Disaster recovery planning of transportation networks: Problem structuring and decision attributes

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M.Sc.
Milad Zamanifar

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Vorsitzender: Univ.-Prof. Dr.-Ing. Wolfgang Huhnt
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Erfurt- 2020

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List of Publications

This dissertation is written in an accumulative format and is founded based on the following three published peer-reviewed journal papers. The accepted manuscript versions of those papers have been used in this dissertation. The three papers have been slightly modified to better integrate them into this dissertation and improve the overall consistency and coherence.

Paper 1; Chapter 2 (Published -Open access):

Zamanifar M, Hartmann T, (2020), Optimization-based decision models for disaster recovery and reconstruction planning of transportation networks, Journal of Natural Hazards, Vol. 104, P. 1-25, Springer. https://doi.org/10.1007/s11069-020-04192-5

Paper 2; Chapter 3 (Published-Open access):

Zamanifar M, Hartmann T, (2021), A prescriptive decision model for selecting attributes of infrastructure risk reduction problems, Environ Syst Decis 41, 633–650 (2021). https://doi.org/10.1007/s10669-021-09824-0

Paper 3; Chapter 4 (Preprint of the following published paper):

Zamanifar M, Hartmann T, (2021), Decision attribute for disaster recovery planning of transportation networks; A case study, Journal of Transportation Research Part D: Transport and Environment. Volume 93, 102771, Elsevier. https://doi.org/10.1016/j.trd.2021.102771

Summary

The way to disaster-resilient transport infrastructures is paved with effective recovery planning. Disaster Recovery Planning of Transportation Networks (DRPTN) is a critical and complex concept that often relies on recommendations of decision models and decision support systems. To develop such decision systems and draft a reliable recovery plan, a well-structured modeled problem with equitable decision attributes is essential. This dissertation aims to address problem structuring and methodological identification of DRPTN decision attributes. To do so, the research begins with a systematic analysis of the DRPTN optimization models, divided into four phases: problem definition, problem formulation, problem-solving, and model validation. For each of these phases, challenges and opportunities are articulated, as well as suggestions to overcome the identified gaps. To address the knowledge gaps in the problem structuring of DRPTN models, I developed a prescriptive decision aid mechanism to assist in harnessing experts' knowledge and recommend decision attributes for DRPTN problems. Afterward, I implemented this framework in a real-world DRPTN problem case study to test its performance, analyze the outcomes, and produce a systematically selected set of DRPTN decision attributes. The findings of the research have been reported in three sections, which are outlined in detail below.

The findings of the gap analysis suggest the presence of critical challenges within decision attributes of existing DRPTN models, including insufficient efforts to justify and support the adopted decision factors with theoretical arguments or formal selection processes. Furthermore, the problem-solving phase of DRPTN modeling would benefit from adopting meta-heuristic algorithms when explicit or implicit justifications exist, such as convexity, linearity, or complexity analysis of the mathematical programming. In the problem formulation phase, more effort could integrate traffic management measures and post-event travel demand models into the formulation of network recovery. Addressing the validation phase of DRPTN models, a benchmark system, multi-aspect simulation advances, and a systematically developed level of confidence is needed to support the reliability of the outcomes. The gap analysis results suggest that the method-rich but methodology-poor phenomenon appears as a challenge for disaster recovery models.

With respect to the developed attribute-selection methodology, the framework implementation enabled the use of experts' collaborative input in a structured manner and promoted a disciplined decision process. The multi-stage, non-hierarchical architecture of the framework allowed for the critical and thorough evaluation of candidate attributes in a relatively user-friendly manner. The framework could act as a mechanism to harness decision-makers' knowledge and help them to isolate those elements of the decision context which are most relevant to the problem. Therefore, the recommended set is supposed to result from a thorough, systematic process and collaborative decision-making; hence, it offers tenable attributes for both DRPTN practice and research.

Finally, the process has led to six attributes for the case study’s road network disaster recovery planning: 1) access level to service-providing nodes, 2) integration of link travel delay and traffic flow, 3) travel time improvement per recovery duration, 4) travel time improvement per unit of resource, 5) centrality measures, and 6) link capacity. Using the recommended set of attributes in a DRPTN model is expected to provide effective and efficient recovery solutions that maximize mobility and accessibility in the network. Analysis of the results suggests that the framework leads to an improved attribute set compared to the attributes selected in an unassisted manner. The sensitivity analysis confirms that the outranked outcomes are relatively robust against the assigned preferences. This argument was also supported by an information entropy analysis. Both analyses suggest that "certainty" was an incentive factor for participating experts while evaluating candidate decision attributes.

Throughout this research, I was able to 1) identify knowledge gaps and opportunities in optimized DRPTN decision models through conducting a systematic critical literature review and suggest solutions for detected challenges, 2) formalize the decision process of selecting attributes with a few innovative mathematical formulations and modeling approaches, 3) assist and harness the knowledge of subject-matter experts with a decision aid mechanism customized for this purpose, 4) offer the methodology as a toolkit for further application in both science and practice, and 5) suggest a set of decision attributes of DRPTN for the case study. Finally, besides these main contributions, I also had the chance to observe and report on some new technical improvements, understandings, and knowledge that can be useful for scientists and practitioners in decision analysis, traffic engineering, and disaster management. The dissertation concludes with an emphasis on the art of problem structuring in the DRPTN context.

Keywords*: Decision attribute; Decision analysis; Disaster recovery; Transportation network; Infrastructure; Resilience; Risk reduction.*

Zusammenfassung

Der Weg zu Katastrophenresilienz Verkehrsinfrastrukturen führt über eine effektive Notfall- bzw. Wiederherstellungsplanung (recovery planning). Die Planung der Wiederherstellung von Verkehrsnetzen im Katastrophenfall (Disaster Recovery Planning of Transportation Networks – DR-Planung von Transportnetzen, DRPTN) ist ein kritisches und komplexes Konzept, das sich häufig auf Entscheidungsmodelle und Entscheidungshilfesysteme stützt. Um solche Entscheidungssysteme zu entwickeln und einen zuverlässigen Wiederherstellungsplan zu entwerfen, ist ein gut strukturiertes, modelliertes Problem mit verlässlichen Entscheidungsmerkmalen erforderlich.

Ziel dieser Dissertation ist es, die Problemstrukturierung und die methodische Ermittlung von DRPTN-Entscheidungsmerkmalen zu untersuchen. Zu diesem Zweck beginnt die Untersuchung mit einer systematischen Analyse der DRPTN-Optimierungsmodelle, die in vier Phasen unterteilt ist: Problemdefinition, Problemformulierung, Problemlösung und Modellvalidierung. Für jede dieser Phasen werden Herausforderungen und Möglichkeiten sowie Vorschläge zur Überwindung der festgestellten Defizite formuliert. Um die Wissenslücken bei der Problemstrukturierung von DRPTN-Modellen zu schließen, wurde ein präskriptiver Entscheidungshilfemechanismus entwickelt, mit dem das Wissen von Experten genutzt und Entscheidungsattribute für DRPTN-Probleme empfohlen werden können. Im Anschluss daran wurde dieses Framework in einer realen DRPTN-Fallstudie implementiert, um seine Leistungsfähigkeit zu testen, die Ergebnisse zu analysieren und eine systematisch ausgewählte Menge von Entscheidungsattributen für das DRPTN zu erstellen. Die Forschungsergebnisse wurden in drei Abschnitten zusammengefasst, die im Folgenden kurz beschrieben werden.

Die Ergebnisse der Analyse der Wissensdefizite deuten darauf hin, dass bei den Entscheidungsattributen bestehender DRPTN-Modelle Probleme bestehen. Dazu gehören unzureichende Bemühungen, die angenommenen Entscheidungsfaktoren mit theoretischen Argumenten oder formalen Auswahlprozessen zu begründen und zu stützen. Darüber hinaus würde die Problemlösungsphase der DRPTN-Modellierung von der Anwendung metaheuristischer Algorithmen profitieren, wenn es explizite oder implizite Begründungen wie Konvexität, Linearität oder Komplexitätsanalyse der mathematischen Programmierung gibt. In der Phase der Problemformulierung könnten mehr Anstrengungen unternommen werden, um Verkehrsmanagementmaßnahmen und Modelle für die Verkehrsnachfrage nach dem Notfall (bzw. der Naturkatastrophe) in die Formulierung der Netzwerkwiederherstellung zu integrieren. Für die Validierungsphase von DRPTN-Modellen sind ein Benchmark-System, Fortschritte bei der multiperspektivischen Simulation und ein systematisch entwickeltes Vertrauensniveau erforderlich, um die Zuverlässigkeit der Ergebnisse zu erhöhen. Die Ergebnisse der Analyse der Wissenslücken deuten darauf hin, dass das methodenreiche, aber methodologisch schwache Phänomen eine Herausforderung für Disaster-Recovery-Modelle darstellt.

