. Given that $Q(t)$ is the actual LoP at time t, t_0 is the t_{pre}, and t_1 is the t_{post}, then R1 is expressed as:

$$R_1 = \int_{t_0}^{t_1} [100 - Q(t)]dt \tag{2.9}$$

The second metric, R2, was firstly proposed by [21]. Although its very essence is similar to R1, modifications have been made to the representation of resilience. This metric confines its domain range from zero to one as a ratio between the target (normally 100% LoP) and the actual LoP. The expectation sign in its original computational form, as shown, is designed to obtain the overall expected value of a series of resilience cycles.

$$R_2 = E[\frac{\int_0^T P(t)dt}{\int_0^T TP(t)dt}] \tag{2.10}$$

where, T is the total time of observation, $P(t)$ is the actual LoP at time t, and $TP(t)$ is the target LoP at time t.

The third metric R3 was initially presented by [14]. It is not an "area-based" metric in which one considers the rate of recovery and LoP at critical points are considered. Similar to the proposed metric, it depicts resilience with various post-event performance and is a deterministic metric that can capture adaptive behaviors.

$$R_3 = S_p \times \frac{F_r}{F_0} \times \frac{F_d}{F_0} \tag{2.11}$$

where, S_p is the speed of recovery, F_r is the LoP after recovery, F_0 is the LoP before a disaster, and F_d is the lowest point of LoP.

2.7 EMPIRICAL STUDY

This section presents a step-by-step empirical study of the proposed metric in the time-series performance of two stock market indexes, NASDAQ and SSE.

- **Step 1: Data description and pre-processing**. Basic information about case data and assumptions were introduced. The data was normalized prior to de-noising.
- **Step 2: Initial settings**. We determined the consecutive cycles and set the values for RR and ET in this step.
- **Step 3: Implementation of metrics and illustrative examples**. The implementation procedure of the proposed metric will be presented in detail to facilitate interpretation.
- **Step 4: Quantification results**. This includes a comparison among metrics, as well as distribution analyses of the RI.
- **Step 5: Sensitivity tests**. Performance of our proposed metric was examined against tunning on RR and ET components in this step.

2.7.1 *Data description and pre-processing*

The empirical data are daily closing values of the NASDAQ Composite Index (INDEXNASDAQ:.IXIC) and SSE Composite Index (SHA: 000001), collected from Yahoo Finance [97] with a specific period from 16 September 2013 to 16 April 2018. The time-series performance of a stock market would be an excellent example for multi-cycle cases with hybrid post-event performance.

In general, a common platform for evaluating LoP is a normalized range between zero and one [96]. Therefore, the pre-processing step begins by normalizing the market performance index so that the LoP (y-axis) could be confined to the range [0,1]. In this way, it facilitates the comparison between different metrics as well. Here, given a LoP, $P(t_i)$, at time t_i and conducting a simple statistical normalization, the normalized LoP can be expressed as $P(t_i)/max[P(t)]$. Normalization of the x-axis was done by using a daily interval as the normalized x-axis.

For the volatile performance in a stock market, measurements can be sensitive to background noise [89]. Therefore, we applied the "rlowess" algorithm in the Matlab toolbox [98], a robust version of a local regression using weighted linear least squares and a first-order polynomial model, to de-noise the performance data with a window span of four days. Taking the NASDAQ as an illustrative example, the normalized and de-noised index performance is shown in Fig. 2.4 (a).

2.7.2 *Initial settings*

Implementing metrics requires one to identify, in advance, meaningful "up-and-down" resilience cycles in the market performance [99, 100]. To address this, Johansen, Sornette, *et al.* [90] have developed a straightforward filtering algorithm, called $\tau-$filter. Essentially, if the LoP drops

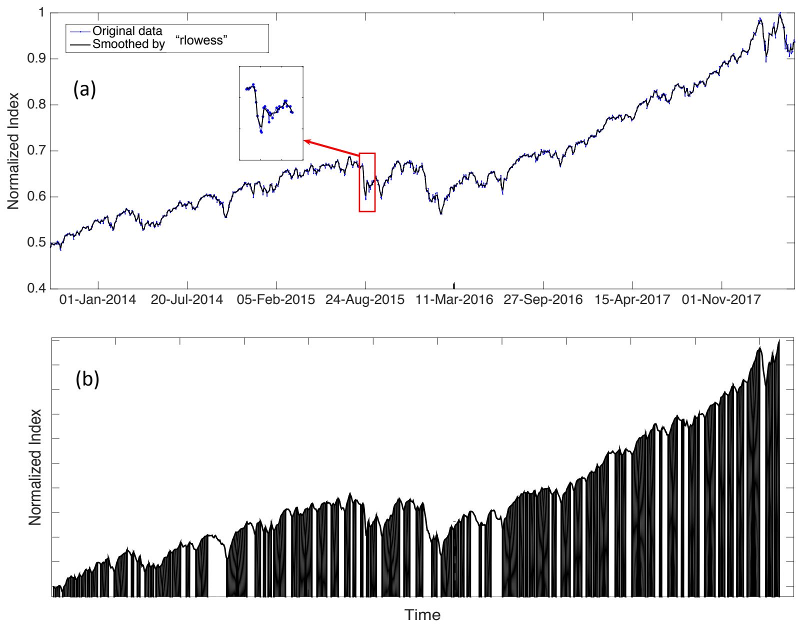


FIGURE 2.4: De-noised data and identification of cycles. (a) original data and de-noised result smoothed by "rlowess" algorithm. (b) identified resilience cycles (black shading, drawups; white shading, drawdowns).

successively for fewer than τ days, then this drawdown can be neglected as a minor fluctuation. Simply put, this filtering process cleans out meaningless cycles by observing their duration. Here, τ was set as three days, so that any drawdown or drawup that lasted less than three days would be merged with its neighbor portion. The final identification outcome of resilience cycles in the NASDAQ over five years of observation is presented in Fig. 2.4 (b) (with black drawups and white drawdowns).

The practical RR and ET for each resilience cycle were initially determined as 0.01% and 80%, respectively. As suggested by [89] and [90], investors could be insensitive to any return fluctuation of 0.01% but will probably be hurt, either financially or psychologically, by a decline of 40%. We assumed that half of this empirical value would cause a phase transition, therefore ET = 1 - 20% = 80%.

2.7.3 *Implementation procedure of RI*

In order to clarify for the readers, we here provide an illustrative example of how exactly the proposed metric can be implemented in each identified cycle. Fig. 2.5 illustrates a typical down-up cycle with "Leveled recovery" scenario. Given that the P_{ET} and P_{RR} are 50% and 1%, respectively. We have the following calculation procedure.

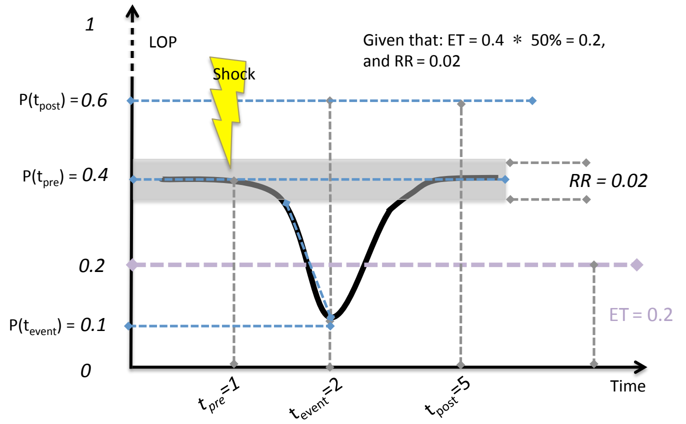


FIGURE 2.5: An illustrative example of a typical down-up cycle in "Just recovery" scenario (values not to scale).

1. Equation (3.1-3.2): **ET** is calculated as $P_{ET} \times P(t_{pre})$ = 0.4 $\times$ 50% $=$ 0.2. Also, **RR** = $\pm 1\% =$ 0.02
2. Equation (3.3): **Resistance** $R_m = 0.1 + 0.02 = 0.12$
3. Equation (3.4): **Re-stabilization** Because ET $> min[P(t)]$, $R_e = \frac{0.2-0.1}{0.2} = 0.5$
4. Equation (3.5-3.6): **Rebuilding** $S_f = \frac{0.4-0.1}{2-1} = 0.3$ and $S_r = \frac{0.4-0.1}{5-2} = 0.1$. Thus, $R_d = \frac{0.1}{0.3} =$ 0.333.
5. Equation (3.7): **Reconfiguration** $R_s = \frac{0.3}{0.3} = 1$
6. Thus, Equation (3.8): $RI = 0.12 \times (1 - 0.5) \times 0.333 \times 1 = 0.020$ for this example

2.7.4 *Quantification and comparative analysis*

Fig. 2.6 presents the quantification outcomes from the NASDAQ case, with subplot (a) showing normalized performance and (b-e) exhibiting the results from RI, R1, R2, and R3, respectively. Upon cross-referencing with the first 10 numerical values in Table 2.1, one can see from the figure that RI provided not only appropriate scores but also outperformed other metrics by assigning larger scores to continuous increasing portions (see indicators in the highlighted segment). Most importantly, RI quantified the resilient performance of the market in an intuitively appropriate way. For example, it is obvious that the overall trend of the highlighted segment is more resilient because of NASDAQ's continuous and strong adaptive performance during that period. Whereas this was well-captured by the proposed metric, the others either failed to indicate such time-varying information (Subplot (c) and (e) for R1 and R3) or else led to a wrong interpretation (roughly equal indicators shown in Subplot (d) for R2).

No. of Cycle	NASDAQ				SSE			
	RI	R1	R2	R3	RI	R1	R2	R3
1	1.23	0.00	1.00	0.0009	0.51	0.02	0.99	0.0023
2	0.82	-0.07	1.01	0.0023	0.04	0.14	0.98	0.0010
3	0.16	0.01	1.00	0.0005	2.23	-0.10	1.01	0.0018
4	6.84	0.00	1.00	0.0017	0.15	0.97	0.93	0.0025
5	1.88	-0.01	1.00	0.0022	18.33	-0.09	1.02	0.0017
6	2.06	0.00	1.00	0.0012	0.06	0.09	0.97	0.0017
7	1.11	0.00	1.00	0.0024	0.22	0.10	0.98	0.0012
8	2.54	-0.03	1.00	0.0011	2.49	-0.01	1.00	0.0023
9	0.76	0.13	0.99	0.0021	0.22	0.29	0.96	0.0022
10	0.48	0.06	0.99	0.0024	0.18	0.05	0.99	0.0008

TABLE 2.1: First 10 resilience indicators obtained by all four tested metrics

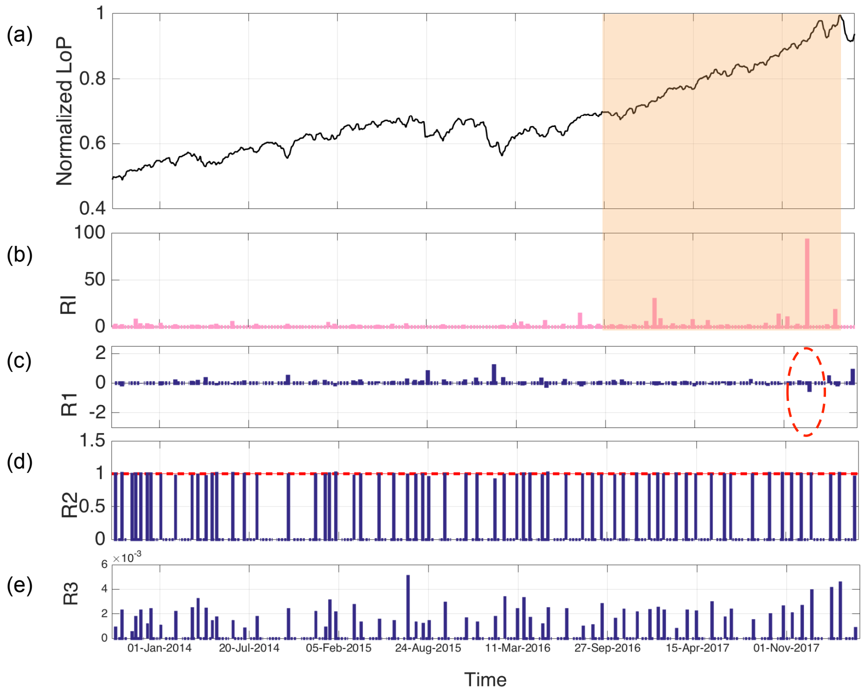


FIGURE 2.6: Results from comparisons among four tested metrics, based on the NASDAQ case. (a) normalised LoP, (b) RI, (c) R1, (d) R2, and (e) R3. Obvious defects are highlighted in red. Indicators are plotted at the t_{event} in each cycle.

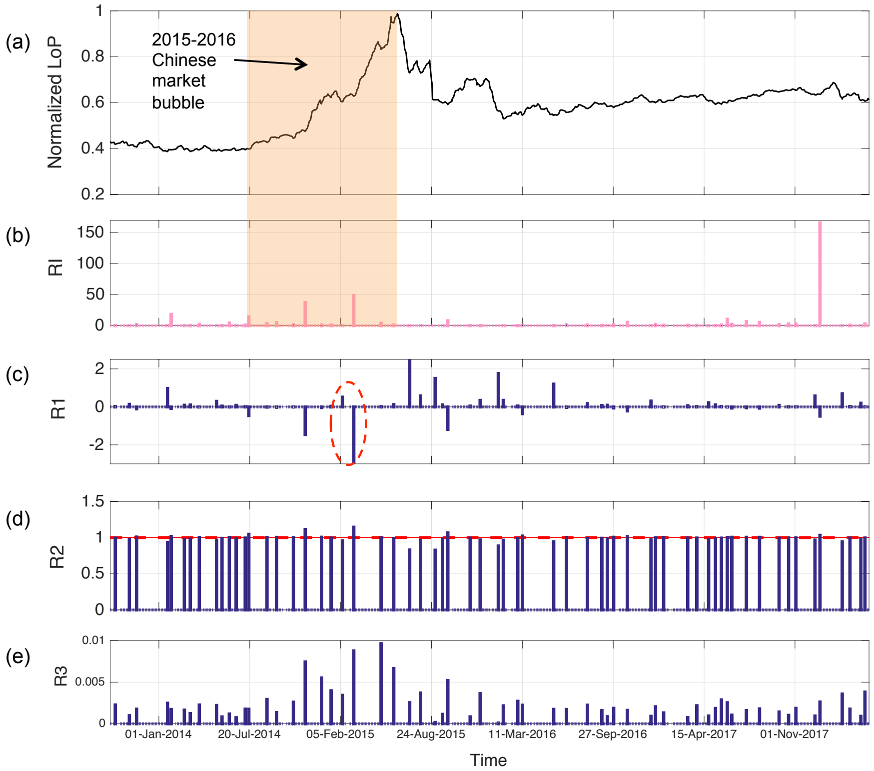


FIGURE 2.7: Results from comparisons among four tested metrics, based on the SSE case. (a) normalised LoP, (b) RI, (c) R1, (d) R2, and (e) R3. Obvious defects are highlighted in red. Indicators are plotted at the t_{event} in each cycle.

Moreover, the results obtained from R1 and R2 were false. By merely setting the targeted LoP (post-event status) at 100% of the pre-event level as described, it is obvious that such a consideration was ill-fitted to adaptive performance. The indicators calculated by R1 showed negative values that conflicted with its value range [0, ∞] (highlighted in red circle). In addition, the result from R2 contained scores greater than one, which also failed to meet its requirement of [0,1] (highlighted in red line). In subplot (e), R3 did demonstrate some merits with adaptive recovery as it lacked any fatal mistakes. However, because of its small value range and failure to differentiate strong resilient behaviors from other cycles, its quantification strength was still unpromising.

Similar observations can be found in the SSE case (Fig. 2.7). There, SSE behaved quite differently than had the NASDAQ during the same period. A major market bubble in the SSE market was also identified according to historical reports [101] during this period. From the quantification results of the proposed metric (subplot (b)), one can see that, prior to the bubble burst, market performance had several strong resilient behaviors as revealed by relatively high resilience scores during that highlighted period. However, after the burst, the following scores dropped dramatically, which correctly indicated a flattened LoP in the overall trend (for further empirical studies, see Appendix A for applicability tests of these four metrics in other two markets).

One of the possible explanations for the less-satisfactory performance of R1 and R2 is associated with their strong assumptions: (1) pre- and post-event performance are equal, with both having 100% of functionality before the shock and after recovery; and (2) the system resilience could be represented by the area of the triangle. We believe that these assumptions must be relaxed to reconcile its disadvantages emerged during comparative studies. For example, two cases as illustrated in Fig. 2.8 would have the same resilience loss according to the "area-based" principle. Intuitively, one would expect the second scenario to have a better adaptive, resilient behavior. Additionally, because post-event LoP is greater than pre-event LoP in adaptive cases, the $Q(t)$ would be greater than 100% in Equation (3.9) and the $P(t)$ would be greater than $PT(t)$ in Equation (3.10). These lead to false values in R1 and R2 that violate their defined value ranges.

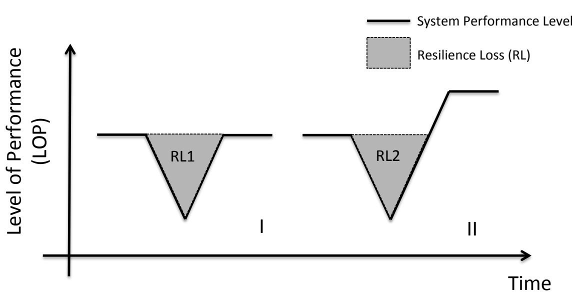


FIGURE 2.8: An illustration of shortcomings in "Resilience-Triangle" approach to characterizing adaptive performance.

2.7.5 *Dynamics of resilience cycles*

Distribution of the quantified resilience cycles can reveal their dynamic features. Rank-size plots were firstly used to visually identify the empirical distribution of the quantified outcomes, fitted to a theoretical power-law distribution. Secondly, their exceedance probabilities were calculated and plotted in a probability-size graph with log-log scale ($\log(P(x_i))$vs. $\log(x_i)$) to check the power-law distribution in the upper tail. Finally, the goodness-of-fit tests were conducted by applying the Kolmogorov-Smirnov (K-S) test based on bootstrap re-sampling for 1000 reps to obtain a mean p values. The p values from both cases were used to examine the null hypothesis H_0: *the data follows a power-law distribution*. In this case, the H_0 can be rejected with the 0.05 level of significance if the p value is < 0.05.

Fig. 2.9 shows the results of the analysis for both NASDAQ and SSE. Subplot (a) and (d) are the rank-size plots of empirical distributions fitted to the theoretical power-law distributions, (b) and (e) are log-log plots for fitting the power-law distribution in the upper tail, and (c) and (f) present bootstrap re-sampling results on p values. As seen in the rank-size and probability-size plots, the empirical resilience indicators of consecutive cycles in both cases could be approximated with a power-law distribution in the upper tail. This is especially true in subplot (e), where the model provided an excellent fit in the upper tail of the SSE case and only slight deviance in the NASDAQ case. The mean p values obtained from the bootstrap K-S tests granted the findings since both cases had a p value > 0.05, meaning we shall accept the null hypothesis at the significance level of 0.05. For both cases, the power-law distribution and the fat-tail feature indicated a non-trivial dynamics and a strongly stochastic and volatile character in their consecutive resilience cycles.

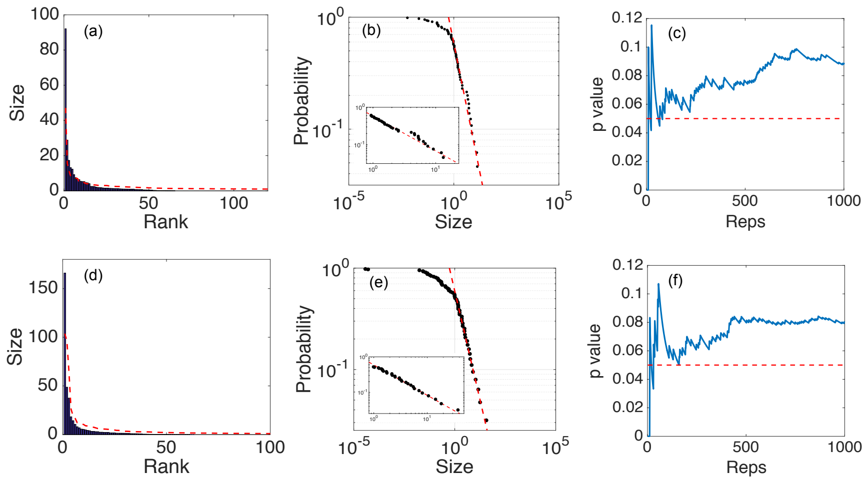


FIGURE 2.9: (a) Rank-size plots of the quantified resilience cycles for NASDAQ case. (b) Log-log size-probability plots of the quantified resilience cycles for NASDAQ case, with the inner plot showing specific power-law fit to the tail section. (c) p values of the K-S test with 1000 bootstrap re-sampling test, note that the mean value is above 0.05 significance level. (d-f) corresponding plots for the SSE case.

2.7.6 *Sensitivity tests*

A practical way to explore and validate a knowledge-based or understanding-developed metric is to test its sensitivity [102]. In doing so, we can schematically understand which parameter in the metric has more impact on the final quantification.

Fig. 2.10 shows the sensitivity analysis of resilience indicators as it pertained to these two parameters. For the NASDAQ case, subplot (a) in this figure shows the analysis of the RR varying from 0.01% to 0.2% with an incremental step of 0.01%. Furthermore, subplot (b) presents results from the analysis of the ET, covering the full range (from 0% to 100%) at 1% increments each time with a narrower test range as shown in the inner plot. Subplots (c) and (d) provides the corresponding results for the SSE case. As seen in subplots (a) and (c), the overall performance of the metric was robust to changes in both RR and ET. However, the quantified RI values were relatively sensitive to RR. Cycles with large RI scores were relatively sensitive to RR variations when compared to those with small scores. This implies that perceptions of strong resilient cycles may vary in investors due to different psychological capabilities to withstand downturns.

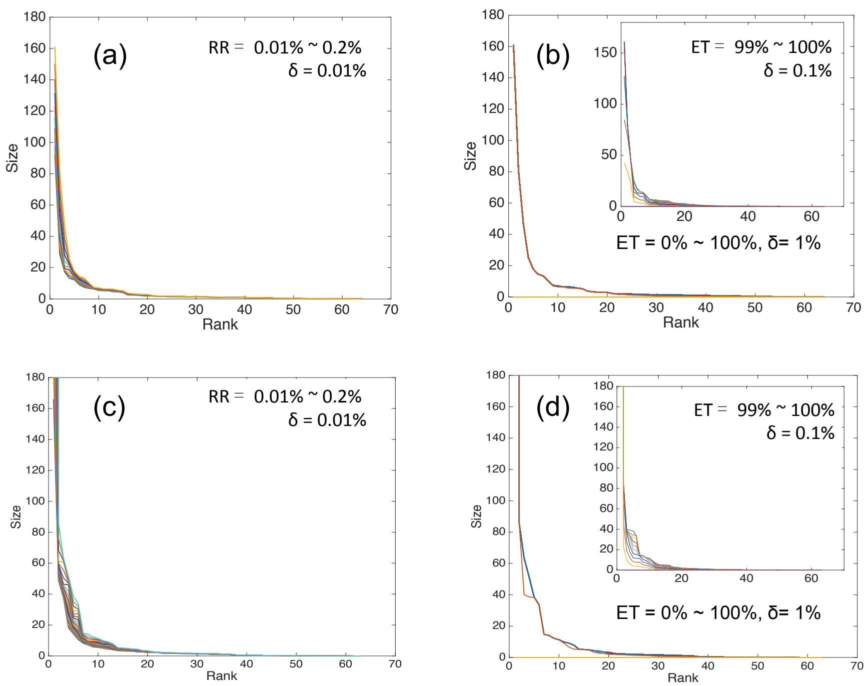


FIGURE 2.10: Sensitivity tests for RR and ET. (a) changes in RI values as RR moved from 0.01% to 0.20% (0.01% increments). (b) changes in RI values as ET was adjusted from 0% to 100% (1% increments). Inner plot: micro (0.1%) steps from 99% to 100%. Note that the y-axes of (c) and (d) were limited to 180, same as (a) and (b), for a clear cross-comparison.