In Bezug auf die entwickelte Methodik zur Auswahl von Attributen ermöglichte die Implementierung des Frameworks die Nutzung des gemeinschaftlichen Inputs von Experten in einer strukturierten Weise und förderte einen disziplinierten Entscheidungsprozess. Die

mehrstufige, nicht-hierarchische Architektur des Frameworks ermöglichte die kritische und gründliche Bewertung von möglichen Attributen auf relativ benutzerfreundliche Weise. Das Framework könnte als Mechanismus dienen, um das Wissen der Entscheidungsträger nutzbar zu machen und ihnen zu helfen, diejenigen Elemente des Entscheidungskontexts einzugrenzen, die für das Problem am wichtigsten sind. Aus diesem Grund sollte die empfohlene Menge das Ergebnis eines gründlichen, systematischen Prozesses und einer kollaborativen Entscheidungsfindung sein; dadurch bietet es sowohl für die DRPTN-Praxis als auch für die Forschung brauchbare Kriterien.

Die Entscheidungsträger haben sechs Attributen ausgewählt, die in die Notfallplanung für das Teheraner Straßennetz einfließen sollen: (1) Art des Zugangs zu Serviceknotenpunkten; (2) Integration von Reisezeitverzögerung und Verkehrsfluss auf den Straßen; (3) Verbesserung der Reisezeit pro Wiederherstellungsdauer; (4) Verbesserung der Reisezeit pro Ressourceneinheit; (5) Zentralitätsmaße und (6) Kapazität der Verbindungen. Es wird erwartet, dass die Verwendung der empfohlenen Attribute in einem DRPTN-Modell effektive und effiziente Wiederherstellungslösungen bietet, die die Mobilität und Zugänglichkeit im Verkehrsnetz maximieren. Die Analyse der Ergebnisse deutet darauf hin, dass das Framework zu einem verbesserten Attributset im Vergleich zu denjenigen Attributen führt, die ohne Unterstützung ausgewählt wurden. Die Sensitivitätsanalyse bestätigt, dass die übergeordneten Ergebnisse relativ robust gegenüber den zugewiesenen Präferenzen sind. Dieses Argument wurde auch durch eine Analyse der Informationsentropie gestützt. Beide Analysen deuten darauf hin, dass „Gewissheit" ein Anreizfaktor für die teilnehmenden Experten bei der Bewertung von Entscheidungsattributen war.

Im Rahmen dieser Forschungsarbeit konnte ich (1) Wissenslücken und Möglichkeiten in optimierten DRPTN-Entscheidungsmodellen durch eine systematische kritische Literaturanalyse identifizieren und Lösungen für die erkannten Herausforderungen vorschlagen; (2) den Entscheidungsprozess zur Auswahl von Attributen mit einigen innovativen mathematischen Formeln und Modellierungsansätzen formalisieren; (3) das Wissen von Fachexperten mit einem für diesen Zweck angepassten Entscheidungshilfemechanismus nutzbar machen; (4) die Methodik als Toolkit für die weitere Anwendung sowohl in der Wissenschaft als auch in der Praxis anbieten; und (5) eine Menge von Entscheidungsmerkmalen von DRPTN für die Fallstudie vorschlagen. Daneben ergab sich auch die Möglichkeit, einige neue technische Verbesserungen, Erkenntnisse und Wissen zu beobachten und darüber zu berichten, die für Wissenschaftler und Praktiker in den Bereichen Entscheidungsanalyse, Verkehrstechnik und Katastrophenmanagement von Nutzen sein können. Die Dissertation schließt mit einem Hinweis auf die Bedeutung und Kunst der Problemstrukturierung im DRPTN-Kontext.

***Schlüsselwörter**:* Katastrophenresilienz, Wiederherstellung Entscheidungsverfahren, Verkehrsinfrastrukturen, Entscheidungshilfemechanismus, katastrophenschutz, katastrophenrisikomanagement

Table of Contents

Acknowledgments i

List of Publications iii

Summary iv

Zusammenfassung vi

Table of Contents viii

1 Introduction 2

1.1 DRPTN: Disaster Recovery Planning of Transportation Networks 2

1.2 Problem Structuring 6

1.3 Problem Structuring in DRPTN Context 7

1.4 A Short Story: An Overview of the Study and Area of Focus 9

1.5 Study Domain 11

1.5.1 The Context of the Case Area 12

1.5.2 Disaster Scenario 14

1.6 Research Objective and Contributions 15

1.7 Research Gap and Motivations 17

1.7.1 Motivation and Knowledge Gap in the Development of Objective 1 19

1.7.2 Motivation and Knowledge Gap in the Development of Objective 2 20

1.7.3 Motivation and Knowledge Gap in the Development of Objective 3 22

1.8 Research Questions 23

1.9 Research Methods 24

1.10 Outline of the Dissertation 25

1.11 References 27

2 Decision Models for DRPTN; Review and Analysis 32

2.1 Summary 32

2.2 Introduction 33

2.3 Optimization-based Decision-Making Models and DRPTN 37

2.3.1 Problem Definition 39

2.3.2 Problem Formulation 40

2.3.3 Problem Solving 41
2.3.4 Model Verification and Validation 43
2.4 Review and Analysis Methodology 44
2.4.1 Search Strategy 44
2.4.2 Content Analysis 45
2.5 Findings 47
2.5.1 Problem Definition 47
2.5.2 Problem Formulation 49
2.5.3 Problem Solving 51
2.5.4 Model Validation 53
2.6 Discussion and Suggestions 54
2.6.1 Problem Definition 54
2.6.2 Problem Formulation 56
2.6.3 Problem Solving 58
2.6.4 Model Validation 60
2.7 Summary and Conclusion 62
2.8 References 64

3 A Methodology for Selection of Attributes 72
3.1 Summary 72
3.2 Introduction 73
3.3 Knowledge Gap and the Necessity 75
3.4 Current Approaches towards the Selection of Attributes 78
3.5 Evaluation Factors and the Decision Environment 81
3.6 Methodology and the Developed Framework 84
3.6.1 Preference Elicitation 85
3.6.2 Models of Transition and Aggregation 88
3.6.3 The proposed Framework 91
3.6.4 Methods of Implementation 94
3.7 Result and Synthase 98
3.7.1 Performance of the Framework in the Implementation Process 98
3.7.2 Synthesis of the Framework’s Outcome and Feedback of Participating DMs 101
3.8 Discussion 104
3.9 Limitations 107
3.10 Conclusion 108
3.11 References 110

4 **Decision Attributes of DRPTN** ... **118**

4.1 Summary ... **118**

4.2 Introduction ... **119**

4.3 Disaster, Transportation Network, and Recovery Process ... **121**

4.4 Knowledge Gap and Motivation ... **123**

4.5 Methods and the Research Design ... **124**

4.5.1 Problem Structuring ... 125

4.5.2 Relative Importance of Compensatory Factors ... 127

4.5.3 Evaluation and Value Aggregation ... 128

4.6 Main results ... **129**

4.6.1 Evaluation and Value Tree ... 129

4.6.2 Recommended Set ... 131

4.6.3 The Selected Set and DRPTN Literature ... 133

4.7 Sensitivity Analysis ... **134**

4.8 Discussion ... **137**

4.8.1 Analysis of the Attribute Set ... 137

4.8.2 Practical Implications ... 139

4.9 Limitations and Future Research ... **140**

4.10 Conclusion ... **141**

4.11 References ... **143**

5 Conclusion ... **150**

5.1 Summary and Main Findings ... **150**

5.2 Contributions ... **155**

5.2.1 Contributions toward Meeting Objective 1 ... 156

5.2.2 Contributions toward Meeting Objective 2 ... 157

5.2.3 Contributions toward Meeting Objective 3 ... 158

5.2.4 Application of Findings ... 159

5.3 Future Research, Open Questions, and Remaining Gaps ... **160**

5.3.1 Sensitivity to Local Minima and Converting Objectives to Constraints ... 160

5.3.2 Future research on the Implementation of the Framework ... 161

5.3.3 Does Preference for a Certain Objective Impact the Selection of Attributes? ... 162

5.3.4 Integrating Traffic Management of Networks with Recovery Planning ... 163

5.3.5 DRPTN modeling: Do Social Vulnerability Variables Matter? ... 163

5.3.6 Lack of Validation Tools ... 164

5.4 Key Recommendations for Decision-Makers and Research ... **165**

5.4.1 Problem Structuring Necessity in the DRPTN Modeling Context 166
5.4.2 Modeling a DRPTN Problem 168
5.4.3 Attributes for a DRPTN Model 171
5.5 The Art of Modeling in Disaster resilience planning Contexts 175
5.6 References 178
Appendix A 180
Appendix B 182

LIST OF ABBREVIATIONS AND ACRONYMS

AADT	Annual Average Daily Traffic
ADT	Average Daily Traffic
AWT	Average Weekday Traffic
DA	Decision Analysis
DM	Decision-Maker
DRPTN	Disaster Recovery Planning of Transportation Network
DRR	Disaster Risk Reduction
DRM	Disaster Risk Management
DSS	Decision Support System
EIII	Error of the third kind
GA	Genetic Algorithm
GIS	Geographic Information System
IESDS	Iterated Elimination of Strictly Dominated Strategies
MADM	Multiple Attribute Decision Making
MAVT	Multiple Attribute Value Theory
MCDA	Multiple Criteria Decision Analysis
MCDM	Multiple Criteria Decision Making
MODM	Multiple Objective Decision Making
NP	Non-deterministic Polynomial-time
O-D	Origin-Destination
S-P	Service-Providing
SAW	Simple Additive Weighting
TOPSIS	Technique of Order Preference Similarity to the Ideal Solution
VIKOR	VIseKriterijumska Optimizacija I Kompromisno Resenje (Serbian)

Chapter I

INTRODUCTION

“What is missing in most decision making methodologies is a philosophical approach and methodological help to understand and articulate values and to use them to identify decision opportunities and to create alternatives.”

Ralf A. Keeney (1992)

1 Introduction

1.1 DRPTN: Disaster Recovery Planning of Transportation Networks

Disaster Recovery Planning of Transportation Networks (DRPTN) is a critical and complex concept that often relies on recommendations of decision models and decision support systems. To develop such decision systems and draft a reliable recovery plan, a well-structured modeled problem with equitable decision attributes is essential. This dissertation aims to address the problem structuring and methodological identification of DRPTN decision attributes in order to provide a foundation for risk-informed decision-making for road network recovery in the aftermath of disasters.

Natural, anthropogenic, or socio-natural hazards (and their combination) can create disasters in vulnerable, exposed, and non-resilient societies. On the one hand, we might not be able to contain or restrain rapid-onset natural hazards in the near future. Nor is it likely that we cease triggering nature to avoid the escalation of the intensity and extensity of socio-natural and climate change-induced hazards. On the other hand, mitigating the exposure of critical infrastructures, as broad interwoven networks on which our civilizations are built, comes at an extreme cost, which renders risk transfer an unreasonable solution. Consequently, in the context of infrastructure Disaster Risk Management (DRM), alternatives are limited to two main concepts of “reducing vulnerability” and “increasing resilience” of infrastructures. Next to the measures that mitigate the risk of disaster occurrence, resilience in the transportation network can be defined through adaptive, absorptive, and restorative capacities. A massive share of these resilience properties is borne by recovery planning to restore the transportation network’s performance to a state that serves the affected community in the times that it is most needed (Bruneau et al. 2003; Zhang et al. 2017; Kurth et al. 2020). In urban areas, the transportation network is one of the most exposed physical infrastructures. Nevertheless, proactive planning for post-event efforts markedly increases the resilience and capacity of the transportation network to recover from the adverse impacts of extreme natural phenomena (Naga and Fan 2017; Quarantelli 1999; Rouhanizadeh 2019).

Transportation systems present both prosperity and calamity. They not only provide mobility and accessibility for people and supply chains but also for armies and diseases. A transportation system is a cyber-physical critical infrastructure system that, as a "lifeline," provides critical utilities and services vital for the well-being and operation of the community it serves. The socioeconomic functioning of many individuals, enterprises, and critical services depends on the efficient, fast, sustainable, disciplined, optimized, and safe operation of transportation networks. Almost all components of social and economic systems directly or indirectly interact with the transportation system (Cova and Cogner 2004). However, a radical, disruptive impact on the performance of a transportation network can be easily perceived as a disaster that imposes a direct threat to individuals and disrupts the socioeconomic continuity. Table 1.1 shows the direct expected annual damage cost due to the destruction of road and rail assets by hazards, excluding landslides (Koks et al. 2019).

Table 1.1: Total expected annual direct damage per hazard in the road and rail sector. Multi-hazard refers to the aggregate of floods, cyclone, and earthquake.

Hazard	Share	Median of Annual expected Damage (approximately)
Flood (River, surface, coastal)	88.9 %	9.6 Billion USD
Earthquake	7.3 %	1 Billion USD
Cyclone	3.8 %	0.4 Billion USD
Multi-hazard	100	11 Billion USD

Hazards cause damage to a transportation network's physical components, disrupt its cyber-physical administration, and drastically shift the behavior of its users. It also impedes users' access to essential services and products as well as the access for users who are critical to the performance of urban systems. Convergence of susceptibility with exposure and non-resilience is a catalyst for the transformation of a hazard to a disaster in transportation networks. As Figure 1.1 shows, transportation networks, globally, are exposed and susceptible to hazards, which render the post-hazard failure of this system a likely event.

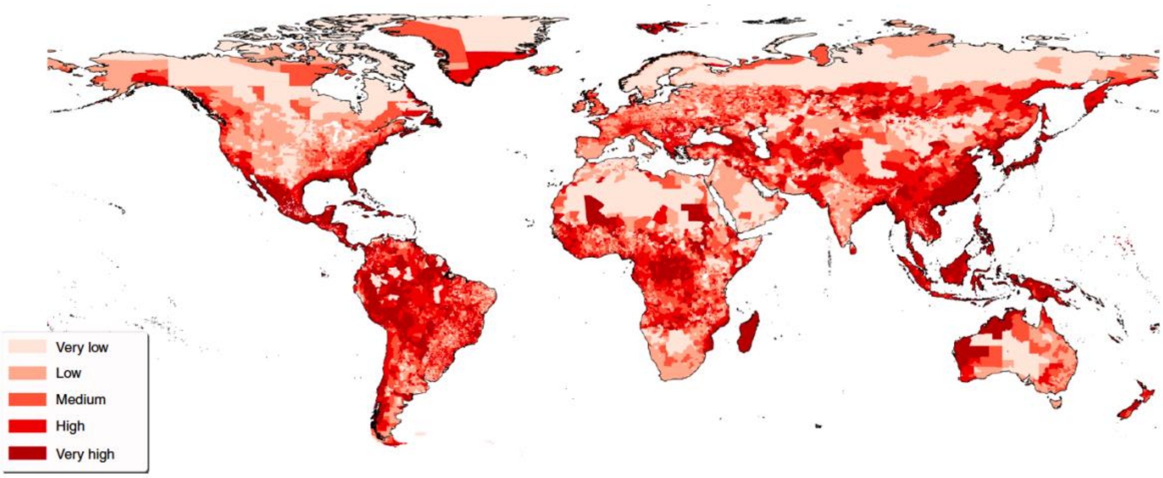

Figure 1.1: Global multi-hazard transport infrastructure exposure (Source: Koks et al. 2019[1])

A damaged road network is both a key challenge and solution for search-and-rescue operations in the emergency response phase, as well as for the community recovery and restoration of socioeconomic affairs in the recovery phase. When a transportation network is not capable of offering the service it was expected to, disaster emerges. Disaster in a transportation network is a set of disruptive conditions that hinder connectivity, accessibility, and mobility, leading to an extreme loss of network functionality. A road network is the sole post-disaster lifeline that grants mass mobility and provides access to essential origin and destinations (ODs) within the affected area. This lifeline is not only structurally vulnerable to hazards but also causes social non-structural vulnerabilities and losses to affected communities. Recovery planning strongly contributes to the resilience of the transportation system as it can alleviate the calamitous effect of hazards and reduce

[1] *Licensed under a Creative Commons CC BY Attribution 4.0 International*

network downtime, while enhancing the network's performance and restoring social life. In fact, resilience, in a transportation context, is partially defined by expedient, effective, and efficient recovery. An ideal recovery and reconstruction planning eventually addresses various post-event issues such as emergency, technical, and socio-economical aspects, since disaster recovery is more of a social process than a mere technical one (Nigg 1995; Lubashevskiy et al. 2017). Providing low-cost, high-impact solutions; accelerating recovery ratio; and promptly establishing access to critical assets are all crucial features of recovery operations that highlight the vital role of Disaster Recovery Planning of Transportation Network (DRPTN). Therefore, successful planning for the disaster recovery process could play an important role in increasing the resilience of an urban area after hazard-induced disasters, thus demonstrating the importance of research in this field. DRPTN is the series of prescribed decision recommendations that respond to the prioritization challenges of recovery operations. DRPTN provides sets of analytic interventions for which elements of a transportation system should be repaired first or which sequence of post-disaster repair and rehabilitation measures yields better system performance by proving more efficient, covering a wider amount of users, better responding to the needs of those who suffer most, having a shorter recovery interval, or a higher rate of recovery. It can be formulated as a ranking model and can either provide a compromise solution to the problem of prioritization of multiple criteria or an optimized solution with one or more objectives. On this ground, DRPTN covers prescriptive decision models, constructed to respond to an extreme hazard that 1) exhibits structural damage to the transportation network's components, 2) directly causes major operational disruption to the traffic functionality of the network or part of it, and 3) can be alleviated only by intervention through physical construction, such as repair and reconstruction operations.