In contrast, the quantification results tended to be rather insensitive to changes in the ET, as shown in subplots (b) and (d). As can be seen, the RI values remained relatively stable until they suddenly became zeros once the ET reached 100% (i.e., no capacity was above the ET, which meant that $R_e = 1$ for all cycles). The term 1 - R_e began to vary until ET = 0.99 (inner plot of Fig. 2.10 (b)). Similar features can also be found in the SSE case as shown in subplot(d). These results imply that this threshold had very limited influence on the final RI values in this case study. Indeed, in most of the resilience cycles, the ET was rarely greater than $min[P(t)]$ because a strongly adaptive and continuously augmented market performance would prevent possible phase transitions. Nevertheless, once the ET was set large enough to allow for a phase transition in most cycles, the RI values began to show sensitivity to small variations in the ET. In practice, this could imply that large market crashes are rare (such as "black swan" or "dragon king" events), but they would significantly alter investors' perception on market resilience when they do occur.

2.8 CONCLUSION

The concept of resilience is becoming ubiquitous, covering a wide range of science disciplines. A vast body of previous works has been published to frame and tackle the issue of resilience assessment through different approaches. However, among those metrics, the system's fault-tolerance thresholds have been relatively overlooked, and the dynamic character of time-varying consecutive resilience cycles has rarely been revealed. In addition, the resilience research still needs a comparative study among different metrics.

In this chapter, we propose a comprehensive function-based resilience metric that takes two fault-tolerance thresholds into account, Robustness Range and Elasticity Threshold, and compare it with three well-established metrics. By taking the time-series performance of two stock markets as empirical studies, this chapter studies the applicability of the proposed metric and the dynamics of time-varying resilience in stock market performance while also looking at the effects of tolerance thresholds in investors. The conclusions are summarized as follows:

- The proposed metric demonstrate satisfactory capability in quantifying time-varying resilience cycles in stock market performance, and it outperforms three well-established metrics in the comparative analysis of applicability.
- Analysis of distribution shows a strong stochastic character in the dynamics of resilience cycles as quantified by the proposed metric. Here, a power-law distribution is featured in the upper tail based on five years of performance for both tested markets.
- Sensitivity tests of two tolerance thresholds reveal that the consideration of these two parameters in resilience metric is essential. Even though the proposed metric is, overall, robust to the tuning, large-value resilience cycles are relatively sensitive to the robustness range. In practice, this range could represent the investor's psychological capability to perceive meaningful downturns. Therefore, the results support that perceptions on market's resilient response could vary among investors.

3

MODELING SURVIVABILITY RESILIENCE IN NETWORKS: A PILOT STUDY

We need a resilient, well-capitalized, well-regulated financial system that is strong enough to withstand even severe shocks and support economic growth by lending through the economic cycle.

— Jerome Powell

3.1 CHAPTER OUTLINE

In this chapter, we model the survivability resilience of stocks in a networked environment. Taking the financial stock market in London stock exchange as a study case, we attempted to model stock's survivability resilience using merely the network measures. We selected 1415 available stocks from London stock exchange (available by 2016) and collected their 40-years historical price. Based on the legal definition of corporate failure, stocks were categorized into Continuing group and Failed group. After, we conceptualized the market into weighted, temporally evolving and signed networks using correlation coefficients. Accordingly, a multivariate logistic model of survivability resilience using network measures, degree ratio (r_i), node degree (k_i), and node strength (s_i) was proposed. This chapter is a pilot study and addresses the second challenge: How can we characterize individuals' resilient performance in a networked environment using complex network approach?

3.2 INTRODUCTION AND BACKGROUND

The understanding of topological characteristics and interdependence between network components have been interesting issues in network theory since such structures and interactions commonly exist in a wide range of academic fields [103, 104]. Also, those topological and interdependence measures often have a strong association with the performance of network components.

As self-explained, the term survivability resilience describes the ability of the subject to survive, to be reliable, and to avoid failure in the environment [105]. It answers the question of how resilient the subject is in a static or dynamic environment to maintain long survival [106]. In the stock market, the survivability is termed to illustrate the ability of stocks/listed firms to prevent corporate failure/bankruptcy or being delisted from the market. Categorizing and predicting corporate failure is essential in bankruptcy studies [107] because it is of great importance in providing early warnings about a company's financial distress to stakeholders, business managers, policymakers, and financial economists [108, 109], and it is hard to be characterized and predicted [110].

*This chapter is based on the publication: Tang, J., Khoja, L. and Heinimann, H.R., 2017,. Modeling Stock Survivability Resilience in Signed Temporal Networks: A Study from London Stock Exchange. **In International Workshop on Complex Networks and their Applications.**

Conventionally, studies in bankruptcy utilize data from business and accounting level, such as cash flow, employment, and annual turnover, etc.

One of the key difference of this study (together with the next chapter) is relying on the way we view the removal of nodes in networks. Majority of previous works have dedicated to network resilience (the overall topological changes in terms of resilience is studied through man-made simulations on nodal removal either randomly or deliberately). Here, we would like to adopt an alternative perspective, by using the network's topological measures to predict removal of nodes (we know some of the nodes will be removed from the network due to bankruptcy or being delisted from the market, and we attempt to use the topological changes of these nodes to predict their consequent removal). Thus, in this chapter, we investigate this alternative approach and try to establish a characterization relation between selected network measures and the survivability resilience of stocks in correlation-based networks.

3.3 RELATED WORKS

3.3.1 *Models for bankruptcy prediction*

Over the past 50 years, various statistical models based on financial or accounting data have been applied to predict corporate bankruptcy [111]. The most frequently used methods for studying stock survivability include genetic fuzzy models [112], artificial networks [113], genetic algorithms [114], and neural networks and deep learning networks [115, 116]. Other traditional statistical models have also been proposed, such as multivariate discriminant analysis and logistic regression [117–121]. In recent years, machine learning models have been popular in bankruptcy predictions due to their excellent performance on accuracy [122]. However, the majority of those models require a substantial amount of accounting-related data as input variables [111](from a company's financial statements). This sometimes leads to an unpromising issue as those accounting data could not always be available.

3.3.2 *Methods for construction of stock networks*

Complex networks usually have so complex topological structures that sometimes its visualization seems to be a "hairball". Therefore, a considerable amount of network studies have been focusing on the methods for reducing and simplifying network structures. For instance, the method of minimal spanning tree (MST) [123, 124], planar maximally filtered graph (PMFG) [125], threshold filtering mechanism [126], and winner-takes-all approach [127]. Several recent studies, on the other hand, focused on the methods of construction of interdependence, including commonly-held Pearson [128] and partial correlation coefficient [129], and covariance and Gaussian graphical model [130]. Apart from construction methods, some works have focused on studying collective behavior and overall correlation synchronicity in the stock market [57, 131]. For years, abundant writings in stock networks have been proposed such as [126, 132–134].

3.3.3 *Problem definition and contributions*

In these previous studies, most of them were merely based on either a short observation period or a small fraction of the population in a market [126, 135]. We also found that most of the previous studies neglected the negative signs/correlations between stock pairs. Furthermore, most studies of bankruptcy have concentrated on only failed firms and overlooked the possibility of using networks perspectives to model stocks/firms with different survivability, including those of exceptionally resilient performance.

Therefore, we focus on modeling individual stock's resilience by converting the market into a networked environment, and specifically address the following two points in this chapter:

1. To construct stock networks as weighted temporal networks with signed edges and study their properties based on long-term observation.

2. To characterize stock resilience through the statistical model using network measures and explore their descriptive strength in the model.

3.4 DATA AND METHODOLOGY

3.4.1 *Data collection and categroization*

The study target was 1415 UK companies in London stock exchange in 2016 (including all active or recent-delisted stocks by the time we observed the market in 2016). We then collected their historical daily closing price from 1976 to 2016 using DataStream^{TM}.

Firstly, we categorized all stocks before constructing networks. The categorization of Delisted companies and Continuing companies were based on their ability to survive in the markets. Stocks that did not belong to either of those two groups were treated as Normal companies. The following definitions were used for our categories:

- **Delisted stocks**(example stocks 1 and 2 in Table 3.1): those companies that were delisted when they have high leverage generally because they were unprofitable, and/or were facing difficulties in gaining additional equity capital during their public life [136]. Consequently, those companies have been delisted to become privately owned companies, acquired companies or in some cases, went bankrupt.

- **Continuing stocks**(example stocks 3 and 4 in Table 3.1): those companies have good opportunities for investment growth, and which showed increases in equity capital when quoted in the market [136]. For our purpose, the continuing group represents the companies which have been continuing to trade in the market for the entire 40-years observation period.

- **Normal stocks**(example stocks 5 and 6 in Table 3.1): those companies were initially listed at some point during the observation period and had not failed yet by the end of the observation period.

Year	Date	stock 1	2	3	4	5	6
Year 1	date 1	232.2	-	732.5	101.0	-	-
	date 2	186.2	-	232.2	106.9	-	-
	date 3	148.7	162.9	186.2	1026.7	-	-
	...	112.7	168.2	148.7	218.8	-	-
...	...	82.2	185.0	112.7	732.8	-	-
Year 10	...	82.2	185.0	112.7	732.8	-	-
	date 100	59.7	108.4	82.2	232.3	-	-
	date 101	82.7	121.2	59.7	186.3	232.2	-
	date 102	163.8	201.0	82.7	148.8	186.2	-
	...	154.8	154.8	163.8	112.8	148.7	2.6
...	...	154.8	154.8	163.8	112.8	148.7	2.6
Year 25	...	108.1	-	154.8	82.2	112.7	2.7
	date 10000	95.4	-	108.1	59.7	82.2	2.8
	date 10001	-	-	59.7	82.8	59.7	1.4
	...	-	-	82.7	163.9	82.7	1.0
...	...	-	-	82.7	163.9	82.7	1.0
Year 40	...	-	-	82.7	163.9	82.7	1.0
	date 10437	-	-	163.8	154.8	163.8	2.1
	date 10438	-	-	154.8	108.1	154.8	2.9

Table 3.1: An illustrative example of stocks from the categorized groups. The "Date" column indicates the number of trading days into the 40-year observation period. Stocks 1 and 2 illustrate the Delisted group, stocks 3 and 4 are examples of the Continuing group, and stocks 5 and 6 represent companies in the Normal group. In each column, values are the average closing prices for that date.

3.4.2 *Network construction*

Next, we determined the edges of these complex financial networks, based on predefined interdependence that characterized a certain relationship or interaction between acting nodes. A considerable number of studies have focused on methods for constructing the edges in stock networks. They include the minimal spanning tree [123, 124, 137], planar maximally filtered graph [125], threshold filtering mechanism [126], and winner-takes-all approach [127]. Other more recent investigations have concentrated on the methods for constructing interdependence, e.g., Pearson correlation coefficients [128], Partial correlation coefficients [129], Pearson product-moment correlation coefficient [138], covariance and Gaussian graphical models [130]. Generally speaking, the Pearson correlation coefficient tends to be the most widely applied methods.

Therefore in our study, we used the Pearson correlation coefficients to construct networks, using pair-wise logarithmic returns for stocks on a daily basis. For this, we let $r_i(t)$ and $p_i(t)$ denote the log-return and closing price of stock i at time t, respectively. The daily log-return can be expressed as follows:

$$r_i(t) = ln[p_i(t)] - ln[p_i(t - \Delta t)] \tag{3.1}$$

where Δt is one trading day, $\Delta t = 1$. Then we write Pearson correlation coefficients [139] $c_{i,j}$ between stock i and j as:

$$c_{i,j} = \frac{< r_i(t) \times r_j(t) > - < r_i(t) > \times < r_j(t) >}{\sigma_i \times \sigma_j} \tag{3.2}$$

where $< . >$ indicates the mean value and σ_i is the standard deviation of the stock i in a time series. The $p-$values were also computed for each coefficient and used as the threshold to prune the networks and filter out those insignificant correlations (a result based on "winner-takes-all" filtering method can be found in Appendix B. This method was not adopted due to its aggressive filtering and consequent information loss on the network topology). In order to avoid severe topological information loss while pruning the edges (according to the evidence shown in [126], the edge density of stock network drops sharply from $c_{i,j}$ = 0.1), we set $p-$value threshold as 0.01 to eliminate weak correlations for $-0.1 < c_{i,j} < 0.1$, replacing them with "0". We then used the coefficient values as edge weights to represent the intensity of connections. Like the positive/negative interactions in social networks [140], we also showed considerations to negative signs in the correlation-based financial networks, and the edge signs were same as the corresponding signs of those coefficients.

In the final step, networks were constructed based on the yearly time window (an comparison with half-yearly time window can be found in Appendix B), which resulted in 40 networks in total (c.f., Table 3.1). One should be aware that we need to identify the population of active stocks in each constructing year. For example, the stock 5 in the table cannot be included until year 10 since it was not listed during those years. However, if a particular stock was newly de-listed in the middle of a given year, e.g., stock 1 in Year 25, it was still considered active for that year because some closing price records remained available in that specific yearly window. It was only counted as inactive thereafter. Thus, for all active stocks in one year, the correlation coefficients were calculated in a "pairwise" manner, meaning that if one of the two columns contained a series of value "NAN" from a certain row, all rows with value "NAN" were omitted, and only the common section was used to calculate the coefficient.

3.5 NETWORK MEASURES

In this section, we discuss and present the acceptability of selected measures for characterizing purpose, that is, we would like to have a preliminary investigation on what network measures could differentiate stocks in different groups. In order to analyze detailed variations of network measures in each group, we focused on the last four years (2013-2016) as a pilot study and constructed networks with a smaller time window of 20 days. In total, there are 1043 trading days from 2013 to 2016 and, therefore, 53 networks were obtained and filtered by the $p-$value.

3.5.1 *Node degree and strength*

Two commonly-applied network measures are briefly explained as follows. **Node degree** is a straightforward nodal measure in complex networks, which indicates the importance of the node in terms of the number of its neighbors. For an undirected network of n nodes, the degree k_i of node i can be expressed in adjacency matrix as:

$$k_i = \sum_{j}^{n} A_{ij} \tag{3.3}$$

Yook *et al.* [141] and Barrat, Barthelemy & Vespignani [142] studied **Node strength** s_i of network properties in weighted networks. It measures the importance of a particular node in terms of its connection intensity. The node strength is defined as the sum of the weights on its total connections/degree. Let W_{ij} denotes the edge weight matrix corresponding to adjacency matrix A_{ij}, the strength s_i can be expressed as:

$$s_i = \sum_{n}^{j} W_{ij} \tag{3.4}$$

The Fig. 3.1(I-A to D) and (II-A to D) are the distribution of node degree and node strength for each group at the same time shots. The results show a similar tendency as revealed in degree ratio distribution. Thus, these three network measures could be appropriate to characterize the performance difference of stocks in each group.

3.5.2 *Degree ratio*

In general, most existing network merely studies encode whether interdependence exists or not [143]. The sign of the interdependence is usually neglected for topological simplification. However, the nodes with a large portion of negative interdependence might have some characters that of great interests for understanding the intriguing features such as hidden community clusters [144] and structure balance [145]. Hence, we paid equal attention to both positive and negative correlations in this chapter to conceptualize our data as signed networks. It is important to notice that a negative edge literately represents the attribute of the edges as a negative relationship or oppo-

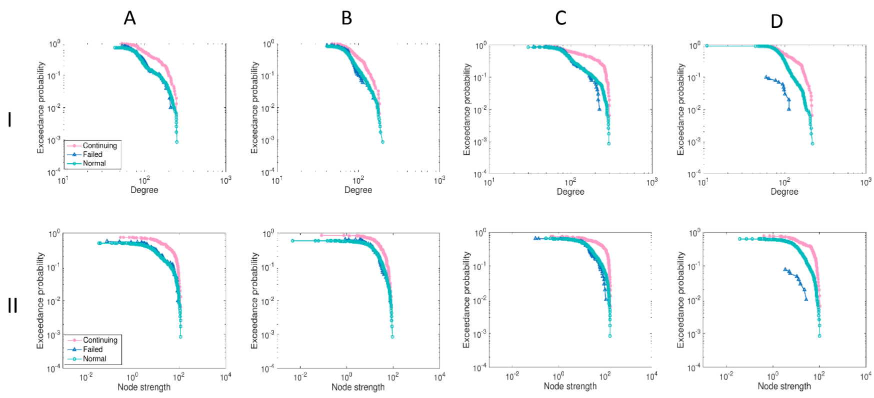


FIGURE 3.1: Distribution of Node degree and Node strength in Continuing, Failed and Normal group. (I) Degree, and (II) Node strength. (A) 2013. (B) 2014. (C) 2015. (D) 2016.

site synchronization, yet not means low or absent interaction between nodes. Two nodes, on the contrary, could be highly interactive and have a strong relationship with negative edge [146].

Different signs on edges could potentially result in clustering phenomenon in balanced and almost-balanced topology [147]. Previous investigations have already shown that a network is clusterable if it is a balanced network [148] so that the edges, which cross boundaries and connect nodes in different cliques, would be negative ones, and positive ones are dispersed towards the center of a clique. This particular feature is similar to what we observed in evolution visualizations of the networks. Hence, we define a network measure, **Degree ratio**, which comprehensively reflects an overall layout of a node's neighborhood, i.e., how central the node is in its clique. Let k_i^+ denotes the number of positive edges of node i and k_i^- denotes the number of negative ones, here, the degree ratio of a node r_i can be correspondingly defined as the following equation. In other words, the ratio is meant to reveal if there could be a possible explanation of survivability of nodes in terms of their associated number of negative neighbors and their positions in a clique.

$$\begin{cases} r_i = \frac{k_i^+}{k_i^-} & \text{if} \quad k_i^- \neq 0 \\ \\ r_i = k_i^+ & \text{if} \quad k_i^- = 0 \end{cases} \tag{3.5}$$

Fig. 3.2 shows a comparative example of normal degree centrality and the proposed degree ratio centrality. One can see that the degree centrality completely ignored the effect of cliques in signed networks. According to the degree centrality, node B is the most important node as it has the highest degree of 5 in the network. However, if we consider the effect of cliques in the network and apply degree ratio to the network, it can be seen that the node B is not the most central node in Clique 1 (degree ratio = 1.5), but node A becomes prominent as it is more "centered" in its Clique 2. In this way, it is clear that using degree ratio can differentiate nodes regarding the central position in their cliques in a signed network, which can provide more information than the traditional degree centrality does.

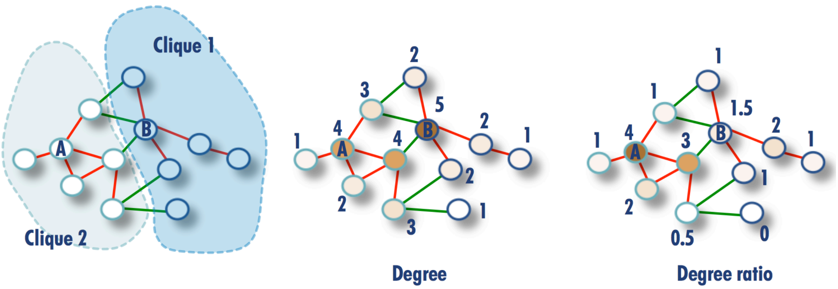


FIGURE 3.2: Comparative illustration of the centrality of degree and degree ratio in a signed network. The green edges represent negative links, and red edges are positive links. Note that there are two cliques in the network and the color of nodes is proportional to their centrality measures.

We then calculated r_i for all stocks in each group and studied its distribution for each year. In Fig. 3.3, of particular note is the fact that the log-log plots of the Continuing group have distinct larger numerical values, compared to the other two groups. On the other hand, there is an evident dynamic changing pattern can be observed for the Failed group. Fig. 3.3(A) and (B) show that by the end of 2013 and 2014 the degree ratio distribution of most stocks in the Failed group overlapped with that of the normal population. This indicates that most of the Failed stocks were acting normally by the end of 2013 and 2014, that is, they were acting with the same characteristic as members of the Normal group did. However, by the end of 2016, the difference among the three groups become significant as shown in Fig. 3.3(D). Note that a larger magnitude distribution in Continuing groups differs a gradual increasing gap between the Failed group and Normal population (see arrows).

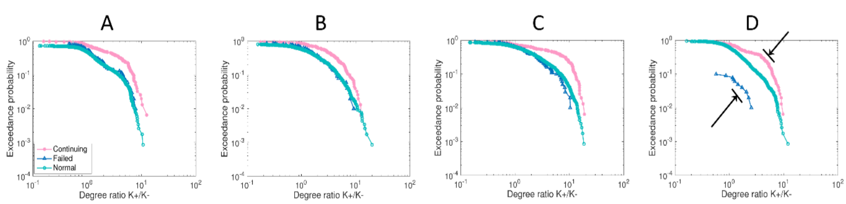


FIGURE 3.3: Distribution of Degree ratio in Continuing, Failed and Normal group. (A) 2013. (B) 2014. (C) 2015. (D) 2016.

Continuing	Intercept A	B (Node degree)	C (Degree ratio)	D (Node strength)
2013	-3.06	0.007	0.018	-0.005
2014	-2.928	0.005	0.048	-0.018
2015	-3.108	0.007	0.01	-0.008
2016	-2.949	0.006	-0.103	-0.028
Failed	Intercept A	B (Node degree)	C (Degree ratio)	D (Node strength)
2013	-2.832	0.007	-0.007	-0.015
2014	-2.569	0	0.032	-0.006
2015	-1.433	-0.015	-0.172	0.024
2016	0.056	-0.034	-1.917	0.155

TABLE 3.2: Coefficients estimated for logit models

3.6 MULTIVARIATE LOGISTIC MODELING

Generalized linear models using logit transformation as link function was applied to perform multivariate logistic regression in both Continuing and Failed groups. The logit models depict the relationship between response probabilities and the predictors, node degree k_i, degree ratio r_i, and node strength s_i, and were presented in the form as:

$$logit(\gamma) = ln(\frac{\gamma}{1-\gamma}) = A + B \times k + C \times r + D \times s \tag{3.6}$$

where γ is the target group, A is the intercept term of the model, and B, C, and D are coefficients of the covariates. The members of the Normal group in modeling were overshadowed since we are primarily interested in identifying the highly-contributed network measures to stock survivability in Continuing and Failed groups. Therefore, we modeled both groups separately and transformed the dependent variable into binomial-distributed responses. For instance, in the modeling of survivability probability members in the Continuing group would be assigned by "1" and others would have values of "0", and vice versa. Of particular note is, in Table 3.2, the fact that the coefficients for both Continuing and Failed groups by the end of 2013 are estimated with relatively low discrepancy comparing with the results obtained in other years. It takes only a moment's reflection to realize that it might be because the features of low survivability of stocks in the Failed group were not prominent at that time.

In Continuing group (Table 3.2), estimated coefficients for Intercept, A, and Node degree, B, are relatively stable throughout entire four years with an average of -3.01 and 0.006 respectively. Results from the Degree ratio, C, and Node strength, D, on the other hand, showed instability and divergent features. Conversely, it is hard to identify any convergent and stability in coefficients of the Failed group, network measures in this group altered in each time, and this could imply the unusual behavior of a node during becoming incrementally vulnerable until it failed. Therefore, we write models for both groups in 2016 as:

$$logit(\textbf{continuing}) = -2.949 + 0.006k - 0.103r - 0.028s \tag{3.7}$$

$$logit(\textbf{failed}) = 0.056 - 0.034k - 1.917r + 0.155s \tag{3.8}$$

In order to investigate further, we performed an analysis of deviance to test the significance of the interactive predictors. Table 3.3 and Table 3.4 consist of significance results from coefficients estimation and analysis of deviance for each predictor. One could notice that the node degree and strength are the first two significant terms in coefficient estimation according to $z-$value tests. Most importantly, the regression can only show us how variation in predictive variables co-occurs with variation in response. What regression cannot show is a cause-and-effect relationship since causation needs extensive studies to be analytically demonstrated. All that regression analysis can tell us is the correlation exists among survivability resilience, node degree, and strength.

2013	Std. Error[a]	Z value	Signif.[b]	Deviance	Resid. Dev.[c]
Continuing					
Intercept	0.206	-14.854	***	Null	969.51
Node degree	0.003	2.225	*	105.374	864.13
Degree ratio	0.025	0.731		2.013	862.12
Node strength	0.006	0.931		0.915	861.2
Failed					
Intercept	0.189	-14.98	***	Null	727.85
Node degree	0.003	2.451	*	0.014	727.83
Degree ratio	0.054	-0.128		6.702	721.13
Node strength	0.006	-2.234	*	4.108	717.02
2014	Std. Error	Z value	Signif.	Deviance	Resid. Dev.
Continuing					
Intercept	0.208	-14.105	***	Null	969.51
Node degree	0.003	1.543		59.59	919.92
Degree ratio	0.081	0.591		28.578	891.34
Node strength	0.008	2.14	*	5.778	885.56
Failed					
Intercept	0.177	-14.536	***	Null	969.51
Node degree	0.003	0.002		0.005	919.92
Degree ratio	0.13	0.246		0.341	891.34
Node strength	0.01	-0.553		0.301	885.56

[a] Standard Error.
[b] Significance indicator: 0 '***',0.001 '**', 0.01 '*', 0.05 '°'.
[c] Residual Deviance.