In the aftermath of a disaster in a transportation system, decision-makers (DMs), either authorities, owners, or operators of infrastructures, seek optimized decision recommendations for the recovery process. To support this process, studies develop DRPTN decision models that prioritize reconstruction operations on the network's components. DRPTN decision models, as any decision model, are based on the objectives that reflect the interests, concerns, and values of stakeholders and all affected parties concerning the decision context. A decision context is a setting in which the decision problem is recognized. Attributes measure the level to which an objective is achieved in a given decision alternative and/or represents the essential characteristic of the modeled system that directly impacts objective values. Achieving a representative, effective, and reliable decision-making model for disaster recovery planning requires a well-thought-out set of decision attributes, among other properties. Equitable attributes of a decision model indicate that the problem is well perceived and properly structured. Determining the essential characteristics of the modeled problem and its attributes falls into the category of problem structuring as an indispensable and challenging task of DRPTN decision modeling, which is introduced in the next section.

1.2 Problem Structuring

Developing a decision model becomes difficult when the problem is not well perceived, defined, or characterized. The first logical step of modeling a shared reality or rationality of a prescriptive decision process is to apprehend the current and desired state that the model is designed to represent and to frame the problem accordingly. Toward this understanding, in-depth typological investigations of the problem and its model are essential to avoid transferring the complexity of the problem into the problem-solving process. This investigation can be achieved through a formal problem structuring approach. Problem structuring is the process of understanding, identifying, and characterizing a problem that ultimately reduces the likelihood of committing the error of the third kind (Type III error or EIII), wherein the incorrect problem is solved correctly, while the correct problem remains concealed or only partially solved (Kimbaal 1957). It is acknowledged that the attempt of solving a problem is secondary to understanding it, and the influence of contextual factors on understanding the decision process is significant (Dillon 1998; Baron 2007; Franco and Montibeller 2009; Belton and Stewart 2010). Mitroff and Featheringham (1974) emphasize that "one of the most important determinations of a problem's solution is how that problem has been represented or formulated in the first place" (Mitroff and Featheringham 1974). Problem structuring stresses first understanding the problem before attempting to solve it. von Winterfeldt (1986) defines problem structuring as "a process of translating an initially ill-defined problem into a set of elements, relations, and operations" and later points out that identifying a problem's elements is the primary task of problem structuring. Corner et al. (2001) refer to problem structuring as the design stage, where objectives, decision attributes, and alternatives are identified. Further, Belton and Stewart (2010) highlight that although problem structuring does not conclude the decision process, sometimes a well-structured problem renders the solution "self-evident."

A major task of problem structuring is selecting decision attributes. Attributes clarify the meaning of each objective and measure the consequences of different alternatives (Keeney and Gregory 2005). The attribute set of a decision model represents essential problem-related characteristics and the performance of the modeled system. The degree to which this representativeness is preserved within an attribute indicates its directness. The primary purpose for establishing an effective set of attributes is to disaggregate a complex decision environment into more analytically tractable components while maintaining the representativeness and collectivity of the modeled problem as "direct" as possible. Therefore, an effective attribute set of a problem is likely to yield a decision model that is representative, direct, and complete, thus providing some degree of confidence in the reliability of the output. Identifying the underlying decision variables and decision factors is considered a preliminary step and a major cornerstone of the problem-structuring process (Corner et al. 2001; Keeney 1992).

1.3 Problem Structuring in DRPTN Context

Belton and Stewart (2010) argue that some problems in decision analysis can be termed "messy" because both the definition and solution to the problem are debatable. The messy nature of decision analysis escalates when it sits in the context of a problem that involves stochastic and uncertain variables in a low-validity decision environment such as disaster recovery planning. A key component to address messy-type problems is the use of facilitation to identify values and frame the multi-criteria problem (Keeney and Mcdaniels 1992). The selection of a tenable attribute set is one important task within this facilitation process. This dissertation offer this facilitation by exploring the problem typology of DRPTN, designing a methodology to assist the selection of DRPTN attributes, and implementing this methodology in a real-world instance of a DRPTN problem.

The significant necessity of problem structuring for DRPTN lies in the fact that DRPTN decision modeling, as is the case for many complex decision analyses, is an error-prone task that mainly relies on the modelers' judgment (Phillips-Wren et al. 2019; Winter et al. 2018; Beven et al. 2015). This inevitable subjectivity may result in committing the error of the third kind (Mitroff and Featheringham 1974). The increase in the likelihood of errors that results from failing to properly structure a DRPTN problem is costly for both the public and authorities due to the impacts of decisions in this sensitive context, since the critical nature of the disaster recovery problem exponentially intensifies the consequence of inaccuracies in DRPTN models. This criticality and sensitivity are due to the cascading impact of disasters in urban areas that propagate on a wide scale and wreak havoc beyond damage to physical assets, as they also adversely affect people, economies, environments, and social systems (Kadri et al. 2014). Furthermore, the non-observability of disaster recovery activities makes the situation all the more difficult, as there is sparse applicable data on disasters that can be compared with the output of developed DRPTN models for evaluation purposes (Sargent 1996; Day et al. 2009; Kadri et al. 2014). Even if data is partly available, performing a retrospective test to validate a model is cumbersome, if not impossible, due to the uncertainties and degree of inconsistency between two datasets representing previous and probable future disasters (Leskens et al. 2014; Celik and Corbacioglu 2010). Non-observable models represent complex problems where real-time data on the system's current and past performance cannot characterize its future behavior, as the modeled system has very little similarity with the past or current state of the system. In a non-observable problem, the regularity of the current state of the system (performance and property) is not valid for the problem under consideration, which yields a low-validity decision environment. The non-observability of a problem emphasizes the pressing need for efforts on problem structuring of prescriptive models that represent critical and sensitive real-life problems. Therefore, the selection of viable decision attributes as well as a methodological problem structuring is of the utmost importance for disaster recovery planning problems.

1.4 A Short Story: An Overview of the Study and Area of Focus

This study is built upon an old premise that “a problem well put is half solved” (Dewey 1938). This assumption was the motivation of this research, that the attempt to delineate a solid, well-grounded problem structuring in DRPTN context is, first, “imperative,” and second, “not yet sufficiently addressed” in the literature. I investigated the latter by conducting a systematic review within the identified DRPTN literature and realized that problem structuring is vastly overlooked. Studies take a well-framed problem as a starting point; thus, very few attempts have been made to generate decision attributes that can be supported by a formal approach or logical arguments. For the second assumption, I harnessed the fact that problem structuring is crucial for decision analysis modeling in general, based on existing, well-established literature of decision analysis, which allowed me to generalize this fact to the sensitive, critical, and complex context of DRPTN. Once my field of inquiry became clear, I designed a strategy to approach it. Attacking the identified problem, I borrowed from the prescriptive decision theory concept to build a model that assisted experts with turning their input into decision attributes of a DRPTN problem. After that, I implemented this methodology and sets of methods in a real-world case study to observe the model's performance and report the outcomes, which are decision attributes of DRPTN for the Iranian context. On this ground, I collected attributes that 46 DRPTN papers suggested and extracted attributes based on the opinions of 23 experts in disaster management. Then I conducted a workshop asking four experienced decision-makers and city planners (who each possessed authority, knowledge, experience, and stake) to evaluate those attributes using the developed framework. I was hoping that the framework could assist (or even guide) their intuitive opinion to a more rational, context-dependent knowledge and allow them to critically – yet at the same time simply – assess both attributes and the combination of them, which constitute a set. For this evaluation process, I used ten criteria as evaluation factors within three sequential stages. Each stage had its own evaluation factors and, therefore, its own rule of evaluation as the decision rule. The first stage operated under a non-compensatory decision rule with three evaluation factors. The second stage functioned in a compensatory fashion with four evaluation factors. The first two stages evaluate individual attributes as a member of an ideal set. Finally, in the last stage, DMs could evaluate sets of attributes with three factors under the optimal decision rule. I built the aggregation method by integrating Elimination by Aspect and Multi-Attribute Value Theory to aggregate experts' inputs, which are both well-known developed Multi-Attribute Decision-Making techniques. I also developed a cardinal rank-based weighting model to find trade-offs among some evaluation factors that operate under the compensatory decision rule by using the input of decision analysis experts. As a result of this implementation of the framework in the Iranian DRPTN context, I showed that the developed methodology could systematically harness the knowledge of decision-makers and perform well for the objective for which it was designed. The framework was relatively user friendly, traceable, and inclusive. It delivered a set of six attributes for the context of the case study. I also performed several analyses on the results and performance of attributes, as well as a post-workshop survey and an interview to assess the performance of the framework and the quality of the attributes produced.