Table 3.3: Results obtained by analysis of deviance

Nevertheless, observations from deviance column suggest that the node degree has the most significant difference in interaction terms. As can be seen from the Continuing group, node degree obtains high deviance in all three predictive variables, followed by degree ratio and node strength, with small differences between them (except 2014). It denotes that the degree of a node contributes more to the resilient response probability comparing with the other two terms.

On the other hand, in the Failed group the deviance of node degree in the first two years, 2013 and 2014, were not as high as them in the Continuing group. However, in last two years (2015 and 2016, the delisted time for most of the stocks in the Failed group), the node degree regains its

2015	Std. Error[a]	Z value	Signif.[b]	Deviance	Resid. Dev.[c]
Continuing					
Intercept	0.258	-12.057	***	Null	969.51
Node degree	0.004	1.896	0	83.667	885.84
Degree ratio	0.022	0.469		1.921	883.92
Node strength	0.006	1.257		1.685	882.23
Failed					
Intercept	0.186	-7.718	***	Null	727.85
Node degree	0.004	-3.997	***	42.928	684.92
Degree ratio	0.121	-1.415		0.057	684.86
Node strength	0.013	1.748	0	3.316	681.54
2016	Std. Error	Z value	Signif.	Deviance	Resid. Dev.
Continuing					
Intercept	0.277	-10.629	***	Null	969.51
Node degree	0.003	1.824	0	65.895	903.61
Degree ratio	0.107	-0.97		8.637	894.97
Node strength	0.009	3.131	**	10.748	884.32
Failed					
Intercept	0.152	0.37		Null	727.85
Node degree	0.012	-2.979	**	348.72	379.13
Degree ratio	0.846	-2.264	*	0.08	379.05
Node strength	0.045	3.437	***	10.21	368.84

[a] Standard Error.
[b] Significance indicator: 0 '***',0.001 '**', 0.01 '*', 0.05 '0'.
[c] Residual Deviance.

TABLE 3.4: Results obtained by analysis of deviance

dominant role in deviance analysis, followed by a slightly increasing deviance in node strength. Therefore, there do, as well, exists a positive influential power of node degree for characterizing low-survivability response probability. Hence, the node degree has more descriptive power to the survivability resilience of stocks in this case.

3.7 CONCLUSION

To conclude, we studied individual stock's survivability resilience in the overall network in this chapter and established a statistical model to characterize their various resilient behavior in this dynamic evolving market. The following remarks can be summarized:

Firstly, the network measure, degree ratio, acts as a useful metric in signed networks and provides information on neighboring edges. Nonetheless, no significant correlation was, in this case, found between stock survivability resilience and degree ratio, i.e., uneven distributed negative connections in stock networks do not necessarily imply the stock's survivability resilience. Conversely, it has correlations with other two network measures, node degree, and strength. Secondly, the analysis of deviance implies that node degree could be one effective parameter to characterize the survivability resilience of UK equities in London stock exchange, but consideration of overall neighborhood, degree ratio and node strength in signed networks, seem to be less descriptive.

4

MODELING SURVIVABILITY RESILIENCE IN NETWORKS: A FURTHER STUDY

We must become more comfortable with probability and uncertainty.
— Nate Silver

4.1 CHAPTER OUTLINE

This chapter is an extended study of the previous chapter. Here we expanded the scope by using a new and more completed dataset to study the long-term evolutionary process of the London exchange market and the dynamic interdependence among stocks in the networks and applying new modeling approaches to predict their survivability resilience. Because the pilot study in the previous chapter has only studied three network measure, we expanded the number of network measures in this chapter. Also, we tested and validated the predictability of the new models and studied their performance regarding various stock behaviors. This chapter addresses the third challenge: How can we identify and predict resilient individuals in a networked environment using network measures as variables?

4.2 INTRODUCTION AND PROBLEM DEFINITION

Complex network approaches are commonly applied in a wide range of academic fields [103, 104], and studies on network topology have always been an interesting topic. The statistical measures of topology and interdependence are often strongly associated with the performance of network components. For example, in financial stock networks, the topology varies with the different condition of nodes (stocks) and edges (correlation-based interdependence).

As an extension of the previous chapter, an in-depth modeling study with more sophisticated data mining method is needed to explore the individual stock's resilient behavior with details. Thus, we further investigated the market's dynamic interdependence and established predictive models using network measures to predict individual stock's survivability resilience in this chapter.

We focus on further development of the characterization models on individual stock's resilience and specifically contribute the following two aims:

1. To explore the correlation-based interdependence of the whole London exchange market by constructing weighted, signed and temporal stock networks and to understand the long-term dynamic evolution of their topological features.

*This chapter is based on the publication: Tang, J., Khoja, L. and Heinimann, H.R., 2018. Characterisation of survivability resilience with dynamic stock interdependence in financial networks. **Applied Network Science, 3(1), p.23.**

2. With the understandings of the long-term historical evolution process, then to characterize the survivability resilience of stocks via a set of statistical probability models (using interdependence and network measures as variables) and test their predictability.

4.3 DATA AND METHODOLOGY

We used DataStream^{TM} to gather historical data on the daily closing stock prices (adjusted stock price, which accounts for actions such as splits and dividends) for all 7206 companies that had ever traded or were still trading on the London Stock Exchange over a 40-year period (total of 10438 trading days), from 04/05/1977 to 05/05/2017. In doing so, we have the full picture and the whole population of the market during this period. Note that the dataset is completely different from the set studied in the previous chapter. However, the methods for stock categorization and network construction remain the same.

4.4 UNDERSTANDING INTERDEPENDENCE

In this section, we investigate the basic network information extracted from the stock networks and study the dynamic evolution of correlation-based interdependence in long-term observation.

4.4.1 *Network topology*

The growth of networks shows a constant fluctuation in terms of the total number of nodes (Fig. 4.1(a)), the number of yearly listed and delisted nodes (Fig. 4.1(b)), the number of edges (Fig. 4.1(c)), and the network density (Fig. 4.1(d)). Counterintuitively, the market did not constantly expand as the population gradually increased. Subplot (a) presents three major shrinkages and expansions of the market population (Table 4.1 and Table 4.2). The first continuous increase occurred during the first eight years when the number of total nodes increased from 1963 to 2336. However, between 1984 and 1986, many stocks (599) were de-listed due to a severe recession in the early 1980s. This was followed by an increasing number of bankruptcy cases [149].

The second expansion was found in 1992 to 1993 (16th year), when the market grew from 1760 stocks to 2093 in 1996-1997 (20th year), after that the number gradually decreased again until 2003-2004. In the following two years (28th, 2004-2005, and 29th, 2005-2006), the market rapidly expanded. However, from the 30th year (2006-2007), the market rapidly downsized to 1627 stocks in 2012-2013. This trend is even more apparent in subplot (b), which shows the rise and fall in the number of newly listed and delisted stocks. It is interesting that a significant network synchronization existed in the number of edges (see subplot (c)), where a dramatic change in the number of nodes did not necessarily lead to a similar change in the number of edges. This synchronization during a period of massive shrinkage might have improved the correlations between stock pairs, possibly leading to a change in the number of edges. This is also manifested in the density measure in subplot (d), where the network appeared to evolve with same-shape fluctuations. These network measures were strongly associated with the distribution and number of edges, indicating a dynamic "shrinking-and-expanding" behavior in network sparsity and topology. This could have been a set of responses by the market to external stimuli that resulted in a "fission-fusion" evolving behavior.

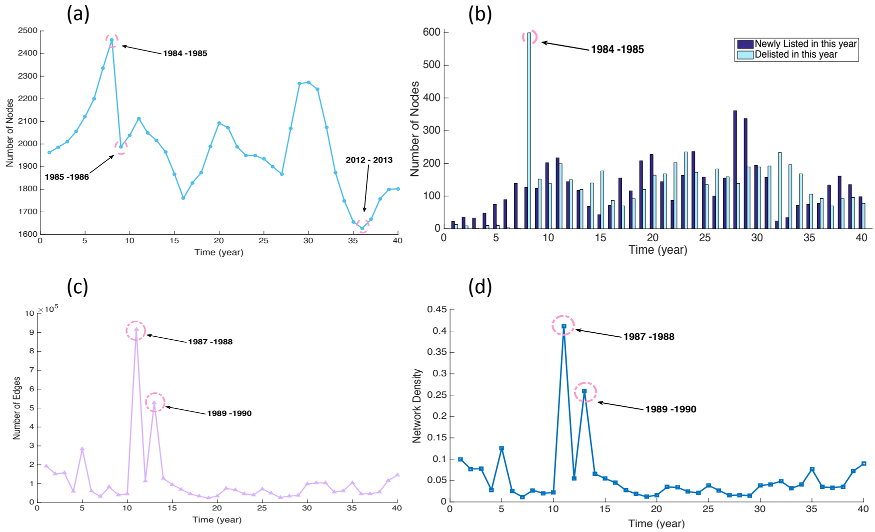


FIGURE 4.1: Evolution of network attributes in time. (a) number of nodes, (b) number of yearly listed and delisted nodes, (c) number of edges and (d) density of the network

4.4.2 *Visualization and basic features of dynamic evolution*

We used *Gephi* with Fruchterman Reingold layout algorithm [150] to visualize eight networks which were roughly selected with an equal time gap. This algorithm is a famous member of a force-directed family, utilizes nodes that are symbolized as solid objects and the edges acting as "springs" between them. By minimizing the energy of the system, the algorithm moves the nodes and changes the forces between them until finally achieves an equilibrium state and then terminates.

Fig. 4.2 shows the visualization results for eight selected networks. Each network has a strong "atom-like" structure, wherein a few nodes were highly interconnected while the rest were sparsely connected around the core. Here, the color and the size of the nodes corresponded to their degree centrality, ranging from large red (high degree) via medium-green to small blue (low degree). Positive edges (positive correlation/interdependence) were indicated with yellow, and negative ones, with light-blue. The thickness of the edges was proportional to their correlation weights.

As can be seen, several high-degree nodes formed a core in each network, which indicated an uneven distribution of edges, i.e., nodes in the core area have a high tendency to connect with other high-degree nodes while nodes with fewer connections were more likely to be marginalized. The core area (highly interconnected stocks) changed in size, possibly due to the "fission-fusion" evolving behavior, which denotes a dynamic and unstable picture of interdependence among stocks.

In addition, most of the positive edges were concentrated around the core area while the negative edges were positioned toward the periphery, such as in subplots (a), (c), (d), (e), and (h). This

No.	Year	Number of nodes	Number of edges	Mean degree	Density	Yearly listed	Delisted	Net growth
1	1977-78	1963	192913	196.5	0.1002	22	13	9
2	1978-79	1986	152314	153.4	0.0773	36	9	27
3	1979-80	2010	157144	156.4	0.0778	33	2	31
4	1980-81	2056	58959	57.4	0.0279	48	10	38
5	1981-82	2121	283672	267.5	0.1262	75	10	65
6	1982-83	2200	60651	55.1	0.0251	89	3	86
7	1983-84	2336	32044	27.4	0.0117	139	2	137
8	1984-85	2461	82441	67.0	0.0272	127	599	-472
9	1985-86	1988	40221	40.5	0.0204	124	152	-28
10	1986-87	2039	45687	44.8	0.0220	202	138	64
11	1987-88	2113	917427	868.4	0.4112	217	199	18
12	1988-89	2049	114460	111.7	0.0546	144	150	-6
13	1989-90	2016	528287	524.1	0.2601	117	120	-3
14	1990-91	1964	127319	129.7	0.0660	68	140	-72
15	1991-92	1867	95383	102.2	0.0548	43	177	-134
16	1992-93	1760	70120	79.7	0.0453	71	87	-16
17	1993-94	1828	45818	50.1	0.0274	155	70	85
18	1994-95	1874	33363	35.6	0.0190	116	92	24
19	1995-96	1989	23959	24.1	0.0121	208	120	88
20	1996-97	2093	34956	33.4	0.0160	227	164	63

TABLE 4.1: Statistic summary of 1977-1997 constructed networks.

interesting distribution of edge signs indicates that, in some years, the core stocks play influential roles as they not only positively interdependent with each other, but also have positive connections with other marginalized stocks. However, it also can be observed that this intriguing pattern does not stably last throughout the time. For example, in subplots (b), (f), and (g), it is difficult to observe the aforementioned evident polarization on the distribution of positive and negative edges around the core.

Table 4.3 shows some basic features of the corresponding networks. The small diameters (most of the networks have a diameter no greater than four) and small average path lengths (less than three) again verify a highly interactive and interdependent feature of the stock networks, which also denote a "small-world" character. Taking a closer look at the percentage of edge signs in each network, we found that the ratio of positive and negative edges can be, although with fluctuations, approximated as 9:1, which indicated that a large number of the interdependence between stock pairs was positively correlated based on our network construction method. Such a high percentage of positive correlations could be one of the consequences of simultaneous market synchronization under market crisis [57] (N.B. Because various methods exist for constructing the correlation coefficient matrix, the pattern we observed here is inferred by applying the Pearson correlation method. In other cases, such as using excess returns with Partial correlation coefficients, the percentage and distribution of the edge sign would be different, see an illustrative example of the year 2016-2017

No.	Year	Number of nodes	Number of edges	Mean degree	Density	Yearly listed	Delisted	Net growth
21	1997-98	2072	75287	72.7	0.0351	144	168	-24
22	1998-99	1988	67088	67.5	0.0340	87	202	-115
23	1999-00	1949	46248	47.5	0.0244	163	235	-72
24	2000-01	1949	39917	41.0	0.0210	236	173	63
25	2001-02	1934	72085	74.5	0.0386	158	135	23
26	2002-03	1900	49091	51.7	0.0272	100	183	-83
27	2003-04	1867	26718	28.6	0.0153	155	159	-4
28	2004-05	2069	34537	33.4	0.0161	361	139	222
29	2005-06	2267	37860	33.4	0.0147	337	189	148
30	2006-07	2273	98924	87.0	0.0383	194	189	5
31	2007-08	2242	103821	92.6	0.0413	157	192	-35
32	2008-09	2073	104141	100.5	0.0485	24	233	-209
33	2009-10	1874	55845	59.6	0.0318	34	196	-162
34	2010-11	1749	62130	71.0	0.0406	71	168	-97
35	2011-12	1656	105045	126.9	0.0767	75	106	-31
36	2012-13	1627	46304	56.9	0.0350	78	93	-15
37	2013-14	1667	46774	56.1	0.0337	134	70	64
38	2014-15	1758	55231	62.8	0.0358	161	92	69
39	2015-16	1800	116737	129.7	0.0721	135	96	39
40	2016-17	1802	145024	161.0	0.0894	98	78	20

TABLE 4.2: Statistic summary of 1998-2017 constructed networks.

Visualization	Year	Diameter	Average path length	Positive edges	Negative edges
a	1977-1978	3	1.848	97.91%	2.09%
b	1983-1984	4	2.129	89.72%	10.28%
c	1988-1989	3	1.955	96.71%	3.29%
d	1993-1994	3	2.013	89.36%	10.64%
e	1997-1998	3	1.958	92.58%	7.42%
f	2003-2004	3	2.175	82.29%	17.71%
g	2009-2010	4	2.152	83.61%	16.39%
h	2016-2017	4	2.013	78.63%	21.37%

TABLE 4.3: Network statistics of illustrated networks.

in Appendix C. However, the comparative study on various methods is beyond the scope of this study. The interested readers can refer to [151, 152]).

4.5 TIME-SERIES NETWORK MEASURES

Based on the understandings of the interdependence and features of topology evolution, we then investigated the possibility of using more detailed network measures to characterize stocks with

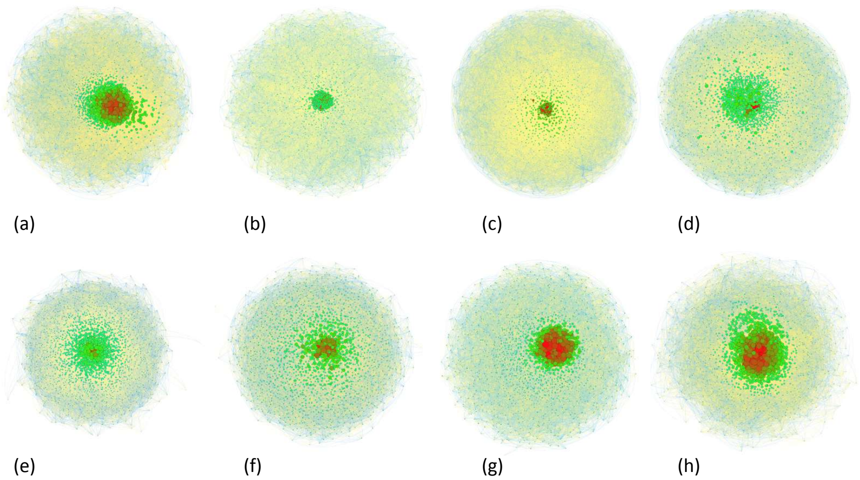


FIGURE 4.2: Dynamic evolution of companies in London Stock Exchange from 1977 to 2017, depicting small-world effect in networks at each step. Node color and size: large red, high degree of centrality; small blue, low degree. Edge color: yellow, positive edge; light-blue, negative edge. Thickness of edges is proportional to weight. (a) 1977-1978; (b)1983-1984; (c) 1988-1989; (d) 1993-1994; (e) 1997-1998; (f) 2003-2004; (g) 2009-2010; and (h) 2016-2017.

different survivability performance. Like what we have done in the previous chapter, we excluded the flow- and route-oriented network measures, such as betweenness centrality and closeness centrality, because the flow and route choice are not the primary concerns in correlation-based networks.

The six selected network measures chosen for our review were: (1) Degree, k; (2) Strength, s; (3) Negative degree, k^-; (4) Eigenvector centrality, e; (5) Clustering coefficient (CC), c; and (6) Average neighbor degree (Ave. neighbor. degree), x. The selection criteria were based on the consideration of their popularity and universality in network literature. We also paid particular attention not only to the interdependence of a target node, but also to the condition of its neighbor nodes as well (i.e., eigenvector centrality, CC, and Ave. neighbor. degree). Because we have introduced the first two measures, degree centrality, and node strength, in the previous chapter, we only briefly explain the rest as follows here.

1. Recalling the degree ratio proposed in the previous chapter, we acknowledge the unique negative attribute on the negative interdependence between stock pairs. However, because we have found that the degree ratio has limited effects on characterizing stock resilience, we here regress to the very basis of considering negative correlations in the stock networks by directly using **Negative degree** in this chapter to conceptualize our data as signed networks. Again, a negative edge literately represents the attribute of the edge as a negative relationship or opposite synchronization but does not indicate a low or an absent interaction between nodes. Let A^-_{ij} denote the negative correlation identified in an adjacency matrix, then:

$$k_i^- = \sum_j^n A_{ij}^- \tag{4.1}$$

2. **Eigenvector centrality** can be seen as an extension of the degree centrality but shows consideration to the relative importance of a node's neighbors. This centrality measure, firstly proposed by Bonacich [153], defines centrality e_i as proportional to the sum of the centrality of neighbor nodes of i, let κ_1 be the largest eigenvalue of matrix A, we have:

$$e_i = \frac{1}{\kappa_1} \sum_j A_{ij} e_j \tag{4.2}$$

3. A useful centrality measure for depicting the relation between pairs of nodes is known as **Clustering coefficient** (CC), sometimes also referred to as transitivity. For each node, the CC is always defined as the local clustering coefficient, which represents the average probability that a pair of node i's neighbors are also connected [146].

$$c_i = \frac{number \quad of \quad pairs \quad of \quad i's \quad neighbor \quad that \quad are \quad connected}{number \quad of \quad pairs \quad of \quad i's \quad neighbor} \tag{4.3}$$

4. The last one is a fairly straightforward measure of node i's neighborhood condition. The **Average neighbor degree** (Ave. neigh. degree) measures the average number of degree that connected to i's neighbors. Let i has n neighbors and their degree can be expressed as k_j, then:

$$x_i = \frac{\sum_j^n k_j}{n} \tag{4.4}$$

We calculated all six network measures for each stock in every stock group during the 40-year period. Using 1988-1989 as an example, Fig. 4.3(a-f) illustrates the exceedance probability distribution of network measures in the three groups. As can be seen, an apparent gap existed as well based on these six network measures, indicating that the Delisted stocks behaved differently regarding all six measures. However, the differences were not as easily spotted between the Continuing and Normal groups, except in the degree and strength distribution plots (Fig. 4.3(a-b)). We found it interesting that subplot (c) revealed a reverse order in the distribution of negative degree for a node, i.e., stocks from the Delisted group tended to have larger negative degrees when compared with stocks from the Continuing group, while Normal stocks fell in the middle.

A similar tendency was found for other years, such as those seen from 1993 to 1994 (Fig. 4.4(a-f)). There, the negative degree distribution profile indicated some variations, and even some crossing and entanglement were found. However, the gaps between each pair of groups were generally clear and distinct, such as the significant difference noted in 2003-2004 (see Appendix D). Thus, we confirmed that each group differed in terms of their nodal features, thereby allowing us to use those differences as appropriate features when characterizing the survivability performance of stocks within each group.

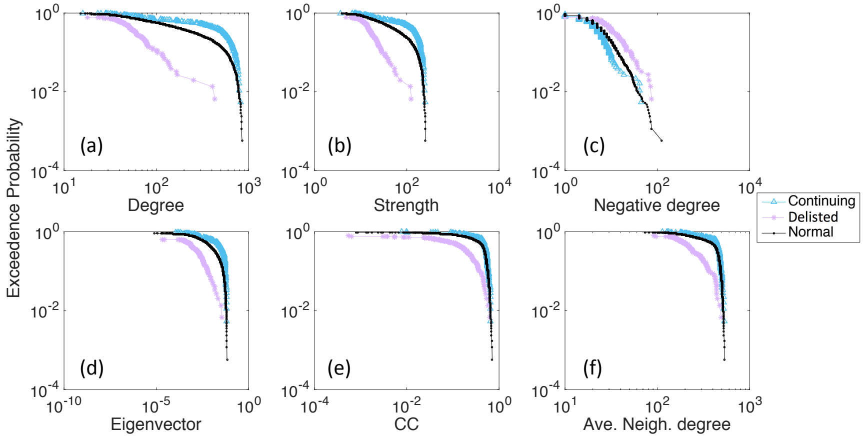


FIGURE 4.3: Distribution of the six network measures in 1988-1989.

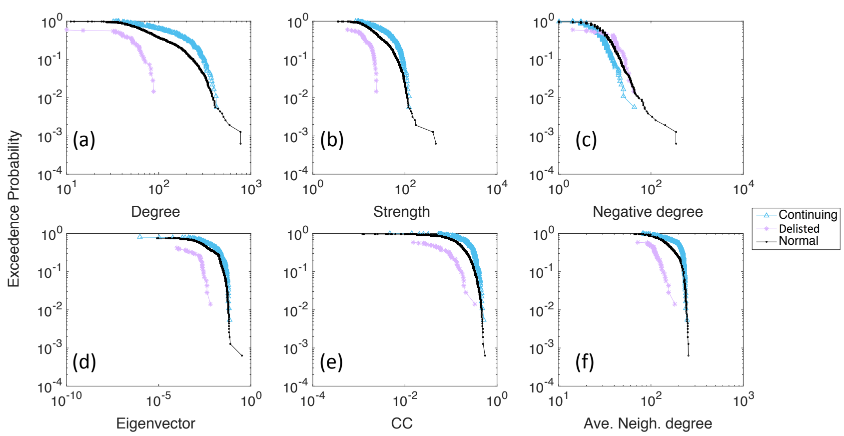


FIGURE 4.4: Distribution of the six network measures in 1993-1994.