Throughout this research, I was able to 1) identify knowledge gaps and opportunities in optimized DRPTN decision models through conducting a systematic critical literature review and suggest solutions for detected challenges; 2) formalize the decision process of selecting attributes with a few innovative mathematical formulations and modeling approaches; 3) assist and harness the knowledge of subject-matter experts with a decision-aid mechanism customized for this purpose; 4) present the methodology as a toolkit for further application in both science and practice; and 5) suggest a set of decision attributes of DRPTN for the case study. Finally, besides these main contributions, I also had the chance to observe and report on some new technical improvements, understandings, and knowledge that can be useful for scientists and practitioners in decision analysis, uncertainty analysis, traffic engineering, and disaster management.

Problem structuring for Disaster Recovery Planning of Transportation Networks (DRPTN) encompasses the fields of civil engineering, operations research, and disaster management. Within the field of disaster management, this conducted study is based on notions and concepts of urban emergency management and resilient infrastructure, focusing on urban recovery planning. It also draws on civil engineering to incorporate knowledge of traffic and transportation planning with a touch of construction management. Insights offered by Operations Research also enrich this study while applying decision analysis and developing decision models. Figure 1.2 shows the overlap of the three major disciplines and the research area of focus. In bringing these fields together, this dissertation links the domain of disaster recovery planning to decision modeling in the context of transportation networks to provide a foundation for decision analysis in (re)construction management and recovery planning of transportation networks.

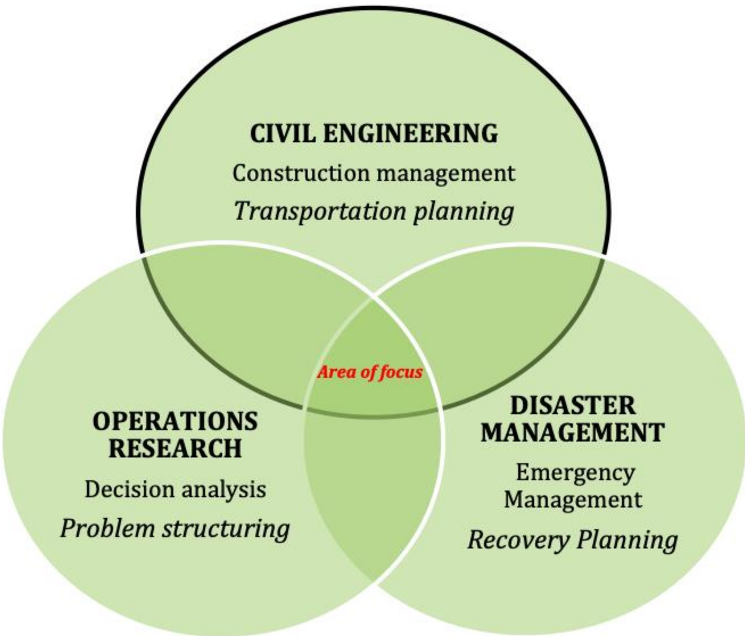

Figure 1.2: The discipline-wise focus area of this research

1.5 Study Domain

The problem of selecting DRPTN attributes exists in general but is contextually specific for each transportation network setting. Accordingly, the DRPTN problem requires contextualized inputs based on local urban properties such as social parameters, topologies, vulnerability states, and resilience capacities. The knowledge of those properties can be obtained from local disaster recovery decision-makers, owners, and operators of urban infrastructures. Therefore, I implemented the proposed framework in the context of Tehran's DRPTN, to realize the opportunity of harnessing the experience and knowledge of decision-makers who have been engaged with urban disaster management and transportation planning with first-hand experience and current involvement in the field.

1.5.1 The Context of the Case Area

Iran is a hazard-prone and disaster-prone country. Hazards such as deforestation, drought, earthquakes, floods, landslides, and wildfires impose tremendous long-term economic, social, and environmental losses. Among common hazards, earthquakes are a major perceived hazard risk in the country. The Greater Iranian plateau embeds active faults and volcanic high-surface elevations along the Himalayan-Alpied earthquake belt. Tehran, the capital of Iran, is exposed to droughts, floods, extreme heat, freeze-thaw, and earthquakes. The seismic status of the Tehran region subordinates to the geomorphologic and tectonic condition of the Iranian plate. This area is located over alluvium sediments of the southern foothills of the central Alborz Mountains accommodating Gondwana–Eurasia collision in the Late Triassic along the Alpine–Himalayan orogeny belt. Due to the northward convergence of the great Iranian plateau and Eurasia, the southern foothill areas of the Alborz Mountains are relatively active zones, subject to massive tectonic stresses (Kamranzad et al., 2020). According to historical notes, major earthquakes have destroyed Tehran at least six times in history (Ghodrati Amiri et al. 2003). Based on the pattern of major earthquakes in Tehran's history, an earthquake of magnitude 7 is rather likely every 158 years as the estimated recurrence interval (Ambraseys and Melville 1982; Ghodrati Amiri et al. 2003). The last major earthquake struck Tehran 191 years ago.

Besides the consistent seismic risk in the Tehran metropolitan area, the city currently and frequently suffers hazards such as floods, landslides, cave-ins, subsidence, fire, snow, frost, and extreme heat. Tehran's transportation network consists of over 200 bridges, 931 km of highways and freeways, 1,053 km of main streets, 1,552 km of collector and access streets, 18.7 km of bus rapid transit track, and 460 km of subway track that operates 18.9 million daily trips (TDTM 2017). Figure 1.3 shows some components of Tehran's transportation network.

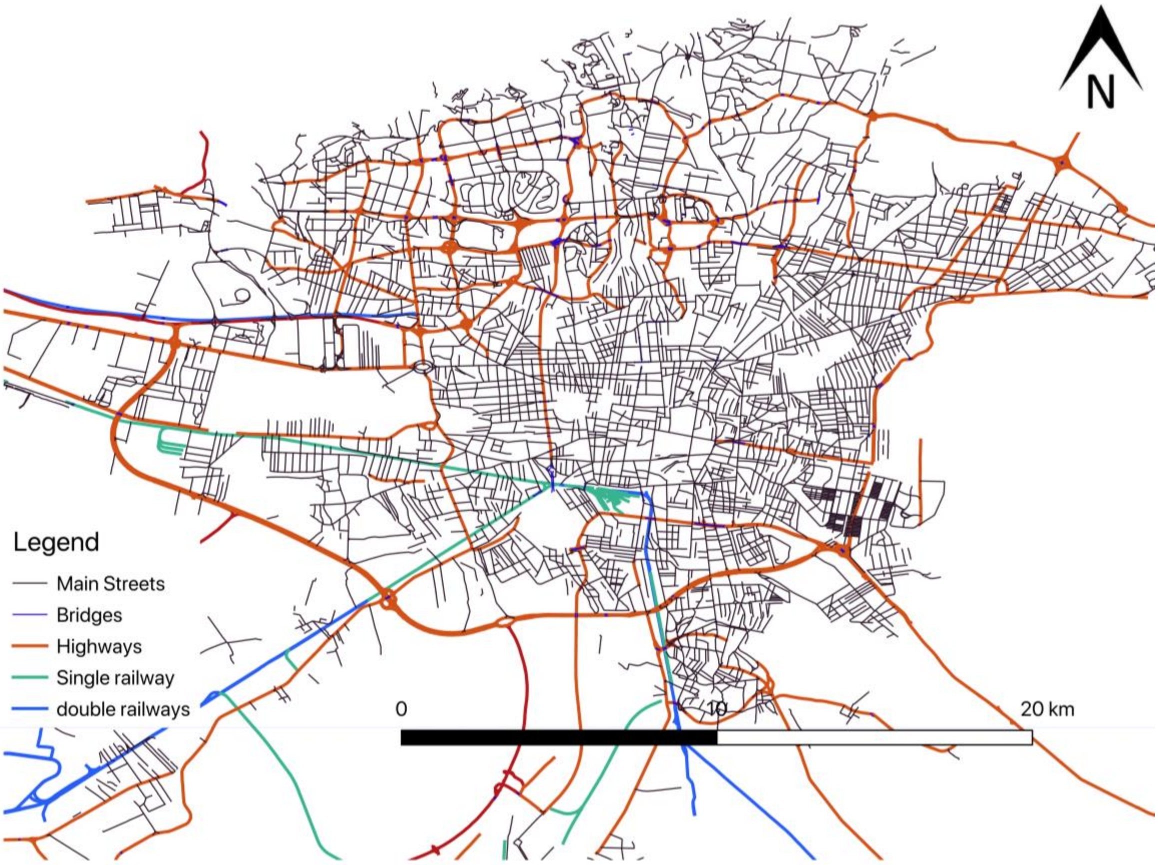

Figure 1.3: Tehran network modeled in QGIS with transportation network components