4.6 RESILIENCE MODEL

In order to study the possible relationship between stock survivability resilience and dynamic network measures, we constructed a model to characterize the different groups and explored the explanatory strength of each variable. The method applied here was selected as weighted multinomial logistic modeling. The particular reason for such selection is three-fold: First, we categorized all stocks into three nominal groups, and that raises a problem of dealing with multi-class classification. Multinomial logistic regression is suitable for handling the dependent variable which has more than two levels. Second, because the populations of three groups were unbalanced (a large portion of stocks are from the Normal group), we used penalized/weighted multinomial logistic regression to "re-balance" the groups by specifically assigning biased weights according to their actual number of observations. Third, as explained previously [154], the logistic-based classifiers have been shown to possess high transparency when understanding the detailed parameters. Even though their accuracy may not be as excellent as other popular machine-learning classifiers, their capability to facilitate decomposition analysis is still outstanding. It is worthy to note that the regression could only show how the variation in predictive variables co-occurs with variation in response. There is no cause-and-effect relationship guaranteed between survivability resilience and nodal interdependence just based on regression analysis [155].

4.6.1 *Weighted multinomial logistic modeling*

Multinomial logistic models depict the relationship between response probabilities and all six predictors, node degree k_i, node strength s_i, negative degree k_i^-, eigenvector e_i, cluster coefficient c_i and average neighbor degree x_i. According to their nature, such models provide the estimated probability or odds of a target group against a reference group and, in our case, can be presented in the form as:

$$ln(\frac{\alpha}{\gamma}) = A + B \times k + C \times s + D \times k^- + E \times e + F \times c + G \times x \tag{4.5}$$

where α is the target group, γ is the reference group, A is the intercept term of the model, and B, C, D, E, F and G are coefficients of the six covariates. Because we were more interested in the Delisted and Continuing groups as our targets, we used the Normal population as the reference group. Therefore, we modeled the first two against the Normal group and transformed the dependent variables into nominally distributed responses, where "1" represented the Delisted group, "2" was for the Continuing group, and "3" indicated stocks in the Normal group.

The data used to calibrate the models were network data from 1984-2012. The first seven years of networks, cross-referencing Fig. 4.1(b), were not used due to the extremely unbalanced number in the Delisted group (very low number of observations) and the last five years, 2012-2017, were used as testing sets in later sections. This left 28 networks, from 1984 to 2012, for model training and calibration. From there, we gained a total of 55903 stock observations, among which 4875 were in the Delisted group; 5096, in the Continuing group; and the remaining 45932 stocks, in the Normal group.

Coefficients							
	Intercept	Degree	Strength	Neg.degree	Eigenvector	CC	Ave.neighbor.degree
Delisted/Normal	0.841	-0.047	0.140	0.003	-6.372	-5.184	0.003
Continuing/Normal	-0.421	0.003	-0.005	-0.003	1.346	3.805	-0.004
Standard Errors							
	Intercept	Degree	Strength	Neg.degree	Eigenvector	CC	Ave.neighbor.degree
Delisted/Normal	0.0190	0.0013	0.0038	0.0008	0.0007	0.0155	0.0001
Continuing/Normal	0.0218	0.0007	0.0021	0.0009	0.0039	0.0939	0.0001

TABLE 4.4: Estimated coefficients and standard errors

Before starting the model training, it takes only a moment's reflection to realize that apart from two special groups (Delisted and Continuing) the majority of the population would be in the Normal group. The class imbalance problem, if left untreated, could have potentially biased the estimated calibration results and lose accuracy due to different distributions of each class. Treatments for such issue have always been a topic in statistics and machine learning communities [156]. There are several methods claimed as effective such as over-sampling, under-sampling, synthetic minority over-sampling technique (SMOTE) [157] and threshold-moving methods. However, those methods have only been empirically observed as effective in most of the binary classifications, and a satisfactory solution for multi-class unbalance problem still needs investigation [158]. Here, we applied penalized/weighted models for two aspects of consideration: First, the over-sampling and under-sampling approaches would have required random deletions or duplicate tuples in groups, which would have involved unavoidable manipulation of the original data. It would have also been difficult to decide which of the majority and minority groups to be under- and over-sampled, respectively. Second, because we had decided on a fixed model type and were unwilling to manipulate tuple data, a good alternative was to assign weights to bias the model, thereby giving more attention to the minority group. Furthermore, by not manipulating the data, our choice provided a different perspective on the problem by adjusting the models per se.

Each stock can be modeled with a penalized weight determined by its class group during the fitting process. Given a series of multi-class as 1,2,3,...i,...n in total, the weight for class i can be determined as:

$$w_i = \frac{(\sum_{i=1}^{n} N_i)/n}{N_i} \tag{4.6}$$

where N_i is the number of observation in class i. In our case, the stocks in the Delisted group had a penalized weight of $(55903/3)/4875 = 3.822$, while the weights of the Continuing group and Normal group were 3.657 and 0.401, respectively. One can see that the two minority groups had relatively higher weights than the majority Normal group.

Table 4.4 lists the estimated coefficients and their standard errors for the log odds of two groups against the Normal group. The coefficients indicate the effects of the predictor variables on the log odds of being in one category versus the reference category. Note that all of the signs for the coefficients estimated in the Delisted and Continuing groups were utterly reverse. In other words, the different behavior of the Delisted and Continuing stocks, concerning network measures, could relate to reverse effects of the same variables. The standard errors for all predictor variables were rather small.

Also, we tested the significance of the estimated coefficients. We firstly performed a two-tailed z test. Table. 4.5 indicates that all estimated coefficients were very significant for estimation on both groups (very small values). Moreover, a Type III analysis of variance (ANOVA) was carried out to verify this result with an overall significance test on all variables. The test contains evaluation on likelihood-ratio chi-square statistic (LR Chisq) test and their significance p-value test. We can see from Table 4.6 that all variables were tested as "significant" in our modeling analysis.

Thus, we write:

$$ln\{\frac{P(Del.)}{P(Nor.)}\} = 0.841 - 0.047k + 0.140s + 0.003k^{-} - 6.372e - 5.184c + 0.003x \tag{4.7}$$

Two-tailed z test							
	Intercept	Degree	Strength	Neg.degree	Eigenvector	CC	Ave.neighbor.degree
Delisted/Normal	0	0	0	1.136×10^{-3}	0	0	0
Continuing/Normal	0	7.841×10^{-6}	2.651×10^{-2}	1.157×10^{-4}	0	0	0

TABLE 4.5: Two-tailed z test on significance level of estimations

Type III ANOVA				
	LR Chisq	Degree of Freedom	Pr(>Chisq)	Significance level[a]
Degree	1937.55	2	$<2.2\times10^{-16}$	***
Strength	1697.76	2	$<2.2\times10^{-16}$	***
Neg.degree	30.79	2	2.056×10^{-7}	***
Eigenvector	65.61	2	5.656×10^{-15}	***
CC	3078.99	2	$<2.2\times10^{-16}$	***
Ave.neighbor.degree	2979.82	2	$<2.2\times10^{-16}$	***

[a] Significance indicator: 0 '***',0.001 '**', 0.01 '*', 0.05 '0'.

TABLE 4.6: Type III ANOVA test on likelihood-Ratio chi-square test and p-value test

$$ln\{\frac{P(Con.)}{P(Nor.)}\} = -0.421 + 0.003k - 0.005s - 0.003k^{-} + 1.346e + 3.805c - 0.004x \tag{4.8}$$

where $P(.)$ is the probability of being a particular category. Let $y1$ denotes $ln(Del./Nor.)$ and $y2 = ln(Con./Nor.)$, then taking exponential on both sides of the equation, we have:

$$\frac{P(Del.) + P(Con.)}{P(Nor.)} = \frac{1 - P(Normal)}{P(Normal)} = e^{y1} + e^{y2} \tag{4.9}$$

therefore, we were able to calculate the probabilities of an observation being in each category as:

$$P(Nor.) = \frac{1}{1 + e^{y1} + e^{y2}} \tag{4.10}$$

$$P(Del.) = \frac{e^{y1}}{1 + e^{y1} + e^{y2}} \tag{4.11}$$

$$P(Con.) = \frac{e^{y2}}{1 + e^{y1} + e^{y2}} \tag{4.12}$$

Here, we obtained Eq (4.10)-(4.12) as quantitative assessments of the survivability resilience of stocks. For a given stock with corresponding network measures, three probabilities were associated with its calculation of survivability resilience, and the final categorization of such stock depended upon the most likelihood (largest probability) of being in each different group.

To investigate further, we performed an analysis of deviance to test the explanatory strength of interactive predictors. As shown in Table 4.7, node degree, average neighbor degree, and strength were the first three influential terms that contributed the most to the reduction of residual deviance, i.e., 10919.2 from k_i, 2979.8 from x_i, and 2777.2 from s_i. This indicated that these three degree-based measures contributed more in terms of reducing deviance to the resilient response probability when compared with other centrality measures. This supports the findings from the previous chapter as well.

Variables	Deviance	Residual deviance
Intercept		122831
Intercept+k	10919	111912
Intercept+k+s	2777	109135
Intercept+k+s+k^-	1520	107615
Intercept+k+s+k^-+e	17	107598
Intercept+k+s+k^-+e+c	737	106861
Intercept+k+s+k^-+e+c+x	2980	103881

TABLE 4.7: Analysis of deviance.

Fig. 4.5 shows the effect displays of these three degree-based variables in terms of quantified probability for all three groups. In subplot (a) to (c), we can see the probability of being modeled as Delisted was relatively sensitive to the changes in these three variables (probability value varies in the full range from zero to one). In contrast, the sensitivity associated with Normal group fluctuated within a small range. For example, no matter how much drop or raise occurs in these three variables, the maximum probability of being modeled as Normal members were always less than 0.5. Meanwhile, their effects on modeling probability for Continuing group seemed to be in the middle of the former two.

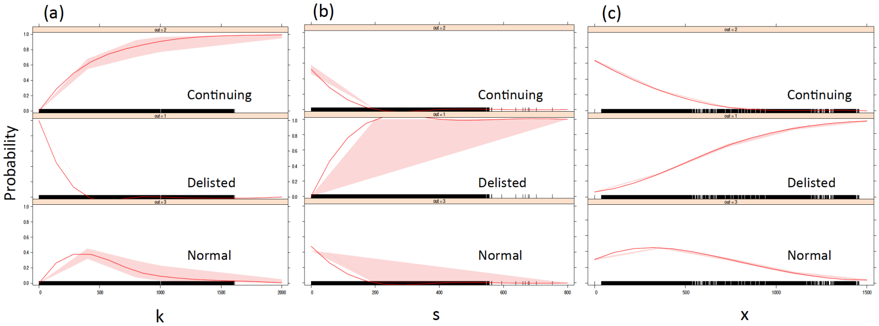


FIGURE 4.5: Effect displays analysis of the three degree-based measures on all stock groups.

4.6.2 *Model testing*

The multinomial logistics model was validated and tested using network data from the last five years of observation, 2012-2017. Taking 2012-2013 as an example, Fig. 4.6 depicts the Receiver Operating Characteristic (ROC) curve analysis of the model performance when predicting the survivability resilience of the stocks during that period. Because the ROC curve is usually used for binary classifiers, we plotted a one-vs-rest ROC curve for each class. The Area Under Curve (AUC) was adopted as an illustrative indicator that quantitatively demonstrated the diagnostic ability of the model. As shown in the figure, model performance with regard to predicting Delisted (AUC=0.733) and Continuing (AUC=0.702) stocks was relatively higher than when it was applied for predicting stocks from the Normal group (AUC=0.626). This might have resulted from the range of dynamic behavior of network measures associated with stocks from different groups, which meant that the uniqueness of nodal interdependence from stocks in the Delisted and Continuing groups could potentially be more abnormal.

By observing ROC plots in Fig. 4.7, it further enhances such interpretation as the AUC values for the Delisted and Continuing groups remained relatively stable around 0.69 to 0.74, while the AUC for Normal group gradually decreased from 0.649 to 0.550, indicating an increasing difficulty in identifying stocks from the Normal group accurately. However, that might have been more achievable if one considered the rationale behind the network measures of these interactive nodes. That is, the continuing stocks would very likely still exist in the near future and, because they were becoming more influential in the core area of the market, then more stocks would tend to correlate with them. This would result in a growing interdependence degree within the networks. Of course, such growth would be heavily subjected to dynamic changes and shifts as the market evolved. However, stocks from the Normal group might also tend to waver between states of failure and continuation, therefore making their accurate identification reasonably tricky. Coincidentally, this matches with the sensitivity insights we found in effect display tests.

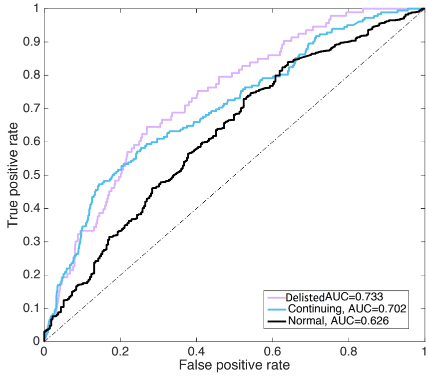


FIGURE 4.6: One-vs-rest ROC analysis of three groups of stocks in 2012-2013.

4.7 CONCLUSION

We addressed the issue of modeling a stock's survivability resilience, using interdependent correlation-based networks. Relying upon big financial market data, we constructed weighted, signed, and temporal networks based on correlations between stock pairs according to their daily adjusted closing prices. As a first step in exploring the dynamically evolving topology of the networks, we identified six suitable measures of network centrality and characterized different stock behaviors

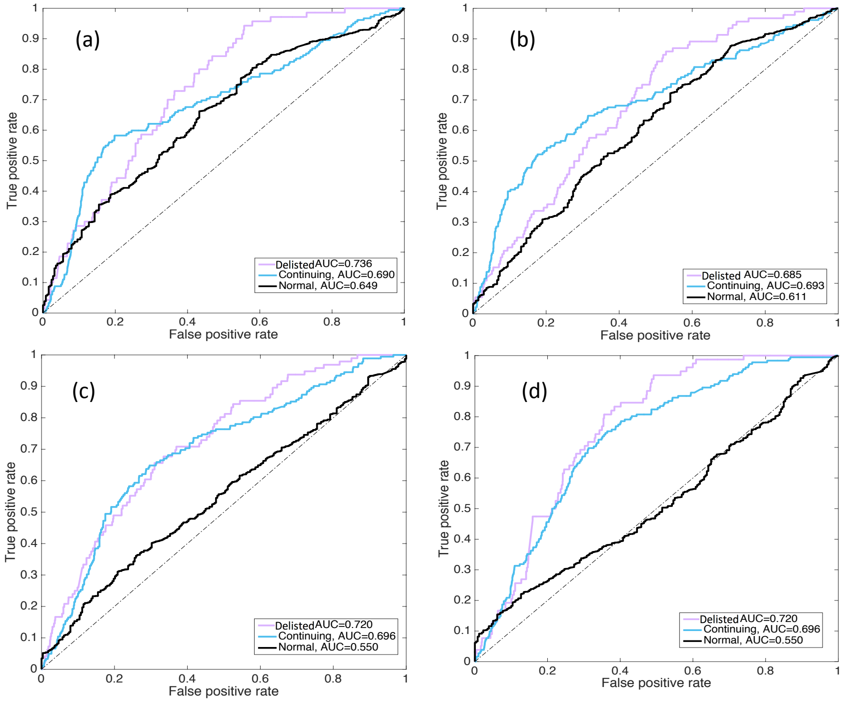


FIGURE 4.7: ROC analysis of three groups of stocks in (a) 2013-2014, (b) 2014-2015, (c) 2015-2016 and (d) 2016-2017.

concerning survivability. To maintain model transparency for each variable, we used those centrality measures as predictor variables to propose a weighted multinomial logistics model and tested the predictability of the model.

This study produced three main findings: First, the market, counterintuitively, does not continually expand exponentially if one considers yearly dynamic "fission-fusion" shifting. Instead, significant fluctuations occur, possibly because the market responds to unexpected external stimuli by dynamically adjusting nodal interdependence. Second, centrality-based network measures were predictive variables when modeling failed or resilient stocks because those measures can adequately capture the abnormal behavior of such stocks. Finally, as supporting evidence for the previous chapter, the results of analysis and model testing suggested that degree-based measures, including node degree, average neighbor degree, and node strength, could be applied as descriptive parameters for modeling the survivability resilience of equities in the London Stock Exchange. However, the effect of variables and AUC values obtained from the Normal group indicated that stocks from this group were more difficult to be predicted.

5

A BAYESIAN NETWORK MODEL FOR ASSESSING SYSTEM RESILIENCE

Infrastructure creates the form of a city and enables life to go on in a city, in a certain way.

— Paul Goldberger

5.1 CHAPTER OUTLINE

In this chapter, we will see how to measure the system resilience by proposing a probability-based graphic model, a Bayesian network model (BNM). We proposed a BNM according to a function-based resilience framework and the ontological interdependence among 10 generic system qualities to probabilistically assess the resilience of infrastructure systems. Taking Beijing's road transportation system as a case study, we tested the model with multi-source data collected from 1997 to 2016 and studied the dynamics of the system's resilience. In addition, the system qualities were examined by analysis of sensitivity and influence. This chapter tackles the fourth challenge of this thesis: How can we use BNM to depict dynamic resilience of infrastructure and study the influence of the system's basic qualities?

5.2 INTRODUCTION AND BACKGROUND

Building resilience in critical infrastructure systems is becoming one of the most concerned priorities for urban governors and practitioners. In this connection, a resilient transportation system is not an exception and assessing the resilience of a city's transportation system is the cornerstone of the study. The methods on how to measure and, most importantly, how to interpret transportation resilience/vulnerability has been continuously developed with topological approaches and system-based approaches [36, 159].

In this chapter, we propose a three-layer hierarchical BNM through a systems perspective, which based on multi-facet system functions and qualities, and evaluate the dynamic resilience of Beijing's road system from 1997 to 2016. After ontologically defining the structure and conditional probability of the model, qualities are valued through multidimensional data, which was collected from various open sources, including annual statistics from central and local governments, transportation bureaus, and private companies.

*This chapter is based on the paper published by *ASCE*: Tang, J*, Heinimann, HR., Han, K., 2019. A Bayesian network approach for assessing the general resilience of road transportation systems: A system perspective. **Proceedings of The 19th COTA Annual meeting (Best Paper Awards).**

5.3 RELATED WORKS

5.3.1 *Resilience of transportation systems*

The mainstream of discussing transportation resilience relies on the application of the percolation theory. Most of the previous works study transportation resilience based on network topology and traffic measurements. By removing links or nodes to mimic deliberate attacks or random failures, topology robustness can then be evaluated through monitoring the performance of the chosen network measures [160, 161]. For example, Cantillo, Macea & Jaller [162] proposed a model for transportation network vulnerability assessments, which can identify critical links for the development of high impact disaster response operations. Wang *et al.* [163] performed a substantial investigation on 10 theoretical and 4 numerical robustness metrics and their performance through the robustness quantification of 33 metro networks under random failures or targeted attacks. An improved approach comes with the consideration of edge weights, which represent additional dimensions to the network topology such as travel time, cost, and travel distance [35]. Also, the travel demand, route choice problems, and user equilibrium are taken into account as well. Proper examples include: a Network Robustness Index that developed based on the change of use equilibrium travel time under edge removal [164], a Vulnerability Index that incorporates traffic flow, travel time, capacities and availability of alternative routes [165], and a combined travel demand model that accounts for trip generation, destination, mode and route choices to measure the long-term equilibrium under single or multiple edge removal [166].

In systems engineering community, the resilience of a system is often perceived as a compounded system capability which consists of critical system functions and qualities [41, 167]. A system perspective considers basic capabilities in system resilience. To differentiate with the network-based approaches, we term the resilience discussed under system frameworks as the general resilience. As one of the urban critical infrastructure systems, some have attempted to study transportation resilience through system perspectives. For instance, Wang *et al.* [168] proposed a day-to-day tolling scheme to promote the rapidity of road traffic resilience in external disruptions. Tang & Heinimann [22] proposed a congestion resilience metric based on "4R" functions for urban roads. Hosseini & Barker [40] proposed a capability-based BNM to measure system resilience in a case of waterway port systems. Boehm & Kukreja [41] studied the system resilience as a compounded capability and explored its ontology relationships with other system qualities.

5.3.2 *Problem definition and contributions*

The following gaps in the literature, including those reviewed above, have been identified here: (1) Most existing studies are based on a single network measure or unilateral capability of the system effectiveness [169]. In the road transportation context, there is a lack of integrated, system-level quantification based on a comprehensive picture of multi-facet enabling functions and system qualities. (2) The long-term and dynamic features of the resilience and strength of the sub-level qualities of a city's road transportation system has been rarely investigated and explored.

Therefore, taking Beijing as the study case, we will specifically contribute the following two aims in this chapter:

1. To propose a BNM for quantifying the resilience of Beijing's road system with multiple qualities from a system perspective.

2. To perform analysis of influence and sensitivity on sub-level qualities and study the overall trend of the dynamic resilience of Beijing's road transportation system in the past two decades.

5.4 METHODOLOGY

5.4.1 *Theory of Bayesian networks*

Bayesian networks (BNs) are widely recognized as an effective and developed technique, based on Bayes' Theorem, for tackling probabilistic assessments and predictions with multiple variables [170]. It is prominent for multi-criteria and multi-facet evaluation but with little application in system resilience modeling [40]. Therefore, we applied this tool in this study.

BNs are graphic representations of uncertain variables and the relationships among them, where the variables are abstracted as nodes, and the interdependence between variable pairs are represented as edges, forming a non-cyclic directed network [38, 39]. The essence of BNs is to compute the posterior probability distribution of target variables (or unobserved variables) conditioned on input variables (or observed variables). Mathematically, let $V = \{X_1, X_2 ... X_n\}$ be the variables in a BNM, where the conditional independence among variables are specified as the topology of the network. An outgoing edge from node X_1 to X_2 indicates that the probability of states in X_2 are dependent on the outcome in node X_1. We call X_1 is the *parent node* of X_2 and X_2 is the *child node*. In general, there are three types of nodes in a given BNM: (1) nodes without ingoing edges (no parent nodes), named *root nodes*, (2) nodes without outgoing edges (no child nodes) are labeled as *leaf nodes*, and (3) nodes with both ingoing and outgoing edges are called *intermediate nodes*. An illustrative example of a BNM is shown in Fig. 5.1.

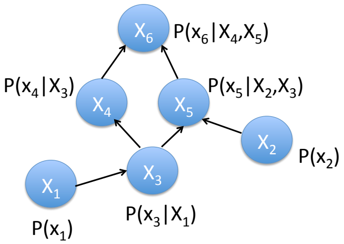


FIGURE 5.1: An illustrative example of a BNM. Here, node X_1 and X_2 are root nodes, X_3, X_4 and X_5 are intermediate nodes and node X_6 is a leaf node.

The dependence or causal relationship between nodes is then defined by conditional probability. Each node in the network is associated with a Conditional Probability Table (CPT) that defines the probability of the node states in the condition of its parent nodes. Therefore, we can calculate the joint probability for full BNM structure, by using the chain rule, into a factorized form with nodes' parents [171]. In this way, for a network contains n variables, its full joint probability distribution can be expressed as:

$$P(X_1, X_2...X_n) = \prod_{i=1}^{n} (P(X_i|\psi_i)) \tag{5.1}$$

where $P(X_1, X_2...X_n)$ is the full joint probability distribution and ψ_i is the parents of node X_i.

In principle, the structure and CPT of a BNM can be learned from a significant amount of observation data. However, these two are generally assessed by expert knowledge for models with unknowns in the leaf node [172, 173]. Therefore, we used specialist knowledge and knowledge-based resilience frameworks to determine the structure and CPT for the proposed BNM.

One of the prominent features of BNM is its ability to perform deductive reasoning, also known as forward analysis, for prediction of the leaf node (T) under the combination of variables ($X_1, X_2, ..., X_n$). The state of variables, certain or uncertain, is input as evidence in the BNM. Compared to fault tree analysis (FTA, a wide-applied method for event prediction), forward reasoning in BNM does not need to obtain minimal cut sets in advance, which significantly increases the computational efficiency [174]. Probability distribution of T, represented by $P(T = t)$, can be calculated as followings.

$$P(T = t) = P(T = t|X_1 = x_1, X_2 = x_2, ..., X_n = x_n) \times P(X_1 = x_1, X_2 = x_2, ..., X_n = x_n) \tag{5.2}$$

where, $t = t_1, t_2, ..., t_P$ is a range of P states for the node T, and $P(T = t|X_1 = x_1, X_2 = x_2, ..., X_n = x_n)$ denotes the conditional probability distribution of T. $P(X_1 = x_1, X_2 = x_2, ..., X_n = x_n)$ represents the joint probability distribution of X_i.

5.4.2 *Elements and structure of the model*

For the structure of the BNM, we established a three-layer hierarchical topology. The first layer includes four resilience capability functions, the second layer consists of 10 system qualities related to the four functions, and the third layer is the indicators that act as elements of root nodes in the quality layer to kick off the calculation and probability propagation in the BNM.

The four resilience capability functions adapted were from a function-based resilience framework proposed by [50]. In this work, they argued that biophysical functions - resistance, restabilization of critical functionality, and rebuilding and reconfiguration of that functionality - could be used to quantify system resilience as a promising start point. In urban road systems, these four functions depict four abilities of being resilient, that is, (1) To keep overall functionality degradation within an acceptable limit; (2) To restabilize the system performance after external disturbance; (3) To rebuild the performance after deteriorations; And (4) To reconfigure the system after recovery for future events. These four elemental functions, in turn, outline the responsive actions of a road system from pre-event to post-event stages, which eventually characterize its overall resilience.

Below the function layer, we identified 10 system qualities as the second layer (quality layer) of the network, which have significant contributions to those four functions and promote general system resilience. They include Availability, Serviceability, Robustness, Safety, Maintainability, Repairability, Affordability, Changeability, and Adaptability. For example, road systems have to maintain a suitable level of serviceability (ability to provide proper services) in order to be resilient in performance during a disruption event such as massive congestion. In the meantime, it only takes seconds to realize that we would expect a resilient road system to be safe against traffic accidents and economically affordable for all users. However, these qualities are not mutually independent. Here in Fig. 5.2, we adapted the ontology structure (interdependence) of these 10 qualities [175] in our BNM.

Next, one more indicator layer was added below the quality layer. These indicators were deliberately chosen from the road system performance. Here, we have 6 root quality nodes in the network (Serviceability, Robustness, Safety, Repairability, Affordability, and Adaptability). Each root node has a various number of indicators attached (Circular nodes in Fig. 5.2) for initial inputs of the BNM. Table 5.1 summarizes the indicators for each root quality nodes in the proposed BNM.

Root nodes	Indicators
Serviceability	1. Total road length
	2. Average annual free-flow index
	3. Average annual passenger capacity
Robustness	1. Economic losses in natural disasters
	2. Investment in disaster prevention in urban roads
Safety	1. Total number of annual injuries in traffic incidents
	2. Total number of annual accidents
Repairability	1. Annual increased area of paved roads
	2. Total number of personnel in the sector
Affordability	1. Ratio of the expense of transportation per capita
Adaptability	1. Ratio of the granted patents in transportation sector

TABLE 5.1: The indicators for root nodes

5.4.3 *Baseline of the proposed model*

In the proposed BNM, we set binary *positive* and *negative* states in all variable nodes for simplification. For example, node "Resilience" has "Resilient" and "Vulnerable" states and "Reliability" has "Reliable" and "Unreliable." In this way, we obtained a baseline BNM in Fig. 5.2. For CPT of each variable node, we used expert judgment on the conditional probability for each table because an exact knowledge of data is not available. Fig. 5.3 illustrates an example of the CPT of variable Reliability.

In this study, the computation process was completed in GeNIe software, a graphical modeling user interface developed by the Decision Systems Laboratory from the University of Pittsburgh [176]. GeNIe allows for interactive model building and learning. It has been thoroughly tested in the field since 1998, has received a wide acceptance within both academia and industry [177].

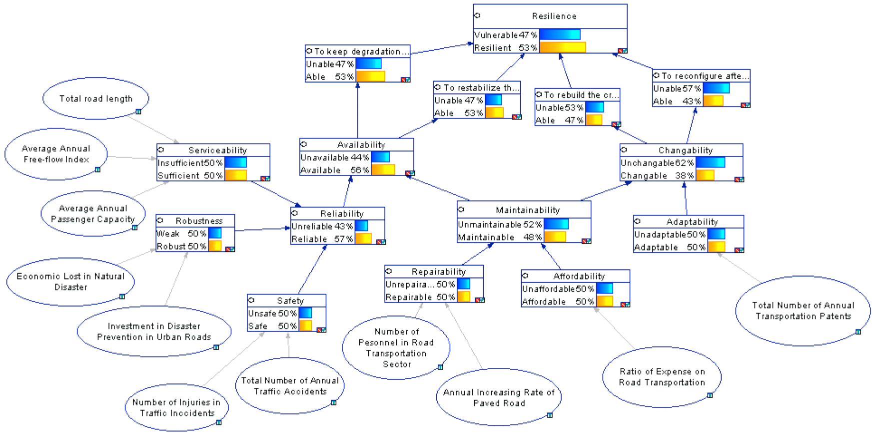
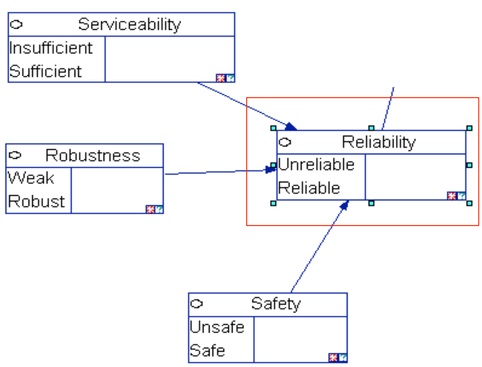


FIGURE 5.2: The structure of the proposed BNM and determined CPT. For illustration, we also include indicators as circular nodes. Note that the grey edges between indicators and root nodes represent "consist of" relationship, not conditional dependence. (Here, we use technological innovation to represent system's ability to make changes, improvements, and adaptations)

(a)



(b)

Safety	Unsafe				Safe			
Robustness	Weak		Robust		Weak		Robust	
Serviceability	Insufficient	Sufficient	Insufficient	Sufficient	Insufficient	Sufficient	Insufficient	Sufficient
Unreliable	0.9	0.4	0.3	0.2	0.85	0.7	0.45	0.1
Reliable	0.1	0.6	0.7	0.8	0.15	0.3	0.55	0.9

FIGURE 5.3: The conditional probability table for node Reliability in the model.

5.5 EMPIRICAL STUDY

5.5.1 *Data collection and treatment*

The data was collected from multiple sources, including the National Bureau of Statistics of China, the Ministry of Transport of the People's Republic of China, TomTom Traffic Index, and Annual reports from Alibaba's Amap traffic group. We collected data for all the indicators from 1997 to 2016 in Beijing's urban area. The original dataset contains missing data and we treated them with the following methods: (1) For those indicators with no apparent growth rate and a small number of missing blanks, we fill in the blanks with the median value; And (2) For those with a linear or exponential growth, we fill in the missing data with regression predictions.

5.5.2 *Initial input in root nodes*

Some qualities have multiple indicators, the overall values of these qualities were taken with an aggregated perspective. For clarification, we here demonstrate an example on how to obtain an aggregated value for a root quality node - Serviceability. We have three indicators contributing to the overall serviceability level of Beijing's road transportation system, namely total road length (million km), average annual congestion index (dimensionless with max. index of 2.5), and average annual passenger capacity (million people). Among them, the annual congestion index can be calculated directly with a form of percentage as 2.06/2.5=82.4%, where 2.06 is the average annual congestion index of Beijing's traffic in 2016 and 2.5 is the upper bound of the index domain. Because congestion is a negative-effect indicator, we converted it as 1-82.4%= 17.6% to represent the free-flow capability. Values of the rest indicators were converted into probabilities with cumulative probability density (Fig. 5.4). After obtaining probabilities of all three indicators, the yearly aggregated probability of the serviceability quality was taken as the algebraic mean of all probabilities contributed from these three indicators. Table 5.2 presents an example on how to obtain the aggregated probabilities of serviceability from raw data. We can see that the overall serviceability of Beijing road transportation system was not as high as expected in those observation years due to severe congestion (calculations for the rest of the root nodes can be found in Appendix E).

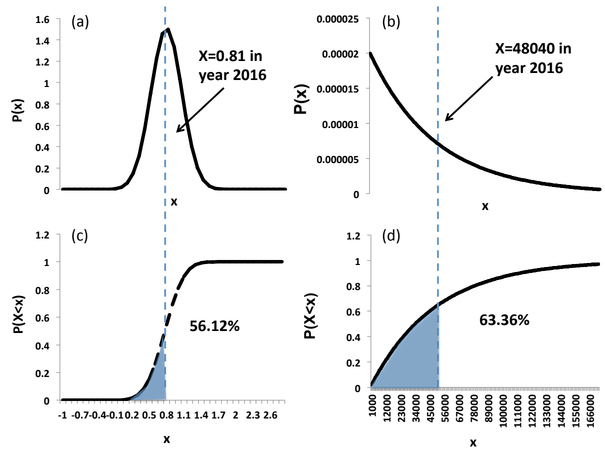


Figure 5.4: Using cumulative probability density to calculate the initial input of indicators

Year	Indicator 1	Probability	Indicator 2	Indicator 3	Probability	Aggregated Serviceability
2016	0.81	0.56	0.176	48040	0.62	0.45
2015	0.81	0.56	0.176	49931	0.64	0.46
2014	0.81	0.56	0.176	52354	0.66	0.46
2013	0.79	0.53	0.176	52481	0.66	0.45
2012	0.79	0.53	0.176	132333	0.93	0.55
2011	0.63	0.30	0.176	129918	0.93	0.47
2010	0.64	0.31	0.176	126130	0.92	0.47
2009	0.62	0.29	0.176	121373	0.92	0.46
2008	0.62	0.29	0.176	117118	0.91	0.457
2007	0.55	0.20	0.176	9275	0.17	0.18
2006	0.59	0.25	0.176	2482	0.049	0.16
2005	1.59	0.99	0.176	2261	0.045	0.41
2004	0.75	0.47	0.176	41463	0.57	0.41
2003	0.75	0.47	0.176	24940	0.40	0.35
2002	0.75	0.47	0.176	22103	0.36	0.34
2001	0.75	0.47	0.176	16630	0.29	0.31
2000	0.75	0.47	0.176	13009	0.23	0.29
1999	0.75	0.47	0.176	9878	0.18	0.28
1998	0.75	0.47	0.176	6704	0.13	0.26
1997	0.75	0.47	0.176	4903	0.095	0.25
Mean	0.77	-	-	49166.3	-	-
STD†	0.27	-	-	50489.61	-	-

$*$ we only have data on Average annual congestion index from 2011 to 2016, the missing data in other years were filled with the mean to the nearest integer.
† Standard deviation.
− Not applicable.

Table 5.2: Converting the raw data into the initial inputs for "Serviceability"

5.5.3 *Resilience of the road system*

The rest of the indicators were converted into probability density and aggregated to obtain values for other root nodes in the same way. Table 5.3 presents the aggregated probabilities of serviceability, robustness, safety, repairability, affordability, and adaptability in the observation years. By illustrating these qualities in time series, we can see from Fig. 5.5 that Serviceability, Robustness, Safety, and Repairability have been increasing with some significant fluctuations since 2002 in the past two decades. In contrast, the Affordability and Adaptability have remained relatively steady with a small increase during the last 10 years.

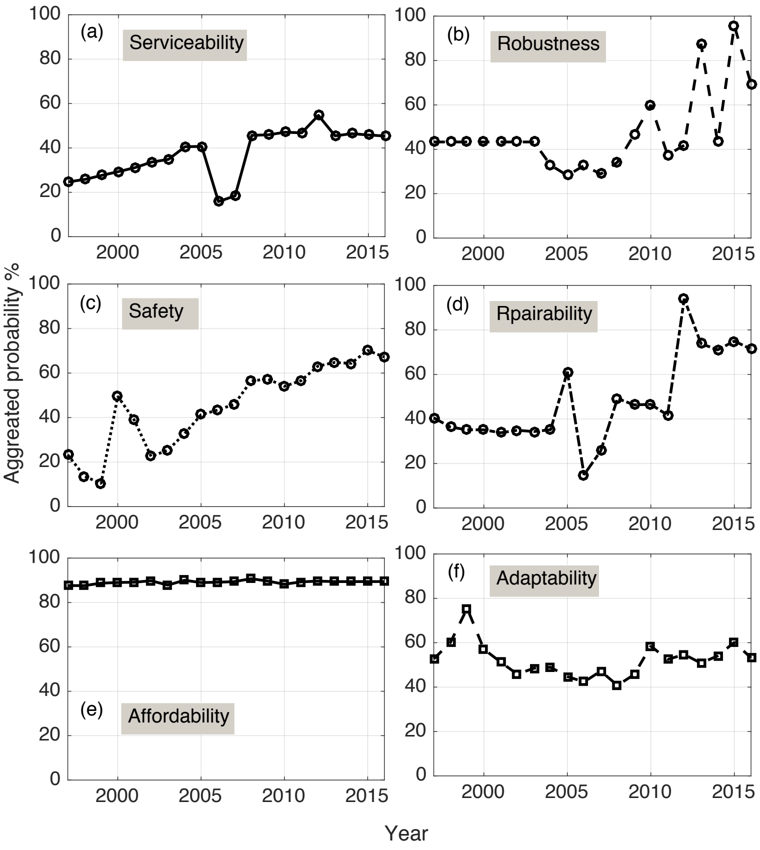


Figure 5.5: Temporal tend of quality nodes

Fig. 5.6 shows the quantification result of the resilience in 2016. As can be seen, the resilience of Beijing's road transportation system in 2016 had a moderate probability of 62% being resilient. The serviceability of the system was relatively unsatisfactory. One possible explanation, as mentioned above, could be that the well-known traffic congestion in Beijing severely deteriorates the overall serviceability. However, the performance of other qualities was mostly adequate with a higher chance of being positive. Notably, the system's probability of being affordable was comparatively high (around 89%). This is true when considering the low cost of transportation in Beijing. In addition, we can also observe that the maintainability, adaptability, reliability, and availability of the system were all positively developed, and eventually led to a moderate level of resilience in 2016.

Year	Serviceability	Robbustness	Safety	Repairability	Affordability	Adaptability
2016	45.36%	69.34%	67.20%	71.41%	89.43%	53.18%
2015	45.83%	95.80%	70.17%	74.96%	89.43%	60.16%
2014	46.41%	43.31%	64.36%	71.03%	89.42%	54.06%
2013	45.45%	87.54%	64.75%	73.88%	89.42%	50.81%
2012	54.65%	41.80%	63.07%	93.99%	89.63%	54.72%
2011	46.81%	37.49%	56.59%	41.76%	89.30%	52.45%
2010	47.06%	59.98%	54.04%	46.55%	88.23%	58.49%
2009	45.92%	46.57%	57.32%	46.34%	89.65%	45.63%
2008	45.67%	34.20%	56.45%	49.18%	90.73%	40.79%
2007	18.39%	28.86%	46.01%	25.64%	89.41%	47.20%
2006	15.81%	32.68%	43.39%	14.95%	89.12%	42.32%
2005	40.67%	28.22%	41.27%	61.24%	88.99%	44.75%
2004	40.56%	32.83%	32.69%	35.16%	90.01%	48.93%
2003	34.83%	43.31%	25.34%	34.35%	87.84%	48.51%
2002	33.64%	43.31%	22.54%	34.92%	89.80%	45.84%
2001	31.13%	43.31%	38.76%	33.80%	89.14%	51.31%
2000	29.32%	43.31%	49.58%	35.14%	89.01%	57.09%
1999	27.64%	43.31%	10.40%	35.14%	88.72%	75.48%
1998	25.82%	43.31%	13.65%	36.36%	87.62%	60.12%
1997	24.73%	43.31%	23.28%	40.51%	87.62%	52.70%

TABLE 5.3: Estimated probability of quality root nodes

We further quantified its resilience for the rest years. Fig. 5.7 shows the quantification results for all 20 years (the list shows the numerical values, and the figure is the bar plot with the approximated trend line). A clear 'bathtub' or a 'V-shape' trend line can be observed. Before 2006, the system had reasonable probabilities of being resilient in each year with some unstable yearly fluctuations. However, in 2006, there was a drastic drop. This instability could be a result of the rapid city expansion, weak urban governance, population growth, and economic volatility during the early years. After 2006, the indicator shows a prominent increase. Because there have been improvements in many aspects of Beijing's road system in recent years, this could be a possible explanation for this steep increasing trend.

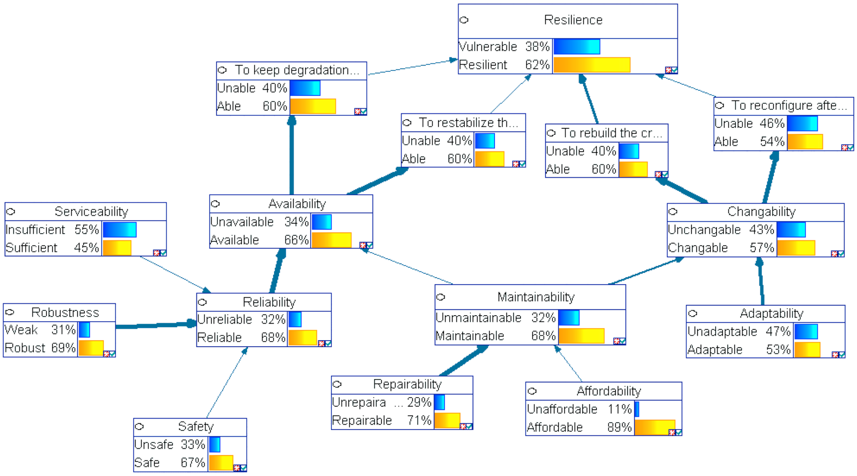


FIGURE 5.6: Estimated the general resilience of Beijing's road system in 2016

Year	Probability of being Resilient
2016	62%
2015	66%
2014	59%
2013	64%
2012	62%
2011	56%
2010	60%
2009	56%
2008	54%
2007	52%
2006	51%
2005	56%
2004	55%
2003	56%
2002	55%
2001	56%
2000	57%
1999	61%
1998	58%
1997	57%

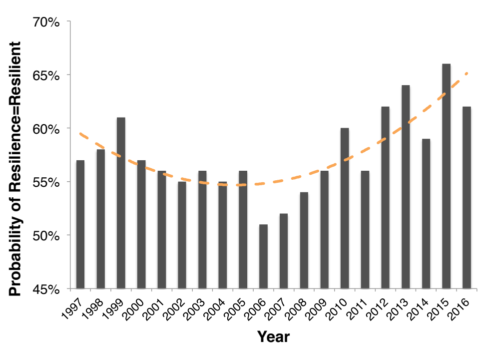


FIGURE 5.7: Temporal result of resilience from 1997 to 2016. (Yellow line: Trend line.)

5.5.4 *Sensitivity analysis and strength of influence*

With the understandings of BNM's quantification strength, this section further tests the sensitivity and influence of the qualities.

Fig. 5.8 presents the illustration of sensitivity and strength of influence for each quality and function. The thickness of the edges demonstrates the strength of influence. At the function level, the ability "to rebuild" had the most power to influence the overall resilience. At quality level, strong influence can be found in two parts. The first part was those strong influence among robustness-reliability-availability and the first two functions, and the second part was among repairability via maintainability, changeability and the last two functions. We also observed a strong influence between Adaptability and Changeability.

Node color represents the degree of sensitivity. The result shows that overall resilience of this transportation system was prominently sensitive to the changes in the ability "to rebuild" at the function layer, and robustness, repairability, changeability, and adaptability at the quality layer. Further exploration of sensitivity confirmed this observation. By plotting the sensitivity tornado (Fig. 5.9), we see that top 20 conditions (with "Resilience = Resilient") involves the function of rebuilding, adaptability, changeability, repairability, and robustness. This intuitively indicates that the ability to rebuild its functionality performance after disruptions, its ability to quickly adapt and make changes, and its robustness and ability to repair damaged parts are essential roles in the resilience of road transportation systems. Most importantly, effective strategies could be possibly developed based on this finding when building resilience into road systems.

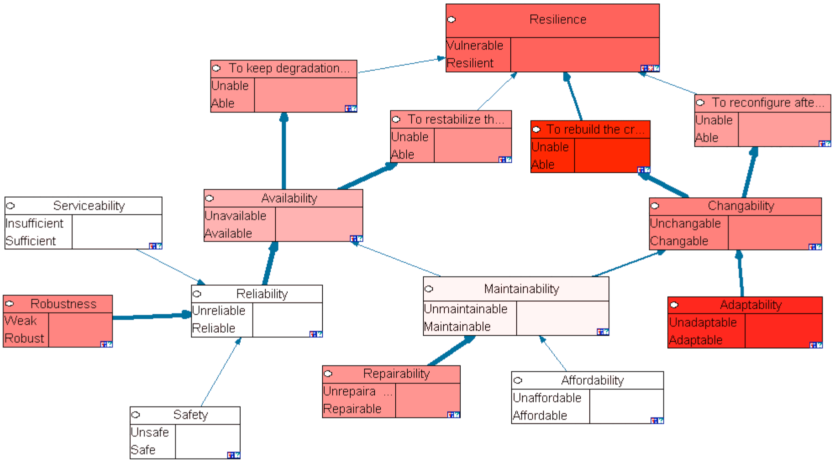


FIGURE 5.8: Sensitivity test and strength of influence analysis. (The thickness of the edges represents the strength of influence, and redness of the box represents the degree of sensitivity).

5.6 CONCLUSIONS

The importance of resilience in the context of infrastructure planning and management is increasingly emphasized in recent years. This chapter addressed the quantification issue of the general resilience in Beijing's road transportation system by proposing a Bayesian network model (BNM) with a system-level perspective. We have concluded the following in this chapter:

- The proposed BNM is a promising tool for multi-dimensional and systematic analysis, instead of finding a one-size-fits-all quantification criterion for the resilience.
- For the past two decades (1997-2016), the general resilience of Beijing's road system exhibits a "V" shape in its trend, with the probability of being generally resilient between 50% and

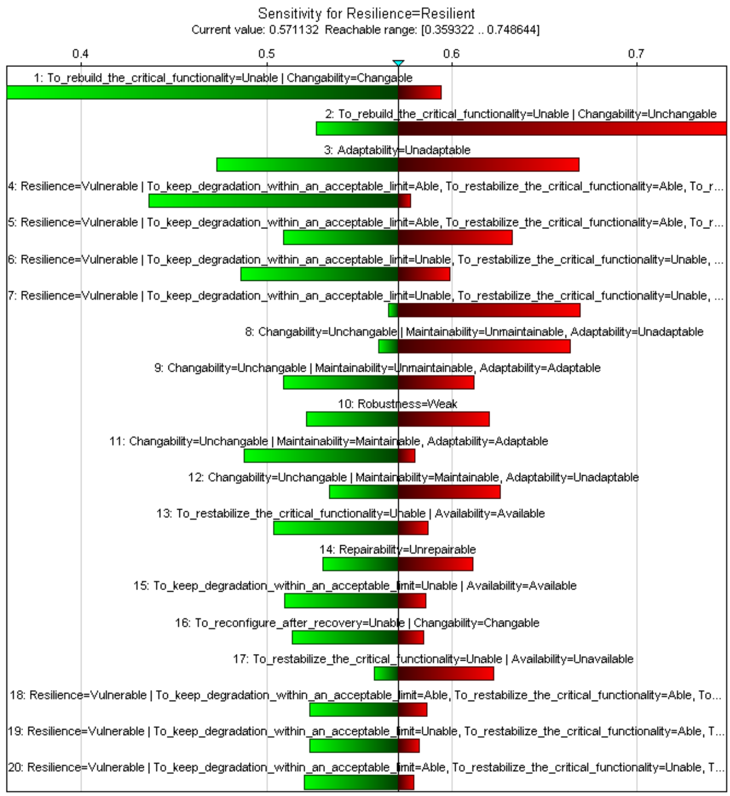


Figure 5.9: Tornado plot of the sensitivity test

70%, and at its minimum in 2006. There was a steep increase in such a probability since 2006.

- The analysis on sensitivity and strength of influence indicates that the general resilience of Beijing's road transportation system is mostly affected by its capabilities: (1) to rebuild its performance, (2) to be robust, (3) to adapt, (4) to change, and (5) to quickly repair damaged parts.

The BN methodology proposed in this chapter has two critical limitations. During the determination of the BN structure, the decision was made heavily depending on a large amount of expert knowledge, including explicit and tacit suggestions and recommendations. However, this process is extremely laborious and replies significantly on experts' subjective knowledge. Also, such knowledge-based models can hardly be validated. As a suggestion, we will attempt to use real event data to validate or even learn the structure and parameters of the BN model in the future.