As a metropolitan area with a population of over 9.000.000[1] and a total area of around 660 square kilometers, Tehran is developed over an asymmetric complex lifeline network and intricately interwoven infrastructures. The city consists of structurally and socially decayed urban environments and vulnerable physical structures. On the one hand, fragile resilience capacities, ripple-effect-prone civil systems, and fragmented coordination in crisis management associated with slow, unorganized decision-making flows raise the likelihood of transforming hazards into disasters. On the other hand, Given the experience of confronting multiple natural and human-made hazards, there is empirical knowledge and practical experience among the local disaster managers and city planners, making it a tenable case for

[1] *Estimated population according to Tehran municipality website (accessed in 2020).*

study. Additionally, due to the author's background, the possibility of identifying, coordinating, and inviting the experienced, educated, and active decision-makers and subject-matter experts who would be willing to participate in the study was the operational motivation of the case selection.

1.5.2 Disaster Scenario

There are usually three main temporal phases after a disaster: emergency response, medium-term recovery, and long-term reconstruction (Feng and Wang 2003; Joakim 2011; Quarantelli 1999). Although the borders between these phases are amorphous and overlap, restoration planning in each of the three phases seeks different targets and addresses different needs. Thus, each phase requires its own specific planning approach. The first phase is called the emergency response or immediate relief; it immediately follows the event (after the confusion period) and usually lasts between three to seven days after the disaster. Common activities include search-and-rescue operations, delivering medical care, debris removal, mass care, and providing shelter. The recovery phase begins during or after the emergency response. This second phase comprises all actions that restore the community function and civil performance to return the situation to a safe and acceptable level, which might not necessarily be the same as the pre-event condition. Mobility and accessibility recovery, medical care, lifeline rehabilitation, and sociocultural and economic continuity have higher significance in this period, which can last for months. The distinction between the recovery and response phases is important because the skills, resources, objectives, time horizons, and stakeholders of the response and recovery phases are dramatically different. The last phase is the long-term reconstruction, which contains all measures for increasing the mitigation of and preparedness for disasters, implementing sustainable development, and completing large-scale reconstruction projects that may take more than two years.

In this dissertation, the focus is on mid-term recovery operations. The disaster scenario includes a major, sudden-onset hazard that creates small-scale and large-scale disasters, which have a disruptive impact that lasts more than weeks. Based on these parameters, a disaster scenario was presented to the participating DMs to familiarize them with the targeted problem. In addition, data of the Tehran region, which is currently the information available for decision-making in disaster situations, was presented to DMs. It includes demographic data of the population such as age, gender, employment situation, education condition, and income rate as well as traffic properties of links and the network including peak hour daily traffic volume and Annual Average Daily Traffic (AADT) of the links, 2D-visualized geometry of the network, along with the location and type of critical facilities and infrastructures of the region. Geospatially assigned information was also mapped and visualized to specify the problem's properties and the situation for which the decision attributes are needed. Appendix (A) provides examples of information that was presented to familiarize DMs with the disaster scenario. Once the experts were familiarized with the problem environment and a shared understanding of a scale and type of disaster was achieved, knowledge extraction began. Chapters three and four demonstrate this process in detail.

1.6 Research Objective and Contributions

This research contributes to the modeling process of constructing disaster recovery DSSs and paves the way for a tenable problem-structuring phase of decision analysis in the DRPTN context. The need for decision-aiding mechanisms to support building DRPTN models motivates this research, since the quality of DRPTN models has a substantial impact on socio-economic losses in disaster-exposed communities and, more importantly, impacts the health and well-being of the affected population. Therefore, this research targets capacity building to increase the resilience of urban areas by offering methods and materials to improve the post-disaster recovery planning process of lifelines. More specifically, the objectives of the study are:

1) Identifying knowledge gaps and emerging methodological demands for optimization-based DRPTN models to understand what improvements are necessary in DRPTN models:

- 1-1) Providing in-depth analytical understanding on the application of optimization programing in DRPTN models and micro-analysis of the methodology of current studies;
- 1-2) Providing suggestions to improve the reliability of DRPTN models and

their application in real-life instances of disaster problems;

1-3) Discussing newly detected gaps and improvement areas for optimization programing in the DRPTN context;

1-4) Exploring the possibility of opening new discussions and suggestions to overcome the detected gaps and future directions of DRPTN research.

2) Supporting analysts who design DRPTN models or develop DSSs for disaster recovery applications with a framework that serves as a decision-aiding toolkit and allows for selecting tenable decision attributes:

2-1) Assisting decision-makers to make informed choices on decision attributes in a structured manner and facilitate elicitation of their knowledge toward selecting a reliable attribute set;

2-2) Formulating the attribute-selection process as a prescriptive choice model;

2-3) Channeling the opinion/preference of experts with a decision-aiding mechanism to produce the knowledge of DRPTN values.

3) Suggesting a viable set of key attributes for disaster recovery planning within the Tehran transportation network as an example:

3-1) Collecting data from DRPTN literature and experts in disaster management with regard to attributes of a DRPTN;

3-2) Harnessing the knowledge of DMs as subject-matter experts for identifying DRPTN key attributes with the implementation of the developed framework;

3-3) Obtaining a degree of confidence in the performance of the developed framework and quality of its outcome.

The following explanation reflects the interrelation and coherency of the three objectives: Meeting the first objective (knowledge gaps) drives the second objective (the framework), while the second objective provides the means for obtaining the third one (selected attributes). Therefore, the outcome of the first objective is identifying the demand for a systematically produced and equitable attributes set of DRPTN problems as an emerging need of the DRPTN field. To meet the second objective, the study explores the possibility of developing a methodology that promises a systematic, effective, and contextual framework to select attributes of DRPTN models. By implementing this framework in the context of Tehran's DRPTN, the study meets the third objective by allowing qualified users acting as subject-matter experts to utilize the developed framework and produce a set of decision attributes for the DRPTN problem. Finally, this study seeks to establish a degree of validity and evaluate to what extent this methodology was successful in serving the purpose for which it was designed as well as the quality of the framework's output.

1.7 Research Gap and Motivations

The DRPTN literature is enriched by valuable studies that focus on DRPTN decision-making models that provide solutions to respond to the post-disaster failures of a network's elements (Karlaftis 2007). Such decision models recommend decisions that significantly impact the life and well-being of the affected people with substantial socio-economic, technical, and environmental cascade effects. While the quality and reliability of these decisions depends on a comprehensive problem structuring and, accordingly, selecting effective decision attributes, the role of problem structuring as a prelude to the framing of a decision-making model is often neglected (Franco and Montibeller 2010; Cochran et al. 2011). In sum, many decision-making models do not benefit from a reproducible and transparent model that assists analysts in selecting decision factors (Tiesmeier 2016). Thus, the task of attribute identification itself remains a challenge that has not been adequately examined (Vaidya and Mayer 2016; Dale et al. 2015).

The significance of problem structuring and the criticality of choosing attributes for a decision-making model is widely evident. Problem structuring methods are already well established in social and management sciences (Franco and Montibeller 2010); however, engineering and construction management fields often find it a trivial task and insignificant contribution to dedicate time and effort to problem structuring. Particularly, in cases of disaster recovery, the certainty and representativeness of the decision model are paramount to producing a reliable decision recommendation. However, problem structuring and the systematic attribute selection process are often overlooked in the construction process of DRPTN decision-making models (Zamanifar and Hartmann 2020). A common understanding has emerged in decision modeling that a good problem formulation is one in which the existence of a unique solution is assured in a reasonable time (e.g., Williams 2013, p., 295). Accordingly, the degree to which the solution drawn from the decision model holds for the real system is not seen as crucial. This mismatch between the core properties of a model and essential characteristics of a real-world instance is even more critical when the decision context must accommodate disaster recovery planning. As such, 77.5% of reviewed optimized DRPTN models are formulated without a systematic approach or a conceptual argument to support the incorporation of attributes in the decision-making models. This observation becomes concerning when, within those studies, efforts toward validation of DRPTN models are limited to 30% of total DRPTN studies, and in 70% of cases, an explicit argument to support the validation phase of the DRPTN modeling process could not be identified. Therefore, the lack of conceptual, theoretical, or methodological underpinning for the selection of decision attributes or to support the model's attribute selection process is a valid concern, since representativeness and completeness of the adopted decision parameters is the main contributor to the quality of the decision model's outcome. This concern has led researchers to call for approaches that allow for a systematic and transparent selection process of contextual and tenable decision attributes (Zamanifar and Hartmann 2020; Ha and Yang 2018; Tiesmeier 2016; Vaidya and Mayer 2016; Dale et al. 2015).