6 SYNTHESIS

We cannot impose our will on a system. We can listen to what the system tells us, and discover how its properties and our values can work together to bring forth something much better than could ever be produced by our will alone.
— Donella H. Meadows, Thinking in Systems: A Primer

6.1 MAIN FINDINGS

This thesis focuses on the quantitative assessment of resilience in complex systems. As a methodology-oriented study that is mainly based on applying various methods in different applications, the thesis studies quantitative tools in three main assessment categories, namely performance-based metrics, network-based approaches, and probability-based graphic models, respectively.

We begin the main findings section with a recapitulation of the objectives of this thesis. The four research challenges in the Introduction section can be summarized as the following objectives: (1) to measure resilience in complex system performance, such as consecutive resilience cycles, with a generic metric built upon a system's elemental functions. (2) To characterize individuals' resilient behaviors in a swarm environment using a complex network approach. After characterization, (3) To identify and predict resilient individuals in such complex networked systems. (4) To use probability-based graphic models to depict dynamic resilience and study the influence of system qualities. In accordance, this section summarizes the main findings of the thesis as follows:

The performance-based resilience metric part (**Chapter 2**) was aimed at developing a resilience metric for quantitative assessment based on more generic functions from system characters and test its strength in the complex performance of stock markets. It answers the question "How to measure resilience in complex system performance, such as consecutive resilience cycles, with a generic metric built upon the system's elemental functions?" This chapter provides a more comprehensive performance-based metric for researchers and practitioners, and the findings could improve the understandings of the resilience dynamics and resilient behaviors in complex system performance. The study resulted in the following major findings:

- This new metric characterizes the performance of consecutive resilience cycles, for which the drawup phase remains below or goes beyond the pre-event performance.
- The application of the metric to a time series of resilience cycles indicated that the resilience performance per se has a stochastic property, the distribution of which can be characterized with a power-law distribution in the upper tail.

The swarm resilience analysis part (**Chapter 3**) was aimed at characterizing the resilience of an individual firm within a swarm of firms, considering the interdependencies between those firms. By doing so, this chapter answers the question "How can we characterize individuals' resilient behavior in a networked environment using a complex network approach?" The applied methodology was a regression modeling technique, and the case study was the London stock market. This chapter provides a novel alternative for inspecting resilient individuals in a highly interactive system environment and is potentially helpful for investors to perceive bankruptcy in stock markets. We can summarize the following main findings in this study:

- Node degree and strength have a descriptive effect on characterizing the survivability resilience of individual stocks in a networked market environment.
- The ability to have more correlated neighbors contributed the most significant effect in the analysis of survivability resilience.

The swarm resilience prediction part (**Chapter 4**) was aimed at developing further statistical models to predict and depict individuals' resilient performance as a function of interdependency parameters. As a further study of the previous chapter, this chapter answers the question "How can we identify and predict resilient individuals in complex networked systems?" The study subject was the entire population of the London stock exchange market in 40 years. This chapter proposes a novel approach for predicting the resilience of the stocks in the market environment and provides quantitative benchmarks for shareholders, decision- and policy-makers. The main findings of this chapter can be summarized as follows:

- The London stock market yielded a "fission-fusion" evolution pattern in terms of the network topologies, which indicated the dynamic and complex characteristics of its evolutionary process.
- The proposed models and associated network variables can be used to predict most and least resilient stocks relatively. This phenomenon might be due to the random features in degree-related centrality measures of each participant in the network, i.e., the resilience of individuals can be revealed by conditions of connectivity in a networked market.

The final part of the compound resilience quantification model (**Chapter 5**) was aimed at developing a Bayesian network model (BNM) that connects interdependent system properties, such as reliability, availability, robustness, and reconfigurability, to estimate the fabric resilience of a complex infrastructure system. This chapter is designed to address the question "How can we use probability-based graphic models to depict dynamic resilience and study the influence of system qualities on it?" Beijing's road transportation system was applied as the empirical study in this chapter. The findings in this chapter indicate that the proposed model is a promising tool for multi-dimensional and systematic analysis, instead of finding a one-size-fits-all quantification criterion for system resilience. The main findings yielded from this study can be summarized as follows:

- We represented systemic compound resilience with a Bayesian network, consisting of a whole range of system properties. Framing resilience as a compound property means that systemic fabric resilience is a property that is located on a Pareto frontier, the exact location of which depends on value judgements. This means that there is no right or wrong resilience, at a resilience trade-space, which allows us to understand the trade-offs between different system properties.

- Application of this BNM to Beijing's road system indicated that its probability of being generally resilient was between 50% and 70%. However, there was a steep increase in such a probability since 2006. This finding provides strong evidence that the system resilience should be assessed and viewed from a dynamic perspective.
- The case study also revealed that the resilience of road transportation systems can be most affected by its capabilities: (1) to rebuild its performance, (2) to be robust, (3) to adapt, (4) to change, and (5) to quickly repair damaged parts. This result supports our perceptions on what system qualities are driving factors in system resilience. Because of the generality of the applied approach, we believe this finding could be generic in other infrastructure systems.

6.2 DISCUSSION

6.2.1 *Body of knowledge*

The resilience metric studied in **Chapter 2** pushed forward the frontier of the studies in the traditional "Resilience-Triangle" and rounded off some basic assumptions of this classic performance-based model. By and large, there are two mainstreams developed in the field of the quantitative resilience metrics. The most well-known one is the "Resilience-Triangle". In particular, if one considers that the performance of a system decreases after an external shock but recovers after a certain length of time, then a very straightforward proxy for a system's resilience loss is the decline in performance, which is defined by the following factors: (1) the failure process (measured from the level of performance immediately before the shock to the lowest performance after the shock), (2) the recovery process (from the lowest performance to the post-event performance after the recovery), and (3) total time between the shock and the end of the post-event recovery. The second research stream consists of state-oriented models, which leverage a multi-state, multi-phase analysis framework to study the resilient behavior in system performance. Models in this stream advance the triangle approach by considering "failure" and "recovery" states. The former phase includes brittle, ductile, and graceful cases, whereas the latter considers six cases: (1) expeditious recovery to better-than-new, (2) expeditious recovery to as-good-as-new, (3) expeditious recovery to better-than-old, (4) expeditious recovery to as-good-as-old, (5) recovery to as-good as-old, and (6) recovery to worse-than-old. This multi-state model accommodates the natural effects of aging, the role of time, the possibility of adaptive recovery performance, and the stochastic property of a system's general behavior.

This triangle approach relies on several fundamental assumptions: (1) the system is bouncing back to the pre-event performance, (2) a single resilience cycle is independent of other resilience cycles, and (3) a system resilience can be derived by integrating resilience of individual components in space. Our work relaxed these assumptions by proposing a novel metric to deal with different post-event performances, i.e., the system is bouncing back to four different levels of performance after the shock, thus providing a better consideration of various real-world cases. In addition, we also investigated the interdependence and dynamics of a series of consecutive resilience cycles, which revealed a strong stochastic character of the system's resilient behaviors and the metric itself.

Chapters 3 and 4 rounded off the studies of survivability behavior in stock networks and confirmed the important role of interdependence in swarm systems from a novel perspective. Not many state-of-the-art investigations of stock markets involve abstracting markets as networked swarms of listed and delisted stocks, let alone studying their long-term patterns. The mainstream of stock market networks has been focusing on predicting bankruptcy and market recession, revealing hidden patterns of the structures, and building models for understanding the markets as complex systems. A common ground for this research stream is that (1) stock markets can be seen as complex systems so that they can be abstracted as complex networks, and the strong assumption for such virtual networks is that (2) the interdependence can be approached by establishing correlations among stocks. Lastly, an important pre-requisite is that (3) the stock price is representing the comprehensive performance of an individual firm and has to be carried out in a time-series manner. For the stream of survivability prediction, a considerable number of previous studies have been dedicated to model construction with high fidelity. Advanced models have been proposed and validated based on detailed company-related accounting data. Because the constraint on the data availability, those studies typically have a much smaller scale, i.e., an extensive scale on the whole market is often unobtainable. Therefore, an emerging trend in the stock market study is to combine network theory with bankruptcy prediction using massive open data.

The same foundation, assumption, and pre-requisite were taken up in these two chapters. These two studies rounded off this research stream by illustrating the "fission-fusion" swarm patterns in a market's evolution process and providing a set of quantitative models with network variables to decode the characteristics of stock survivability resilience further. The studies reveal that the individual survivability can be tackled in a networked market model and the ability to interconnect with others plays an indispensable role in long-term survival and market resilience.

The Bayesian network approach proposed in **Chapter 5** extended the frontier of the scientific knowledge by proposing system resilience as a compound concept that can be integrated with various system qualities. A large portion of the resilience quantification research has been focusing on finding a generic and integrated one-size-fits-all model of depicting system resilience. For example, most of the performance-based resilience metrics are a single metric based on a single key performance indicator or unilateral capability of system effectiveness. The multi-faceted and multi-dimensional characteristics of the system resilience have long been less developed. In this vein, the Bayesian tools provide a good starting point. This model performs probability inference to predict and quantify the resilience of the target system and conduct backward analysis to determine critical components that influence the overall outcome. This particular feature makes it an excellent tool for decision-making and policy-driven analysis. However, the development of Bayesian-based approaches in resilience research is an overall deficient. A small attempt has been made to use this conditional-probability-based graphic model to study system resilience. The most representative previous work was proposed based on a well-established three-stage resilience framework, which strongly relies on the assumption that system resilience can be framed by (1) a stable original state, (2) a disrupted state, and (3) a stable recovered state.

We relaxed these assumptions by exploring new possibilities from a systems-oriented approach. Instead of time-series states, the resilience of an infrastructure system could be approached from its various capabilities, i.e., a multi-faceted consideration from various dimensions of system qualities. The proposed BNM in this chapter contributes to the state-of-the-art knowledge by revealing the long-term and interesting dynamic features of system resilience and providing a systematic roadmap for building resilience in critical infrastructure systems.

All in all, this thesis contributes to the understanding of resilience in complex systems. By enriching the assessment toolkit through proposing novel metrics and models, this thesis draws insightful implications about the characteristics of system resilience for researchers, practitioners, and policymakers.

6.2.2 *Limitations*

While our study made significant contributions, it is also going along with some limitations and challenges that need to be addressed further:

1. The proposed resilience metric that relaxed the bouncing back assumption was only tested in one area of application, a financial market. This raises the question of how robust it is across different financial markets, and even across different fields of application.

2. The test application of the resilience metric was also subjected to only one scale of the market performance. Its performance under different scales of the stock market performance remained unknown. For example, the stock index performance might be subjected to external economic factors and these factors are typically hard to control. This might introduce some bias into the validation process of the resilience metric.

3. The swarm resilience analysis was based on the assumption that the stock price can be used to represent the survivability of an individual firm. It is well known that a firm embedded in an economic system depends on other systems, with each of which it is interacting, such as the governance system, the system of institutional arrangements, and the system of cultural embeddedness. This leaves the question whether those factors have a confounding explanatory power in explaining the resilience of an individual firm.

4. The prediction of the resilience of an individual firm as a member of a warm of firms was based on a limited set of stock market data. The question is whether other stock market data sets would reveal similar results and whether the network properties would have a higher explanatory power.

5. Although using BNM in the Beijing road transportation case to represent the compound resilience of all large-scale infrastructure systems is logically consistent, the underlying availability and quality of data are somewhat limited. Bayesian models have the big advantage that they yield what data would be required to get a full picture of a system's behavior. However, agencies and scientists have to follow a mental model to collect the required data, which will be labor-intensive and time-consuming, and its application is sometimes constrained by the data availability.

6.2.3 *Open questions*

We also outline five open questions here, but we believe it is unlikely that they would significantly affect the key findings.

1. The metric proposed in Chapter 2 consists of four elemental functions. As can be seen from the metric, the two functions, rebuild and reconfigure, are heavily reliant on the post-event performance. It should be noted that this post-event character on these two functions might cause difficulties during a pre-event design and planning. Indeed, the famous "resilience cycles" are all based on a full picture of the whole event, literally from pre-event via during-event to post-event. However, it does not imply that the proposed metric cannot be used for pre-event design and planning. The metric provides an insightful approach to quantitatively understand the dynamic behavior of consecutive resilience cycles in system performance. Through its application, designers and planners could draw useful insights into the dynamics of the system resilience from learning historical data. However, it again emphasizes issues of data availability.

2. The proposed tolerance thresholds, RR and ET, might be challenging to determine in other complex systems. Because these two thresholds represent different levels of the tolerance capabilities to perceive market volatility, we related them to empirical findings of a well-documented concept - investor's psychology - in stock market research and behavioral economics. However, in relation to the investor's psychological tolerance capability, the initial determination of RR and ET could remain as an open question for practitioners when considering the fact that these two tolerance thresholds could be subjective and changeable among different investors and markets. However, to our best knowledge, the alternative perspective we took in Chapter 2, that is, learning from empirical findings, could be a practical approach to start.

3. The sensitivity of the resilience measure could be intractable for practitioners. The results in Chapter 2 indicate that the proposed model was quite robust to the changes made in RR and ET. However, some large-value measures were relatively sensitive to the RR. There, an appropriate determination of RR plays an indispensable role in the study. To avoid such sensitivity, it is better to learn RR from empirical findings and, most importantly, to keep the value of the applied RR within an acceptable and reasonable range. In addition, we could consider reforming the proposed metric by taking its square root, such as computing the geometric mean. Of course, this could be discussed in future work and further investigations.

4. In Chapter 4, we learned that the survivability resilience of stocks in networks could be mostly described through their degree-related network measures. However, questions such as how to use these degree-related network measures to signify our decision-making in practice would remain open for discussion. Also, it is unrealistic to draw an evident causal relationship from only statistical tests. At this stage, the models, at least, provide some insights into the description of survivability resilience in a networked market environment. However, the real reasons why some stocks survived for a long time and some did not are dependent on corporate-level operation and management. For example, those "delisted" stocks may have different reasons for being delisted from the market.

5. The BNM proposed in Chapter 5 could be incorporated or integrated into the metric proposed in Chapter 2, or vice versa. However, we did not attempt to investigate this possibility in the thesis. Since the structure of the BN model was also based on the four elemental functions, we could use function equations at the function layer of the BNM while calculating

the posterior probability. Besides, more data on the post-event performance of the complex transportation system in Beijing could be beneficial for city transportation planners, such as recovery time and cost of recorded hazards. More importantly, because we found that the capability to adapt and change could be important in system resilience, more reliable and detailed indicators on system changeability and adaptability could be vitally needed for further simulation and comparative studies. This open question will be addressed in recent future work.

6.3 MANAGERIAL IMPLICATIONS AND FUTURE WORK

Finally, the author would like to highlight some aspects of drawing resilience into practice. The saying "what gets measured gets managed" might describe why so much attention – analytical and descriptive – has been paid to resilience assessment. Although tools and metrics are not lacking, some intractable hurdles exist for fostering resilient urban systems and effectively assessing them. The following prominent managerial implications could be identified:

- **Fundamental questions about the concept per se are yet to be resolved:** Scholars acknowledge that some fundamental problems still surround the concept itself while it is also at high risk of being overused and employed with unrealistic expectations [1]. As a multi-faceted concept, a large number of "unknowns" must still be examined in the attempt to incorporate resilience effectively into urban systems.
- **There is no finishing line for being resilient:** Infrastructure and other social-ecological systems can self-organize to adapt and optimize the external condition and function of the system, thereby creating and adjusting their states as necessary to cope with the changing patterns they encounter. Indeed, the adaptive capacity of system resilience requires constant adjustments according to external transformations [178]. Therefore, no finishing line can be established for a system to achieve its "ultimate resilient" condition within a certain period.
- **Difficulties of cognitive analysis:** Consensus is widespread that cognitive attributes, such as preparedness, enabling, anticipation, and learning and adaptation, also play indispensable roles in determining resilience, particularly in systems that involve social and human factors (also illustrated in Chapter 2). Because no system can be understood or managed by focusing on one single scale, the cognitive scale becomes a very difficult challenge to achieving a thorough resilience assessment. Similar problems are associated with the concepts of "distributed cognition" [179], and "high-reliability organizations" [180]. Although many question-based methods have been tested for tackling cognitive assessments [180, 181], planners still need successful techniques if they are to build constructive approaches for solving the issue of these "intangible" attributes.

Effective solutions might be offered through interdisciplinary collaboration [182]. Resilience would be facilitated by pluralism that draws upon social-scientific concepts in an era dominated by neoliberal ideology [183]. As explained in this thesis, infrastructure resilience can be designed through good practices. In doing so, some core issues related to resilience assessment cannot be benchmarked merely by preset unification, e.g., margins of safety or the quality of long-term maintenance. This means that engagement is necessary by experts and shareholders from different parties, which involves inter- and multi-disciplinary collaborations. Therefore, this thesis invites a more integrated analysis and interpretation of different system types to further develop this interesting topic.

A

APPENDIX

APPENDIX A: COMPARATIVE RESULTS OF ALL FOUR TESTED METRICS IN KLSE (MALAYSIA) AND N225 (JAPAN).

Fig. A.1 and Fig. A.2 are two more empirical tests of the metrics in KLSE and N225 markets. The data collection and metric implementation are identical to those of NASDAQ and SSE cases demonstrated in the chapter.

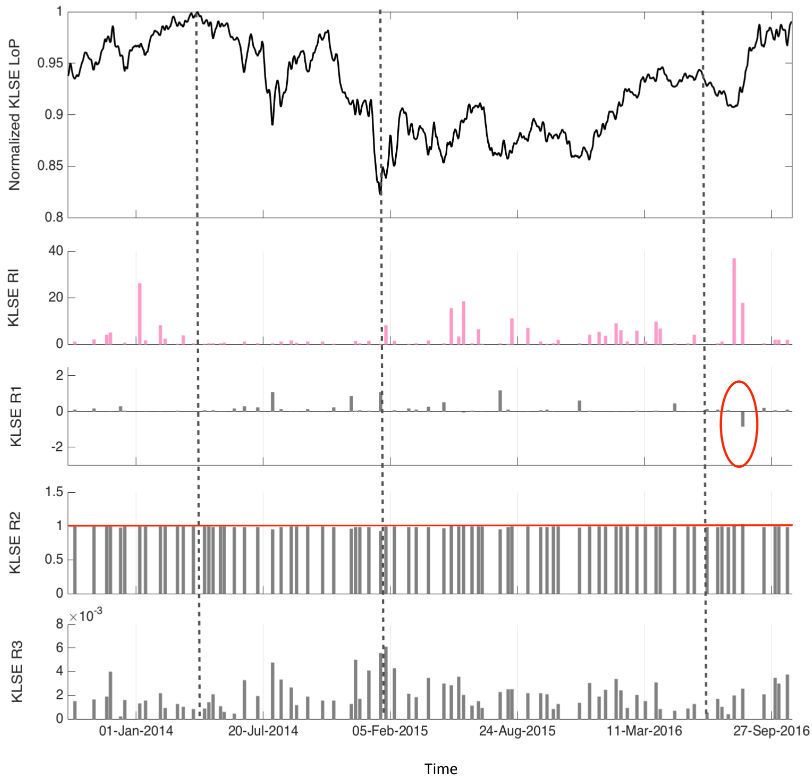


FIGURE A.1: Result comparison of all four tested metrics in KLSE case. (a) normalised LoP, (b) RI, (c) R1, (d) R2, and (e) R3. Obvious defects are highlighted in red.

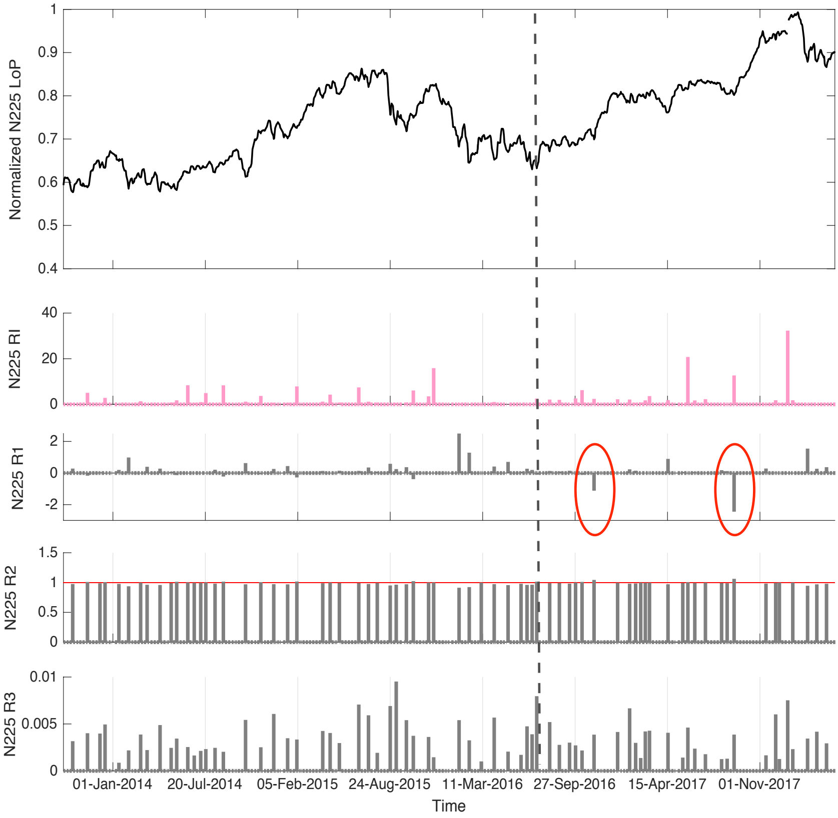


FIGURE A.2: Result comparison of all four tested metrics in N225 case. (a) normalised LoP, (b) RI, (c) R1, (d) R2, and (e) R3. Obvious defects are highlighted in red.

APPENDIX B: EDGE PRUNING AND NETWORK STATISTICS BASED ON DIFFERENT METHODS AND TIME WINDOWS

Fig. A.3 and Fig. A.4 are different visualization results based on "winner-takes-all" filtering methods and five-year and two-year time windows, respectively. It can be seen that this filtering method is aggressive in pruning the edges, causing a significant amount of information loss on network topology. Moreover, large time windows can overlook details of the topology changes during the evolving process of the market.

Fig. A.5 demonstrates a comparative study between results using yearly time window and that of half-yearly time window. As can be seen that the network statistics do not change dramatically.

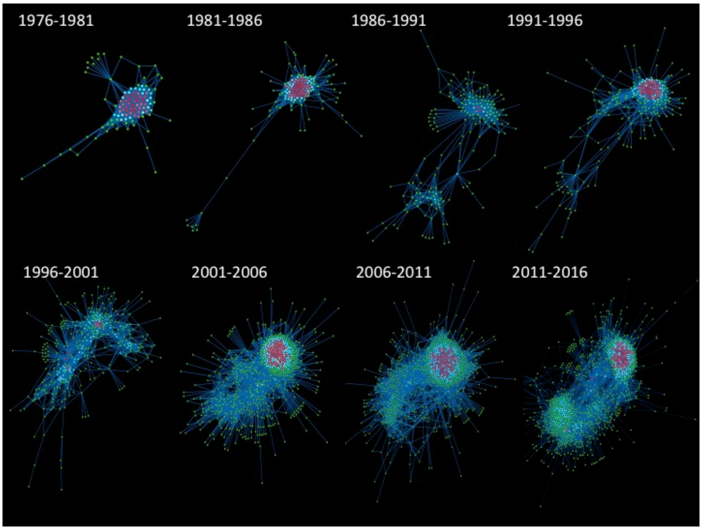


FIGURE A.3: Network visualization based on "winner-takes-all" methods at 90% of correlation coefficients. The time window is five years.

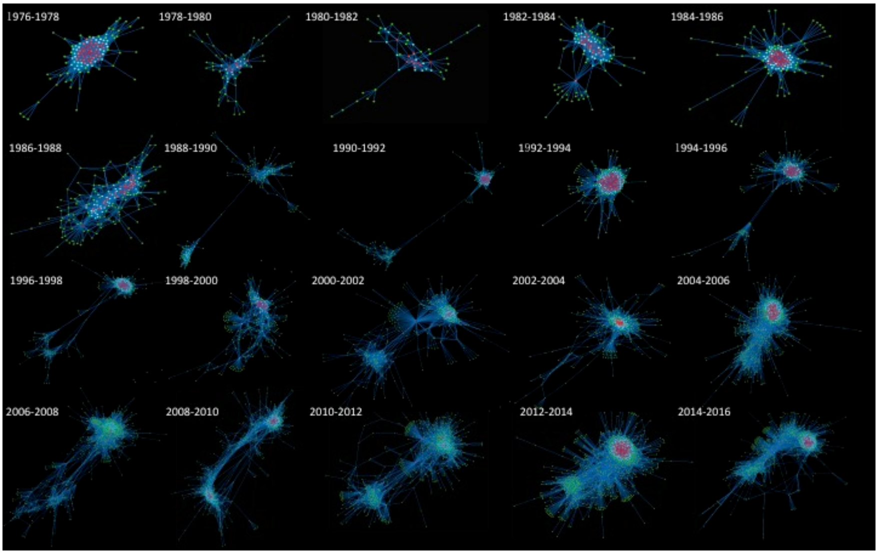


FIGURE A.4: Network visualization based on "winner-takes-all" methods at 90% of correlation coefficients. The time window is two years.

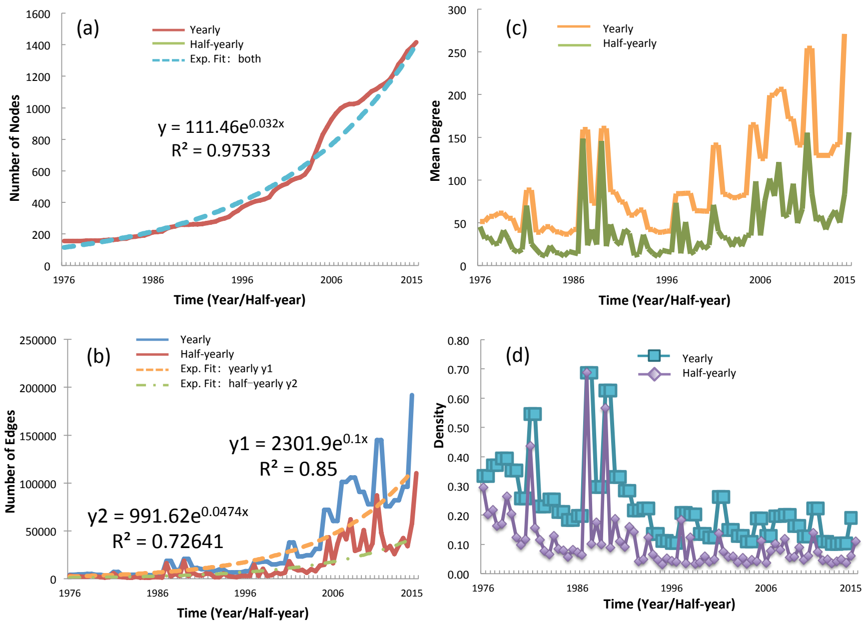


FIGURE A.5: Statistics of the network topology.

APPENDIX C: PARTIAL CORRELATION COEFFICIENTS WITH EXCESS RETURN

Taking 2016-2017 as an example, we constructed the network with Partial correlation coefficient method. The benchmark for calculating excess return was SPDR S&P 500 ETF index, which collected with the same periodicity within 2016-2017. The correlation matrix was obtained by applying Partial correlation coefficient function in MATLAB [184] with the residuals against the benchmark. The percentage of the positive coefficient was around 62.26% (78.63% in Table 4.3) with negative ones around 37.74%. This shows an interesting comparative result as the portion of negative correlations significantly increased.

APPENDIX D: DISTRIBUTIONS OF SIX NETWORK MEASURES IN 2003-2004 AND 2016-2017

Fig. A.6 and Fig. A.7 illustrate the distribution of all six network measures with respect to different groups of companies in 2003-2004 and 2016-2017. The gaps mentioned above were still apparent in those two later years. Because of these differences in distribution remained throughout the observation period, one might infer that they were a general feature associated with each group rather than being merely random outcomes.

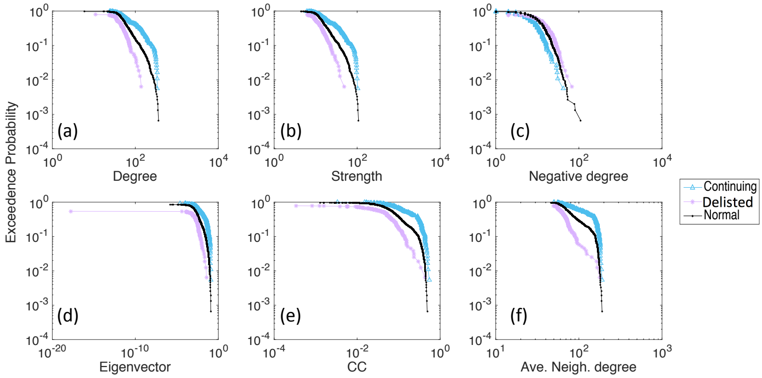


FIGURE A.6: Distribution of the six network measures in 2003-2004.

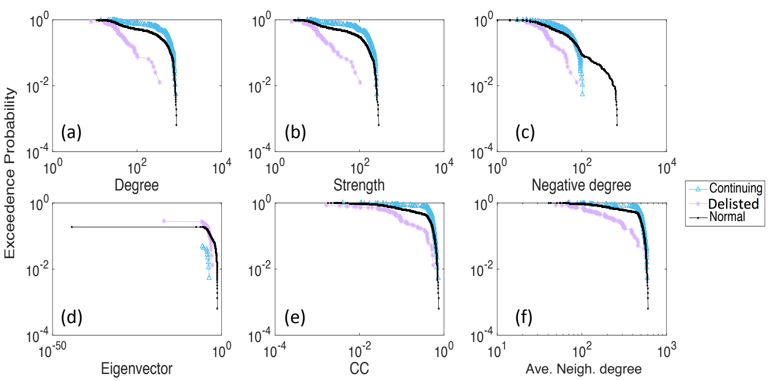


FIGURE A.7: Distribution of the six network measures in 2016-2017.

APPENDIX E: INITIAL INPUTS FOR THE REST OF THE QUALITY ROOT NODES

Year	Indicator 1	%	Indicator 2	%	Aggregated Robustness
2016	16.7	39.31%	11850	99.37%	69.34%
2015	1.3	92.99%	10000	98.62%	95.80%
2014	10.5	55.59%	868	31.03%	43.31%
2013	4.8	76.46%	10000	98.62%	87.54%
2012	171.1	0.01%	4222	83.59%	41.80%
2011	14.7	43.96%	868	31.03%	37.49%
2010	2.1	88.92%	868	31.03%	59.98%
2009	10.5	55.59%	1100	37.55%	46.57%
2008	10.5	55.59%	320	12.80%	34.20%
2007	10.5	55.59%	50	2.12%	28.86%
2006	10.5	55.59%	240	9.76%	32.68%
2005	10.5	55.59%	20	0.85%	28.22%
2004	10.5	55.59%	248	10.07%	32.83%
2003	10.5	55.59%	868	31.03%	43.31%
2002	10.5	55.59%	868	31.03%	43.31%
2001	10.5	55.59%	868	31.03%	43.31%
2000	10.5	55.59%	868	31.03%	43.31%
1999	10.5	55.59%	868	31.03%	43.31%
1998	10.5	55.59%	868	31.03%	43.31%
1997	10.5	55.59%	868	31.03%	43.31%
Mean	17.885	-	2336.5	-	-
STD	45.05370015	-	4423.498053	-	-

TABLE A.1: Estimated probability of node "Robustness"

Year	Indicator 1	%	Indicator 2	%	Aggregated Safety
2016	2784	63.65%	3163	70.75%	67.20%
2015	2617	65.40%	2637	74.94%	70.17%
2014	3333	58.22%	3196	70.49%	64.36%
2013	3359	57.98%	3063	71.53%	64.75%
2012	3613	55.64%	3196	70.49%	63.07%
2011	4503	48.15%	3934	65.03%	56.59%
2010	4857	45.47%	4279	62.62%	54.04%
2009	4426	48.76%	3814	65.89%	57.32%
2008	4530	47.94%	3943	64.96%	56.45%
2007	6257	36.23%	5335	55.79%	46.01%
2006	6681	33.82%	5808	52.97%	43.39%
2005	6888	32.70%	6364	49.85%	41.27%
2004	8284	26.07%	8536	39.30%	32.69%
2003	9877	20.13%	10842	30.54%	25.34%
2002	10456	18.33%	12053	26.75%	22.54%
2001	10424	18.42%	4807	59.10%	38.76%
2000	5638	40.05%	4807	59.10%	49.58%
1999	10607	17.88%	32292	2.92%	10.40%
1998	8469	25.30%	35779	2.00%	13.65%
1997	5638	40.05%	24968	6.51%	23.28%
Mean	6162.05	-	9140.8	-	-
STD	1754.161791	-	1681.499983	-	-

Table A.2: Estimated probability of node "Safety"

Year	Indicator 1	%	Indicator 2	%	Aggregated Repairability
2016	14	47.95%	279180	94.88%	71.41%
2015	468	54.54%	288787	95.38%	74.96%
2014	-50	47.02%	282196	95.04%	71.03%
2013	375	53.19%	273618	94.57%	73.88%
2012	4345	93.66%	269366	94.31%	93.99%
2011	-231	44.40%	46607	39.11%	41.76%
2010	216	50.88%	51532	42.22%	46.55%
2009	238	51.20%	50340	41.48%	46.34%
2008	1207	64.93%	38236	33.44%	49.18%
2007	-2124	20.31%	34816	30.97%	25.64%
2006	-6369	0.87%	32215	29.03%	14.95%
2005	5014	96.17%	28671	26.30%	61.24%
2004	0	47.75%	24037	22.57%	35.16%
2003	0	47.75%	22089	20.95%	34.35%
2002	0	47.75%	23447	22.09%	34.92%
2001	0	47.75%	20803	19.86%	33.80%
2000	0	47.75%	24000	22.54%	35.14%
1999	0	47.75%	24000	22.54%	35.14%
1998	0	47.75%	27000	24.98%	36.36%
1997	0	47.75%	38000	33.27%	40.51%
Mean	155.15	-	93947	-	-
STD	2743.628236	-	122020.8718	-	-

TABLE A.3: Estimated probability of node "Repairability"

Year	Indicator 1	Affordability	Indicator 1	Adaptability
2016	0.11	89.43%	0.53	53.18%
2015	0.11	89.43%	0.60	60.16%
2014	0.11	89.42%	0.54	54.06%
2013	0.11	89.42%	0.51	50.81%
2012	0.10	89.63%	0.55	54.72%
2011	0.11	89.30%	0.52	52.45%
2010	0.12	88.23%	0.58	58.49%
2009	0.10	89.65%	0.46	45.63%
2008	0.09	90.73%	0.41	40.79%
2007	0.11	89.41%	0.47	47.20%
2006	0.11	89.12%	0.42	42.32%
2005	0.11	88.99%	0.45	44.75%
2004	0.10	90.01%	0.49	48.93%
2003	0.12	87.84%	0.49	48.51%
2002	0.10	89.80%	0.46	45.84%
2001	0.11	89.14%	0.51	51.31%
2000	0.11	89.01%	0.57	57.09%
1999	0.11	88.72%	0.75	75.48%
1998	0.12	87.62%	0.60	60.12%
1997	0.12	87.62%	0.53	52.70%

TABLE A.4: Estimated probability of node "Affordability" and "Adaptability"

BIBLIOGRAPHY

1. Alexander, D. E. Resilience and disaster risk reduction: an etymological journey. *Natural Hazards and Earth System Sciences* **13**, 2707 (2013).
2. Young, T. *A course of lectures on natural philosophy and the mechanical arts* (London :Printed for J. Johnson., 1807).
3. Rankine, W. J. M. *A manual of applied mechanics* (Charles Griffin and Co., London, 1858).
4. Timoshenko, S. *History of strength of materials: with a brief account of the history of theory of elasticity and theory of structures* (Courier Corporation, 1953).
5. Holling, C. S. Resilience and stability of ecological systems. *Annual Rreview of Ecology and Systematics*, 1 (1973).
6. Garmezy, N. Competence and adaptation in adult schizophrenic patients and children at risk. *Schizophrenia: The first ten dean award lectures*, 163 (1973).
7. Rose, A. Economic resilience to natural and man-made disasters: Multidisciplinary origins and contextual dimensions. *Environmental Hazards* **7**, 383 (2007).
8. Hosseini, S., Barker, K. & Ramirez-Marquez, J. E. A review of definitions and measures of system resilience. *Reliability Engineering & System Safety* **145**, 47 (2016).
9. Ahern, J. From fail-safe to safe-to-fail: Sustainability and resilience in the new urban world. *Landscape and Urban Planning* **100**, 341 (2011).
10. Fisher, L. Disaster responses: More than 70 ways to show resilience. *Nature* **518**, 35. (2015).
11. Couzin-Frankel, J. The roots of resilience. *Science (New York, NY)* **359**, 970 (2018).
12. Council, N. R. Disaster resilience: a national imperative (2012).
13. Epstein, W. Unforeseen events, resilience, and probabilistic risk assessment. *PSAM11/ESREL12, Helsinki, Finland*, 1 (2012).
14. Francis, R. & Bekera, B. A metric and frameworks for resilience analysis of engineered and infrastructure systems. *Reliability Engineering & System Safety* **121**, 90 (2014).
15. Van der Merwe, S., Biggs, R. & Preiser, R. A framework for conceptualizing and assessing the resilience of essential services produced by socio-technical systems. *Ecology and Society* **23** (2018).
16. Arbon, P. *et al.* Developing a model and tool to measure community disaster resilience. *The Australian Journal of Emergency Management* **29**, 12 (2014).
17. Linkov, I., Eisenberg, D. A., Plourde, K., Seager, T. P., Allen, J. & Kott, A. Resilience metrics for cyber systems. *Environment Systems and Decisions* **33**, 471 (2013).
18. Linkov, I., Eisenberg, D. A., Bates, M. E., Chang, D., Convertino, M., Allen, J. H., Flynn, S. E. & Seager, T. P. Measurable resilience for actionable policy. *Environmental Science & Technology* **47**, 10108 (2013).

19. Heinimann, H. R. & Hatfield, K. Infrastructure Resilience Assessment, Management and Governance: State and Perspectives. *NATO Science for Peace and Security Series C: Environmental Security*, 147 (2017).

20. Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W. A. & von Winterfeldt, D. A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra* **19**, 733 (2003).

21. Ouyang, M. & Dueñas-Osorio, L. Time-dependent resilience assessment and improvement of urban infrastructure systems. *Chaos: An Interdisciplinary Journal of Nonlinear Science* **22**, 033122. (2012).

22. Tang, J. & Heinimann, H. R. A resilience-oriented approach for quantitatively assessing recurrent spatial-temporal congestion on urban roads. *PLoS One* **13**, e0190616. (2018).

23. Henry, D. & Ramirez-Marquez, J. E. Generic metrics and quantitative approaches for system resilience as a function of time. *Reliability Engineering & System Safety* **99**, 114 (2012).

24. Ayyub, B. M. Systems resilience for multihazard environments: Definition, metrics, and valuation for decision making. *Risk Analysis: An International Journal* **34**, 340 (2014).

25. Haimes, Y. Y. On the definition of resilience in systems. *Risk Analysis: An International Journal* **29**, 498 (2009).

26. Watts, D. J. & Strogatz, S. H. Collective dynamics of 'small-world'networks. *Nature* **393**, 440 (1998).

27. Barabási, A.-L. & Albert, R. Emergence of scaling in random networks. *Science* **286**, 509 (1999).

28. Callaway, D. S., Newman, M. E., Strogatz, S. H. & Watts, D. J. Network robustness and fragility: Percolation on random graphs. *Physical Review Letters* **85**, 5468 (2000).

29. Newman, M. E. & Watts, D. J. Scaling and percolation in the small-world network model. *Physical Review E* **60**, 7332 (1999).

30. Schwartz, N., Cohen, R., Ben-Avraham, D., Barabási, A.-L. & Havlin, S. Percolation in directed scale-free networks. *Physical Review E* **66**, 015104 (2002).

31. Shao, S., Huang, X., Stanley, H. E. & Havlin, S. Percolation of localized attack on complex networks. *New Journal of Physics* **17**, 023049 (2015).

32. Dorogovtsev, S. N., Goltsev, A. V. & Mendes, J. F. F. K-core organization of complex networks. *Physical Review Letters* **96**, 040601 (2006).

33. Achlioptas, D., D'souza, R. M. & Spencer, J. Explosive percolation in random networks. *Science* **323**, 1453 (2009).

34. Ash, J. & Newth, D. Optimizing complex networks for resilience against cascading failure. *Physica A: Statistical Mechanics and its Applications* **380**, 673 (2007).

35. Calvert, S. C. & Snelder, M. A methodology for road traffic resilience analysis and review of related concepts. *Transportmetrica A: Transport Science* **14**, 130 (2018).

36. Mattsson, L.-G. & Jenelius, E. Vulnerability and resilience of transport systems–a discussion of recent research. *Transportation Research Part A: Policy and Practice* **81**, 16 (2015).

37. Murray-Tuite, P. M. *A comparison of transportation network resilience under simulated system optimum and user equilibrium conditions* in *Simulation Conference, 2006. WSC 06. Proceedings of the Winter* (2006), 1398.

38. Jensen, F. V. *An introduction to Bayesian networks* (UCL press London, 1996).

39. Heckerman, D. *A tutorial on learning with Bayesian networks* in *Learning in graphical models* (Springer, 1998), 301.

40. Hosseini, S. & Barker, K. Modeling infrastructure resilience using Bayesian networks: A case study of inland waterway ports. *Computers & Industrial Engineering* **93**, 252 (2016).

41. Boehm, B. & Kukreja, N. An Initial Ontology for System Qualities. *INSIGHT* **20**, 18 (2017).

42. Boehm, B. *Tradespace and Affordability-Phase 3* tech. rep. (Systems Engineering Research Center Hoboken NJ, 2013).

43. Boehm, B., Jacques, D., Columbi, J., Ryan, E., Ender, T., Peak, R., Sitterle, V., Curry, M., Rhodes, D., Ross, A., *et al. System Qualities Ontology, Tradespace and Affordability (SQOTA) Project: Phase 5* tech. rep. (Stevens Institute of Technology Hoboken United States, 2017).

44. Brudermann, T., Hofer, C. & Yamagata, Y. in *Urban Resilience* 135 (Springer, 2016).

45. Macal, C. M. & North, M. J. Tutorial on agent-based modelling and simulation. *Journal of Simulation* **4**, 151 (2010).

46. Cimellaro, G., Roh, H. & Koh, Y. Applying control theories and ABM to improve resilience-based design of systems. *Network for Earthquake Engineering Simulation (distributor). Google Scholar* (2014).

47. Gao, J., Li, D. & Havlin, S. From a single network to a network of networks. *National Science Review* **1**, 346 (2014).

48. Macal, C., North, M., Macal, C. & Sallach, D. *Simulating energy markets and infrastructure interdependencies with agent based models* in *Social Agents: Ecology, Exchange, and Evolution Conference, University of Chicago, Chicago, IL US* (2002), 195.

49. Kotov, V. *Systems of systems as communicating structures* (Hewlett Packard Laboratories, 1997).

50. Heinimann, H. R. & Hatfield, K. *Infrastructure Resilience Assessment, Management and Governance–State and Perspectives* in *Resilience and Risk* (Springer, 2017), 147.

51. Gorod, A., Sauser, B. & Boardman, J. System-of-systems engineering management: A review of modern history and a path forward. *IEEE Systems Journal* **2**, 484 (2008).

52. Nan, C., Sansivini, G. & Kröger, W. *Building an Integrated Metric for Quantifying the Resilience of Interdependent Infrastructure Systems* in *International Conference on Critical Information Infrastructures Security* (2014), 159.

53. Tierney, K. & Bruneau, M. Conceptualizing and measuring resilience: A key to disaster loss reduction. *TR News* **250** (2007).

54. Bruneau, M. & Reinhorn, A. *Overview of the resilience concept* in *Proceedings of the 8th US National Conference on Earthquake Engineering. USA.* (2006), 18.

55. Alcaraz, C. & Zeadally, S. Critical infrastructure protection: requirements and challenges for the 21st century. *International journal of critical infrastructure protection* **8**, 53 (2015).

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

57. Kauê Dal'Maso Peron, T., da Fontoura Costa, L. & Rodrigues, F. A. The structure and resilience of financial market networks. *Chaos: An Interdisciplinary Journal of Nonlinear Science* **22**, 013117 (2012).

58. Lilienfeld-toal, U. V. & Ruenzi, S. CEO ownership, stock market performance, and managerial discretion. *The Journal of Finance* **69**, 1013 (2014).

59. Lehkonen, H. & Heimonen, K. Democracy, political risks and stock market performance. *Journal of International Money and Finance* **59**, 77 (2015).

60. Joo, K., Shim, H. S. & Sul, W. The Long-Run Effect of Environmental Issues on Stock Market Performance: Evidence from the US Stock Market. *International Business Journal* **28**, 101 (2017).

61. Pereira, E. J. d. A. L., da Silva, M. F., da Cunha Lima, I. & Pereira, H. Trump's Effect on stock markets: A multiscale approach. *Physica A: Statistical Mechanics and its Applications* **512**, 241 (2018).

62. Leal, S. J. & Napoletano, M. Market stability vs. market resilience: Regulatory policies experiments in an agent-based model with low-and high-frequency trading. *Journal of Economic Behavior & Organization*, In press. (2017).

63. Bookstaber, R., Foley, M. D. & Tivnan, B. F. Toward an understanding of market resilience: market liquidity and heterogeneity in the investor decision cycle. *Journal of Economic Interaction and Coordination* **11**, 205 (2016).

64. Erragragui, E., Hassan, M. K., Peillex, J. & Khan, A. N. F. Does ethics improve stock market resilience in times of instability? *Economic Systems* (2018).

65. Drakos, K. Behavioral Channels in the Cross-Market Diffusion of Major Terrorism Shocks. *Risk Analysis: An International Journal* **31**, 143 (2011).

66. Tang, J., Khoja, L. & Heinimann, H. R. *Modeling Stock Survivability Resilience in Signed Temporal Networks: A Study from London Stock Exchange* in *International Workshop on Complex Networks and their Applications* (2017), 1041.

67. Tang, J., Khoja, L. & Heinimann, H. R. Characterisation of survivability resilience with dynamic stock interdependence in financial networks. *Applied Network Science* **3**, 23 (2018).

68. Farmer, J. D., Gallegati, M., Hommes, C., Kirman, A., Ormerod, P., Cincotti, S., Sanchez, A. & Helbing, D. A complex systems approach to constructing better models for managing financial markets and the economy. *The European Physical Journal Special Topics* **214**, 295 (2012).

69. Sornette, D. A complex system view of why stock markets crash. *New Thesis* **1**, 5 (2004).

70. Zhao, L., Wang, G.-J., Wang, M., Bao, W., Li, W. & Stanley, H. E. Stock market as temporal network. *Physica A: Statistical Mechanics and its Applications* **506**, 1104 (2018).

71. Rose, A. Defining and measuring economic resilience to disasters. *Disaster Prevention and Management: An International Journal* **13**, 307 (2004).

72. Wein, A. & Rose, A. Economic resilience lessons from the ShakeOut earthquake scenario. *Earthquake Spectra* **27**, 559 (2011).

73. Duval, R., Elmeskov, J. & Vogel, L. Structural policies and economic resilience to shocks. *Organisation for Economic Co-operation and Development (OECD-SSRN)* (2007).

74. Simmie, J. & Martin, R. The economic resilience of regions: towards an evolutionary approach. *Cambridge Journal of Regions, Economy and Society* **3**, 27 (2010).

75. Martin, R. Regional economic resilience, hysteresis and recessionary shocks. *Journal of Economic Geography* **12**, 1 (2011).

76. Hill, E., Clair, T. S., Wial, H., Wolman, H., Atkins, P., Blumenthal, P., Ficenec, S. & Friedhoff, A. in *Urban and Regional Policy and Its Effects: Building Resilient Regions* 193 (Brookings Institution Press, 2012).

77. Zobel, C. W. & Khansa, L. Characterizing multi-event disaster resilience. *Computers & Operations Research* **42**, 83 (2014).

78. Tran, H. T., Balchanos, M., Domercant, J. C. & Mavris, D. N. A framework for the quantitative assessment of performance-based system resilience. *Reliability Engineering & System Safety* **158**, 73 (2017).

79. Parsons, M., Glavac, S., Hastings, P., Marshall, G., McGregor, J., McNeill, J., Morley, P., Reeve, I. & Stayner, R. Top-down assessment of disaster resilience: A conceptual framework using coping and adaptive capacities. *International Journal of Disaster Risk Reduction* **19**, 1 (2016).

80. Platt, S., Brown, D. & Hughes, M. Measuring resilience and recovery. *International Journal of Disaster Risk Reduction* **19**, 447 (2016).