While some research discusses how existing attributes of decision problems are likely subjective, intuitive, or adopted without contextual justification (e.g., Tiesmeier 2016; Xiaofei et al. 2018), it is critical for the integrity of the model that attributes are selected based on a reliable and structured approach. The critical nature of this task is highlighted in disaster recovery planning research due to 1) the extreme socio-economic stakes, 2) the challenges to the validation of models due to the problem's non-observability, and 3) the existing gap in DRPTN literature on formalizing the attribute selection process. Additionally, DRPTN literature mainly focuses on the problem-solving step of the decision modeling, while making insufficient effort for systematic formalized selecting of DRPTN attributes (Zamanifar and Hartmann 2020). In this study, we intend to flip the focus and underline the importance of problem structuring in establishing tenable attributes for the sensitive and critical problem of DRPTN. In the following section, the knowledge gaps and motivation for meeting the three defined objectives are presented.

1.7.1 Motivation and Knowledge Gap in the Development of Objective 1

Over the last decade, a number of review papers addressed several disaster management fields in both pre-event and post-event phases, covering areas such as vulnerability, evacuation planning, emergency response, and reconstruction planning. Among these, only a few were exclusively devoted to the recovery of the transportation network or its functionality after disruptive events (e.g., Faturechi and Miller-Hooks 2015; Konstantinidou et al. 2014; Abdelgawad and Abdulhai 2009; Dehghani et al. 2013; Galindo and Batta 2013). Additionally, I could not identify a review that investigates the problem structuring of optimization methods within DRPTN models. Nevertheless, due to the increasing application of optimization programming in the DRPTN context and the critical result-sensitive characteristics of such problems, it is important to conduct such an investigation.

A review of optimization programming has been performed in many contexts. Existing studies review the optimization methods based on how they are formulated and solved, as well as on the context in which they are applied and how they can be compared. While a survey of techniques used in solving or formulating optimization problems can be viewed as common state-of-the-art optimization review studies, the phases of validation, problem structuring, and problem identification are not the focus. Additionally, it was not possible to identify a review reporting on the limitations in problem structuring of optimization methods within a specific application. When dealing with a context-sensitive problem, it is necessary to identify the parts of DRPTN methodologies on which the quality of findings depends and, at the same time, are not sufficiently addressed.

The existing practical knowledge on DRPTN is indeed extremely costly, if not the most priceless one. Researchers have investigated many disasters that took invaluable lives and caused overwhelming environmental and socio-economic losses. The outcomes of studies on disaster recovery planning provide valuable insights for future research and measures in practice. Given that scholars have been producing detailed seminal studies of DRPTN for three decades, it is logical that a review reflects this valuable accumulation of knowledge and points out possible challenges and opportunities arising in different research trends.

1.7.2 Motivation and Knowledge Gap in the Development of Objective 2

In both disaster management practice and research, insufficient effort is made to identify contextual, representative, and complete attribute sets (Girod 2003; Belton and Stewart 2010; Ha and Yang 2018). Attributes are often selected arbitrarily and without contextual justification or the application of a formal approach to control for the inevitable subjectivity associated with selecting decision factors (Tiesmeier 2016; Zamanifar and Hartmann 2020). This is perhaps because systematic approaches toward selecting attributes and indicators are close to rare or users do not sufficiently integrate them into the decision modeling process (Dale et al. 2015; Niemeijer and de Groot 2006). Following a methodological approach, such as a decision-aiding framework, is critical for ensuring the quality of problem structuring and decision models. This is even more critical for complex problems of DRPTN due to the socio-economic and technical consequences of decision recommendations.

Several studies highlighted that too little attention has been paid to how to obtain a suitable list of attributes and a contextual structure among them (e.g., Maier and Stix 2013; Belton 1999; Keeney and Gregory 2005). Niemeijer and de Groot (2006) argued that the attribute-selection process is mainly subject to arbitrary decisions and have called for a straightforward process for selecting indicators, while Lin et al. (2009) stated that attribute-selection processes generally suffer from being insufficiently systematic and transparent. Moreover, Ma et al. (2016) highlighted that answering the question of how to select the optimal decision attributes presents a compelling future research direction, which is a critical process for many MCDM domains. Accordingly, several researchers have called for a systematic, context-related, step-by-step guide to act as a reliable decision-aid mechanism for attribute selection in decision problems (Tiesmeier 2016). On this ground, to improve the quality of decision models in this sensitive and critical context of DRPTN, a formal approach for establishing effective and comprehensive decision attributes is an imperative need.

Generally, four main approaches inform the selection of attributes. The expert-based approach refers to extracting information from stakeholders, DMs, and subject-matter experts to articulate the important decision factors in a specific context (e.g., Mahdiyar et al. 2018; Hockey and Branch 1997). Literature-based attribute selection is an adoption approach in which the selection task is based on the attributes applied in previously conducted studies (e.g., Abidi et al. 2019; Desmond 2007). The third approach is a combination of expert opinion and previous literature of the field (e.g., Kassem et al. 2016; Amer and Attia 2017). The mixed approach integrates two available sources to develop a more comprehensive and complete set of attributes. Finally, the systematic model-driven attribute selection approach (e.g., Otto et al. 2018; Axel et al. 2017; Dale et al. 2015; Convertino et al. 2013) presents an alternative to overcome several challenges associated with other approaches, such as 1) contextual adaptability of literature to the problem at hand; 2) temporal validation and generalizability of literature-based attributes; 3) interview intensity of an expert-based approach; 4) completeness and inclusiveness of the attribute set; 5) the challenge of selecting from a broad list of attributes proposed by the literature and experts; and 6) reducing the subjectivity involved in the process of attribute selection. A model-driven approach formulates and solves the choice problem by selecting among a finite number of attributes drawn from the literature and experts of the field based on evaluation factors that reflect the properties of desired attributes. Many DRPTN studies do *not* apply any of these approaches to attribute selection; only 22.5% of studies exhibit arguments or a methodological set-up that support and justify the selection process of attributes. Acknowledging the possibility that some researchers might avoid reporting on such attempts, limitations concerning selected DRPTN attributes, as well as the overall lack of problem structuring in general (e.g., Belton and Stewart, 2010), provide sufficient indications to believe that improving the approach toward the selection of attributes is worthy of time and effort. Based on this premise, chapter three is a response to the call of several studies for a framework for identifying decision attributes (Zamanifar and Hartmann 2020; Ha and Yang 2018; Tiesmeier 2016; Vaidya and Mayer 2016; Dale et al. 2015).

1.7.3 Motivation and Knowledge Gap in the Development of Objective 3

Defining attributes for the problem of disaster recovery, as in any decision model, is inherently subjective and error- and bias-prone due to the low validity decision environment of the post-disaster DRPTN prescriptive model and the inevitable subjectivity associated with the problem structuring (Cochran et al. 2011). Challenges arise during the selection of attributes since epistemic and aleatoric errors can influence the decision model's output even if the model is mathematically solvable and verifiable (Phillips-Wren et al. 2019; Wesley and Dau 2017; Beven et al. 2015). Furthermore, some reviews have highlighted the absence of systematically produced attribute sets for disaster management models and pointed out their inadequacies (e.g., Zamanifar and Hartmann 2020; Fekete 2019; Gutjahr and Nolz 2016). As a likely result of neglecting the problem structuring process, some shortcomings concerning decision attributes were identified within the DRPTN literature reviewed. For instance, attribute sets that address both mobility and accessibility aspects of the modeled problem appeared only in 17.5% of the studies; this may pose challenges to the completeness of DRPTN models. Disregarding the topological properties of a network to measure each link's accessibility index can also raise concerns over the representativeness of models. Similarly, only 12.5% of the studies included the level of access to critical facilities, which shows access restoration to service-providing nodes (e.g., medical centers, strategic nodes and critical facilities) has not been sufficiently acknowledged. Additionally, some of the attributes can be perceived as ambiguous such as "importance," "urgency," or "capability of the repair team," as they are too broad and qualitative to allow for a standard, constant, and certain understanding of their definition. Furthermore, non-operational and decomposable attributes such as "risk of recovery in sensitive areas" or "traveler convenience" also introduce uncertainty into the DRPTN models. It is cumbersome – if not impossible – to quantify such metrics with reasonable certainty and operational efforts. Moreover, some DRPTN studies rely on sets that, despite hosting well-established attributes, introduce attribute redundancy by simultaneously measuring related properties of the traffic performance, e.g., link flow, link capacity, and travel time. Redundancy in attribute sets creates an unbalanced emphasis on one objective, which adversely influences the set's equitability. Conversely, to reach a complete set of attributes, using a relatively large attribute set size imposes a high computational cost and uncertainty in reaching a convergent, optimal, or compromise solution. Therefore, it is meaningful to associate the existing challenges outlined above with the absence of a formal problem-structuring phase in the reviewed decision models.