81. Cere, G., Rezgui, Y. & Zhao, W. Critical review of existing built environment resilience frameworks: Directions for future research. *International Journal of Disaster Risk Reduction* **25**, 173 (2017).

82. Bhamra, R., Dani, S. & Burnard, K. Resilience: The concept, a literature review and future directions. *International Journal of Production Research* **49**, 5375 (2011).

83. Martin-Breen, P. & Anderies, J. M. *Resilience: A Literature Review* tech. rep. (Brighton: Institute of Development Studies, Brighton, UK., 2011).

84. Van Breda, A. D. *et al. Resilience theory: A literature review* tech. rep. (Pretoria, South Africa: South African Military Health Service, 2001).

85. Biringer, B., Vugrin, E. & Warren, D. *Critical infrastructure system security and resiliency* (CRC press, 2016).

86. González, O., Shrikumar, H., Stankovic, J. A. & Ramamritham, K. *Adaptive fault tolerance and graceful degradation under dynamic hard real-time scheduling* in *Real-Time Systems Symposium, 1997. Proceedings., The 18th IEEE* (1997), 79.

87. Haimes, Y. Y. On the complex definition of risk: A systems-based approach. *Risk Analysis* **29**, 1647 (2009).

88. Hashimoto, T., Stedinger, J. R. & Loucks, D. P. Reliability, resiliency, and vulnerability criteria for water resource system performance evaluation. *Water Resources Research* **18**, 14 (1982).

89. Filimonov, V. & Sornette, D. Power law scaling and "Dragon-Kings" in distributions of intraday financial drawdowns. *Chaos, Solitons & Fractals* **74**, 27 (2015).

90. Johansen, A., Sornette, D., *et al.* Shocks, crashes and bubbles in financial markets. *Brussels Economic Review* **53**, 201 (2010).

91. Kacperski, K. & Holyst, J. A. Phase transitions and hysteresis in a cellular automata-based model of opinion formation. *Journal of Statistical Physics* **84**, 169 (1996).

92. Strogatz, S. H. Exploring complex networks. *Nature* **410**, 268. (2001).

93. Kerner, B. S. Experimental features of self-organization in traffic flow. *Physical Review Letters* **81**, 3797 (1998).

94. Kaizoji, T. Speculative bubbles and crashes in stock markets: An interacting-agent model of speculative activity. *Physica A: Statistical Mechanics and its Applications* **287**, 493 (2000).

95. Heinimann, H. R. A Generic Framework for Resilience Assessment. *In Resource Guide on Resilience. IRGC, Editor. EPFL International Risk Governance Center: Lausanne.* (2016).

96. Nan, C. & Sansavini, G. A quantitative method for assessing resilience of interdependent infrastructures. *Reliability Engineering & System Safety* **157**, 35 (2017).

97. Yahoo. *Historical data of NASDAQ Composite.* tech. rep. (Yahoo Finance., 2018).

98. Mathworks. *Filtering and Smoothing Data* tech. rep. (Matlab R2018a Documentations. [Available at] http://www.mathworks.com/help/curvefit/smoothing-data.html, 2016).

99. Johansen, A. & Sornette, D. Stock market crashes are outliers. *The European Physical Journal B-Condensed Matter and Complex Systems* **1**, 141 (1998).

100. Johansen, A. & Sornette, D. Large stock market price drawdowns are outliers. *Available at SSRN 244563.* 1 (2000).

101. Riley, C. & Yan, S. *China's stock market crash...in 2 minutes.* tech. rep. (CNN Money. [Available at] http://money.cnn.com/2015/07/09/investing/china-crash-in-two-minutes/index.html, 2015).

102. Hosseini, S., Al Khaled, A. & Sarder, M. A general framework for assessing system resilience using Bayesian networks: A case study of sulfuric acid manufacturer. *Journal of Manufacturing Systems* **41**, 211 (2016).

103. Barabási, A.-L. *Network science* (Cambridge University Press, 2016).

104. Münnix, M. C., Shimada, T., Schäfer, R., Leyvraz, F., Seligman, T. H., Guhr, T. & Stanley, H. E. Identifying states of a financial market. *Scientific Reports* **2** (2012).

105. Singpurwalla, N. D. Survival in dynamic environments. *Statistical Science*, 86 (1995).

106. Sterbenz, J. P., Hutchison, D., Çetinkaya, E. K., Jabbar, A., Rohrer, J. P., Schöller, M. & Smith, P. Resilience and survivability in communication networks: Strategies, principles, and survey of disciplines. *Computer Networks* **54**, 1245 (2010).

107. Khoja, L., Chipulu, M. & Jayasekera, R. Analysing corporate insolvency in the Gulf Cooperation Council using logistic regression and multidimensional scaling. *Review of Quantitative Finance and Accounting* **46**, 483 (2016).

108. Amendola, A., Giordano, F., Parrella, M. L. & Restaino, M. Variable selection in high-dimensional regression: a nonparametric procedure for business failure prediction. *Applied Stochastic Models in Business and Industry* **33**, 355 (2017).

109. Jones, S., Johnstone, D. & Wilson, R. Predicting corporate bankruptcy: An evaluation of alternative statistical frameworks. *Journal of Business Finance & Accounting* **44**, 3 (2017).

110. Allen, F. & Babus, A. in, 367 (Wharton School Publishing Upper Saddle River, New Jersey, 2009).

111. Du Jardin, P., Veganzones, D. & Séverin, E. Forecasting Corporate Bankruptcy Using AccrualBased Models. *Computational Economics*, 1 (2017).

112. Kuo, R. J., Chen, C. & Hwang, Y. An intelligent stock trading decision support system through integration of genetic algorithm based fuzzy neural network and artificial neural network. *Fuzzy Sets and Systems* **118**, 21 (2001).

113. Zhang, G., Hu, M. Y., Patuwo, B. E. & Indro, D. C. Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis. *European Journal of Operational Research* **116**, 16 (1999).

114. Zelenkov, Y., Fedorova, E. & Chekrizov, D. Two-step classification method based on genetic algorithm for bankruptcy forecasting. *Expert Systems with Applications* **88**, 393 (2017).

115. Ticknor, J. L. A Bayesian regularized artificial neural network for stock market forecasting. *Expert Systems with Applications* **40**, 5501 (2013).

116. Chong, E., Han, C. & Park, F. C. Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies. *Expert Systems with Applications* **83**, 187 (2017).

117. Beaver, W. H. Financial ratios as predictors of failure. *Journal of Accounting Research*, 71 (1966).

118. Altman, E. I. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance* **23**, 589 (1968).

119. Shumway, T. Forecasting bankruptcy more accurately: A simple hazard model. *The Journal of Business* **74**, 101 (2001).

120. Mossman, C. E., Bell, G. G., Swartz, L. M. & Turtle, H. An empirical comparison of bankruptcy models. *Financial Review* **33**, 35 (1998).

121. Lee, K. C., Han, I. & Kwon, Y. Hybrid neural network models for bankruptcy predictions. *Decision Support Systems* **18**, 63 (1996).

122. Barboza, F., Kimura, H. & Altman, E. Machine learning models and bankruptcy prediction. *Expert Systems with Applications* **83**, 405 (2017).

123. Bonanno, G., Caldarelli, G., Lillo, F. & Mantegna, R. N. Topology of correlation-based minimal spanning trees in real and model markets. *Physical Review E* **68**, 046130 (2003).

124. Vandewalle, N., Brisbois, F., Tordoir, X., *et al.* Non-random topology of stock markets. *Quantitative Finance* **1**, 372 (2001).

125. Tumminello, M., Aste, T., Di Matteo, T. & Mantegna, R. N. A tool for filtering information in complex systems. *Proceedings of the National Academy of Sciences of the United States of America* **102**, 10421 (2005).

126. Huang, W.-Q., Zhuang, X.-T. & Yao, S. A network analysis of the Chinese stock market. *Physica A: Statistical Mechanics and its Applications* **388**, 2956 (2009).

127. Chi, K. T., Liu, J. & Lau, F. C. A network perspective of the stock market. *Journal of Empirical Finance* **17**, 659 (2010).

128. Heiberger, R. H. Stock network stability in times of crisis. *Physica A: Statistical Mechanics and its Applications* **393**, 376 (2014).

129. Xu, R., Wong, W.-K., Chen, G. & Huang, S. Topological Characteristics of the Hong Kong Stock Market: A Test-based P-threshold Approach to Understanding Network Complexity. *Scientific Reports* **7** (2017).

130. Xuan, X. & Murphy, K. *Modeling changing dependency structure in multivariate time series* in *Proceedings of the 24th international conference on Machine learning* (2007), 1055.

131. Harmon, D., Lagi, M., de Aguiar, M. A., Chinellato, D. D., Braha, D., Epstein, I. R. & Bar-Yam, Y. Anticipating economic market crises using measures of collective panic. *PloS One* **10**, e0131871 (2015).

132. Bonanno, G., Caldarelli, G., Lillo, F., Micciche, S., Vandewalle, N. & Mantegna, R. N. Networks of equities in financial markets. *The European Physical Journal B-Condensed Matter and Complex Systems* **38**, 363 (2004).

133. Mantegna, R. N. Hierarchical structure in financial markets. *The European Physical Journal B-Condensed Matter and Complex Systems* **11**, 193 (1999).

134. Onnela, J.-P., Chakraborti, A., Kaski, K., Kertesz, J. & Kanto, A. Dynamics of market correlations: Taxonomy and portfolio analysis. *Physical Review E* **68**, 056110 (2003).

135. Gao, Y.-C., Wei, Z.-W. & Wang, B.-H. Dynamic evolution of financial network and its relation to economic crises. *International Journal of Modern Physics C* **24**, 1350005 (2013).

136. Pour, E. K. & Lasfer, M. Why do companies delist voluntarily from the stock market? *Journal of Banking & Finance* **37**, 4850 (2013).

137. Kwapień, J., Oświecimka, P., Forczek, M. & Drożdż, S. Minimum spanning tree filtering of correlations for varying time scales and size of fluctuations. *Physical Review E* **95**, 052313 (2017).

138. Zhang, X., Zheng, X. & Zeng, D. D. The dynamic interdependence of international financial markets: An empirical study on twenty-seven stock markets. *Physica A: Statistical Mechanics and its Applications* **472**, 32 (2017).

139. Benesty, J., Chen, J., Huang, Y. & Cohen, I. in *Noise reduction in speech processing* 1 (Springer, Heidelberg, 2009).

140. Leskovec, J., Huttenlocher, D. & Kleinberg, J. *Signed networks in social media* in *Proceedings of the SIGCHI conference on human factors in computing systems* (2010), 1361.

141. Yook, S.-H., Jeong, H., Barabási, A.-L. & Tu, Y. Weighted evolving networks. *Physical Review Letters* **86**, 5835 (2001).

142. Barrat, A., Barthelemy, M. & Vespignani, A. *Dynamical processes on complex networks* (Cambridge university press, 2008).

143. Chiang, K.-Y., Hsieh, C.-J., Natarajan, N., Dhillon, I. S. & Tewari, A. Prediction and clustering in signed networks: a local to global perspective. *The Journal of Machine Learning Research* **15**, 1177 (2014).

144. Ma, Y. & Zhang, X.-D. Estimating the number of weak balance structures in signed networks. *Communications in Nonlinear Science and Numerical Simulation* **62**, 250 (2018).

145. Anchuri, P. & Magdon-Ismail, M. *Communities and balance in signed networks: A spectral approach* in *Proceedings of the 2012 International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2012)* (2012), 235.

146. Newman, M. *Networks: an introduction* (Oxford University Press, 2010).

147. Davis, J. A. Clustering and structural balance in graphs. *Human Relations* **20**, 181 (1967).

148. Harary, F. *et al.* On the notion of balance of a signed graph. *The Michigan Mathematical Journal* **2**, 143 (1953).

149. Rhim, A. Reorganization Schemes Under UK Insolvency Act of 1986: Chapter 11 as a Springboard for Discussion. *Loyola of Los Angeles International and Comparative Law Review* **16**, 985 (1993).

150. Fruchterman, T. M. & Reingold, E. M. Graph drawing by force-directed placement. *Software: Practice and Experience* **21**, 1129 (1991).

151. Baba, K. & Sibuya, M. Equivalence of partial and conditional correlation coefficients. *Journal of the Japan Statistical Society* **35**, 1 (2005).

152. Kenett, D. Y., Tumminello, M., Madi, A., Gur-Gershgoren, G., Mantegna, R. N. & Ben-Jacob, E. Dominating clasp of the financial sector revealed by partial correlation analysis of the stock market. *PloS One* **5**, e15032 (2010).

153. Bonacich, P. Power and centrality: A family of measures. *American Journal of Sociology* **92**, 1170 (1987).

154. Alaka, H. A., Oyedele, L. O., Owolabi, H. A., Kumar, V., Ajayi, S. O., Akinade, O. O. & Bilal, M. Systematic review of bankruptcy prediction models: Towards a framework for tool selection. *Expert Systems with Applications* (2017).

155. Montgomery, D. C., Peck, E. A. & Vining, G. G. *Introduction to linear regression analysis* (John Wiley & Sons, New Jersey, 2012).

156. Mosley, L. A balanced approach to the multi-class imbalance problem. *Iowa State University Digital Repository* (2013).

157. Chawla, N. V., Bowyer, K. W., Hall, L. O. & Kegelmeyer, W. P. SMOTE: synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research* **16**, 321 (2002).

158. Han, J., Pei, J. & Kamber, M. *Data mining: concepts and techniques* (Elsevier, Waltham, 2011).

159. Reggiani, A., Nijkamp, P. & Lanzi, D. Transport resilience and vulnerability: the role of connectivity. *Transportation Research Part A: Policy and Practice* **81**, 4 (2015).

160. Zhang, X., Miller-Hooks, E. & Denny, K. Assessing the role of network topology in transportation network resilience. *Journal of Transport Geography* **46**, 35 (2015).

161. Bhatia, U., Kumar, D., Kodra, E. & Ganguly, A. R. Network science based quantification of resilience demonstrated on the Indian Railways Network. *PloS One* **10**, e0141890 (2015).

162. Cantillo, V., Macea, L. F. & Jaller, M. Assessing Vulnerability of Transportation Networks for Disaster Response Operations. *Networks and Spatial Economics*, 1 (2018).

163. Wang, X., Koç, Y., Derrible, S., Ahmad, S. N., Pino, W. J. & Kooij, R. E. Multi-criteria robustness analysis of metro networks. *Physica A: Statistical Mechanics and its Applications* **474**, 19 (2017).

164. Scott, D. M., Novak, D. C., Aultman-Hall, L. & Guo, F. Network robustness index: a new method for identifying critical links and evaluating the performance of transportation networks. *Journal of Transport Geography* **14**, 215 (2006).

165. Murray-Tuite, P. & Mahmassani, H. Methodology for determining vulnerable links in a transportation network. *Transportation Research Record: Journal of the Transportation Research Board*, 88 (2004).

166. Chen, A., Yang, C., Kongsomsaksakul, S. & Lee, M. Network-based accessibility measures for vulnerability analysis of degradable transportation networks. *Networks and Spatial Economics* **7**, 241 (2007).

167. Bruneau, M. & Reinhorn, A. Exploring the concept of seismic resilience for acute care facilities. *Earthquake Spectra* **23**, 41 (2007).

168. Wang, Y., Liu, H., Han, K., Friesz, T. L. & Yao, T. Day-to-day congestion pricing and network resilience. *Transportmetrica A: Transport Science* **11**, 873 (2015).

169. Faturechi, R. & Miller-Hooks, E. Measuring the performance of transportation infrastructure systems in disasters: A comprehensive review. *Journal of Infrastructure Systems* **21**, 04014025 (2014).

170. Wu, X., Liu, H., Zhang, L., Skibniewski, M. J., Deng, Q. & Teng, J. A dynamic Bayesian network based approach to safety decision support in tunnel construction. *Reliability Engineering & System Safety* **134**, 157 (2015).

171. Sun, L. & Erath, A. A Bayesian network approach for population synthesis. *Transportation Research Part C: Emerging Technologies* **61**, 49 (2015).

172. Zhang, L., Wu, X., Skibniewski, M. J., Zhong, J. & Lu, Y. Bayesian-network-based safety risk analysis in construction projects. *Reliability Engineering & System Safety* **131**, 29 (2014).

173. Doguc, O. & Ramirez-Marquez, J. E. A generic method for estimating system reliability using Bayesian networks. *Reliability Engineering & System Safety* **94**, 542 (2009).

174. Zhang, L., Wu, X., Ding, L., Skibniewski, M. J. & Yan, Y. Decision support analysis for safety control in complex project environments based on Bayesian Networks. *Expert Systems with Applications* **40**, 4273 (2013).

175. Boehm, B. *Tradespace and Affordability-Phase 4* tech. rep. (Systems Engineering Research Center Hoboken NJ, 2016).

176. Sarshar, P., Granmo, O.-C., Radianti, J. & Gonzalez, J. J. *A Bayesian network model for evacuation time analysis during a ship fire* in *Computational Intelligence in Dynamic and Uncertain Environments (CIDUE), 2013 IEEE Symposium on* (2013), 100.

177. BayesFusion, L. *GeNIe User Manual* tech. rep. 2.2.4 (University of Pittsburgh, 2018).

178. Folke, C., Carpenter, S., Elmqvist, T., Gunderson, L., Holling, C. S. & Walker, B. Resilience and sustainable development: building adaptive capacity in a world of transformations. *AMBIO: A Journal of the Human Environment* **31**, 437 (2002).

179. Hollan, J., Hutchins, E. & Kirsh, D. Distributed cognition: toward a new foundation for human-computer interaction research. *ACM Transactions on Computer-Human Interaction (TOCHI)* **7**, 174 (2000).

180. Weick, K. E., Sutcliffe, K. M. & Obstfeld, D. Organizing for high reliability: Processes of collective mindfulness. *Crisis Management* **3**, 81 (2008).

181. Smith, T., Gildeh, N. & Holmes, C. The Montreal Cognitive Assessment: validity and utility in a memory clinic setting. *The Canadian Journal of Psychiatry* **52**, 329 (2007).

182. Thorén, H. & Persson, J. The philosophy of interdisciplinarity: Sustainability science and problem-feeding. *Journal for General Philosophy of Science* **44**, 337 (2013).

183. Olsson, L., Jerneck, A., Thoren, H., Persson, J. & O'Byrne, D. Why resilience is unappealing to social science: Theoretical and empirical investigations of the scientific use of resilience. *Science Advances* **1**, e1400217 (2015).

184. Mathworks. Linear or rank partial correlation coefficients. *[Available at] www.mathworks.com* (2018).

CURRICULUM VITAE

PERSONAL DATA

Name	Junqing Tang
Date of Birth	June 18, 1991
Place of Birth	Xi'an, Shaanxi, China
Citizen of	China

EDUCATION

2015–2019	Swiss Federal Institute of Technology, Zürich Zürich, Switzerland *Final degree:* Doctor of Science ETH Zürich
2013–2014	Imperial College London University College London London, U.K. *Final degree:* Master of Science
2010–2013	Cardiff University Cardiff, U.K. *Final degree:* Bachelor of Engineering

EMPLOYMENT AND EXPERIENCE

2018–2019	Visiting Student *University of Tokyo*, Tokyo, Japan *Massachusetts Institute of Technology (MIT)*, Cambridge, U.S.A.
2016.01–07	Exchange Student *National University of Singapore*, Singapore
2015–2019	Ph.D Researcher *Future resilient Systems, Singapore-ETH Centre*, Singapore
2015.01–09	Assistant Transport Planner *WSP/Parsons Brinckerhoff Consulting Ltd*, Shanghai, China

PUBLICATIONS

Published papers

1. **Tang, J***. 2018. Assessment of resilience in urban complex systems. *Encyclopedia of the UN Sustainable Development Goals. Industry, Innovation and Infrastructure*. Edited by Walter Leal Filho et al., Springer.
2. **Tang, J*.**, Heinimann, HR., 2019. A bayesian network approach for assessing the general resilience of road transportation systems. *Proceedings of The 19th COTA International Conference for Transportation Professionals* **Best Paper Awards**.
3. **Tang, J***, and Heinimann, HR., Quantitative evaluation of consecutive resilience cycles in stock market performance: A systems-oriented approach. *Physica A: Statistical Mechanics and its Applications.*
4. **Tang, J***, Khoja, L., and Heinimann, HR., 2018. Characterisation of survivability resilience with dynamic stock interdependence in financial networks. *Applied Network Science* 3:23.
5. **Tang, J***, Heinimann HR., 2018. A resilience-oriented approach for quantitatively assessing recurrent spatial-temporal congestion on urban roads. *PLoS One* 13(1): e0190616.
6. **Tang, J***, Khoja, L., and Heinimann, HR., 2017. Modelling stock survivability resilience in signed temporal networks: A study from London stock exchange. *Proceedings Book of The 6th International Conference on Complex Networks and Their Applications: Studies in Computational Intelligence*, 689, pp.1041-1052.
7. Piccoli, B., Han, K., Friesz, T.L., Yao, T. and **Tang, J.**, 2015. Second-order models and traffic data from mobile sensors. *Transportation Research Part C: Emerging Technologies*, 52, pp.32-56.
8. Zhang, H., Xie, Y., Xiao, G., Zhai, C., Long, Z., Kang, H., and **Tang, J.**, 2018. Tracking differentiator via time criterion. In *2018 Annual American Control Conference (ACC)* pp. 3514-3519.

Forthcoming papers

1. **Tang, J*.**, Heinimann, HR., Han, K., 2019. Evaluating the resilience of urban road transportation systems: A Bayesian network model. *Transportation Research Part A: Transportation and Policy*. (Preparing for submission)

CONFERENCES AND PRESENTATIONS

1. **Tang, J*.**, 2018, Resilient management in modern information systems. **The 3rd Harbin Institute of Technology Shenzhou Forum for International Young Scholars**., Harbin, China, 28-30/12/2018. *Keynote presentation.*
2. **Tang, J*.**, 2018, Resilience in infrastructures. **The 7th East Lake International Forum for Outstanding Overseas Young Scholars, Huazhong University of Science and Technology**., Wuhan, China, 26-27/12/2018. *Keynote presentation.*

3. **Tang, J*.**, 2018, Quantitative assessment of resilience in urban complex adaptive systems. **The 2nd China System Science Conference, 2018**, Beijing, China, 12-13/05/2018. *Oral presentation*.
4. **Tang, J*.**, and Heinimann, R.H., 2018, Dynamic resilience index and survivability of nodes in correlation-based networks. **International Conference on Infrastructure Resilience**, Zürich, Switzerland, 14-16/02/2018. *Oral presentation*.
5. **Tang, J***, Khoja, L., and Heinimann, HR., 2017. Modelling stock survivability resilience in signed temporal networks: A study from London stock exchange. **The 6th International Conference on Complex Networks and Their Applications**, Lyon, France, 29/11/-01/12/201. *Oral presentation*.
6. Yan, J., **Tang, J.**, 2017, Resilience-oriented analysis of risk management and ontology-based categorisation of hazards in interdependent infrastructure systems. **2017 Annual Meeting, Society for Risk Analysis**, Virginia, U.S.A., 10-14/12/2017. *Poster presentation*.
7. **Tang, J*.**, and Heinimann, HR., 2017, Assessment of community resilience with complex network perspective. **Pathways to Resilience IV Conference**, Cape Town, South Africa, 14-16/06/2017. *Poster presentation*.
8. **Tang, J*.**, 2018, **The 18th COTA International Conference of Transportation Professionals 2018**., Beijing, China, 05-08/07/2018. *Invited*.
9. **Tang, J*.**, 2015, **Singapore Scientific Conference 2015**., Singapore, 16-17/09/2015: Attendance at this conference is by invitation only. *Invited*.

INVITED TALKS

1. "Quantitative assessment of system resilience in complex urban systems" **Huazhong University of Science and Technology**, Wuhan, China, 26/12/2018.
2. "Resilience assessment of urban complex systems" **Government visiting delegates from Guangdong Province**, Singapore, 24/07/2018.
3. "Review on quantitative methods for resilience and vulnerability" **Capital Normal University**, Beijing, China, 28/09/2017.
4. "Topological evolution and pattern evaluation in temporal networks" **University of Tokyo**, Singapore, 09/12/2016.
5. "Resilience metric and its quantification in urban complex systems" **Singapore National Defence Organisation**, DSO National Laboratories, Singapore, 13/07/2016.
6. "Highway traffic simulation using agent-based modelling" **Future City Lab**, Singapore, 13/03/2016.