1.8 Research Questions

The questions below reflect three central research questions, which correspond to the three objectives of the study. Answering these questions provided the opportunity to address the key question of *how can researchers and disaster managers best structure the problem of DRPTN*?

RQ/1: What are the challenges and opportunities in DRPTN decision modeling and emerging improvement areas of the field?

RQ/2: How can we develop a decision-aiding framework to assist DMs in selecting decision attributes?

RQ/3: What is an equitable set of decision attributes for the Tehran DRPTN context?

The first research question has been approached in chapter two, where I analyzed the identified DRPTN optimization models based on four phases, including problem definition, problem formulation, problem-solving, and model validation. The second research question is answered in chapter three by developing a prescriptive decision aid mechanism to assist in harnessing experts' knowledge and recommend decision attributes. In chapter four, I addressed the third question, where I implemented the framework in a real-world DRPTN problem case study to test its performance, analyze the outcomes, and produce a systematically selected set of DRPTN decision attributes.

1.9 Research Methods

Within the structure of those three research papers, I adopted and developed several methods. While in chapters two, three, and four, the research methods have been described in detail, this section briefly present an overview of those methods. Questionnaires were used to collect the attributes from experts, whereas content analysis and descriptive statistics were used for the literature review. Using a visualized slider, I collected the input of MCDM experts on the relative importance of compensatory evaluation factors and then used an ordinal-cardinal mathematical formulation to convert their assigned input to numerical weights. I used prescriptive decision theory as a guide to build the attribute-selection framework as a fit-for-purpose method and used it to identify the decision attributes of the DRPTN problem. A focus group workshop helped to implement the framework. GIS visualization was the means to present a disaster scenario and familiarize the DMs with the decision environment. Direct rating point allocation helped the DMs assign numerical values to the performance of alternatives within the evaluation process. Further, Multi-Attribute Value Theory was selected to aggregate the DMs' inputs in the compensatory region, while an aspect-based screening approach was used to screen the alternatives in the screening region. Value tree concept mapping allowed DMs to evaluate sets of attributes in the optimal region and select the set. For analyzing the framework's output, I used retrospective comparison, information entropy analysis, and sensitivity analysis. Finally, a semi-structured interview with a Likert scale and an open discussion interview allowed for the collection of DMs' feedback on the experience of using the framework and its performance.

Table 1.2 summarizes the methods employed for performing the three tasks of problem structuring, data collection, and data analysis within the framework of the research design. Conceptual methods were used to frame the problem and to establish the research design. Qualitative methods were mainly used to collect data from DRPTN literature and experts. I then analyzed the data and the outcome of the developed research design using quantitative methods. In the method section of chapters two, three, and four, those methods are explained more in detail.

Table 1.2: Adopted tools and methods for framing the research design and addressing the three main objectives

	Conceptual	Qualitative	Quantitative
Problem structuring	- Prescriptive decision theory modeling	-Deductive content analysis - Literature review - Attribute selection methodology	- GIS visualization and spatial modeling - Attribute selection method
Data collection		- Secondary data sources - Systematic search - Semi-structured interview - Brainstorming - Survey	- Point allocation, direct rating - Rank-based orderings - Directed content analysis - GIS data analysis
Data analysis	Value tree concept mapping	- Content analysis - Focus group workshop	- Descriptive statistics - Elimination by aspect - Multi attribute utility theory - Cardinal rank-based preference elicitation method - Entropy information analysis - Sensitivity analysis

1.10 Outline of the Dissertation

This dissertation consists of five chapters, three of which are based on published materials in peer-reviewed journals with a focus on hazard and disaster, transportation and resilience, and environment and decision systems. Chapter two demonstrates a systematic, comprehensive, and critical analysis of the knowledge gaps within DRPTN decision models and highlights challenges and opportunities in the DRPTN modeling process. The findings presented in this chapter shape other research questions that are answered in chapters three and four. Chapter three responds to the gaps identified in the previous chapter and presents a set of methods and a framework to systematically evaluate and select decision attributes. The developed decision support framework is an attempt to formalize the process of attribute selection. This chapter focuses on how users can apply the proposed framework as a decision-aid mechanism for problem structuring when tackling complex multi-criteria engineering and planning problems.

Chapter four describes the process of data collection and the implementation of the methodology proposed in chapter three in a real-life DRPTN scenario. In this chapter, case study data is analyzed and inputted into the framework to produce a set of decision attributes for the Tehran DRPTN decision problem. This chapter focuses mainly on DRPTN decision attributes by providing an analysis of the resulting attributes. The last chapter summarizes the results of this research, highlights the key findings, elaborates on open questions, presents avenues for possible future research, and provides practical recommendations for research and practice. This chapter ends with a call to action to better understand challenges and opportunities in DRPTN and the vital role of problem structuring in a decision-modeling process that could also be generalized for other domains. Complementary contents including research data and analyses (e.g., list of decision factors in DRPTN studies, categories of formulated optimization problems, literature review's parametric findings, utility scores of attributes in the selection process, and list of attributes of the alternative pool) that could be interesting for readers are available as supplementary materials of papers. There are two sets of supplementary materials for chapters two and three, which I made available on the institutional repository at TU Berlin. The links for accessing those files are provided within the respective chapters.

Although I have tried to minimize repetition, some recapitulation was necessary to ensure that each chapter is comprehensible on its own. Chapters two, three, and four are papers co-authored with Timo Hartmann; therefore, I refer to "we" and "our" while "I" is used in the rest of the dissertation. Finally, the three papers in chapters two, three, and four have been slightly modified to better integrate them into this dissertation and improve the overall consistency and coherence.

There are limits to this dissertation and research design, many of which I am aware, and many I am not. However, I have chosen not to include a dedicated limitation section in the concluding chapter. Instead, at the end of two published papers in chapters two and three, the limitations are separately outlined. I would be grateful if readers of this dissertation would be willing to share their critiques and comments with me.

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Chapter II

DECISION MODELS FOR DRPTN; REVIEW & ANALYSIS

"…The problem appears hard to solve only because it is badly stated."

Jean-Jacques Rousseau (1762), The social contract

2 Decision Models for DRPTN; Review and Analysis

(Accepted Manuscript) [1] Zamanifar M, Hartmann T, (2020), Optimization-based decision models for disaster recovery and reconstruction planning of transportation networks, Journal of Natural Hazards, Vol. 104, P. 1-25, Springer. https://doi.org/10.1007/s11069-020-04192-5

2.1 Summary

The purpose of this study is to analyze optimization-based decision-making models for the problem of Disaster Recovery Planning of Transportation Networks (DRPTN). In the past three decades, seminal optimization problems have been structured and solved for the critical and sensitive problem of DRPTN. The extent of our knowledge on the practicality of the methods and performance of results is however limited. To evaluate the applicability of those context-sensitive models in real-world situations, there is a need to examine the conceptual and technical structure behind the existing body of work. To this end, this paper performs a systematic search targeting DRPTN publications. Thereafter, we review the identified literature based on the four phases of the optimization-based decision-making modeling process as problem definition, problem formulation, problem solving, and model validation. Then, through content analysis and descriptive statistics, we investigate the methodology of studies within each of these phases. Eventually, we detect and discuss four research improvement

[1] ***Contributions***: *The first author had the idea and performed the literature search, data analysis, drafting the discussions, and result development. The second author proposed the structure, supervised, contribute to improving the discussion and communication of the paper as well as series of edits and proofreads. The second author also revised the paper.*

areas as 1] developing conceptual or systematic decision support in the selection of decision attributes and problem structuring, 2] integrating recovery problems with traffic management models, 3] avoiding uncertainty due to the type of solving algorithms, and 4] reducing subjectivity in the validation process of disaster recovery models. Finally, we provide suggestions as well as possible directions for future research.

2.2 Introduction

We define the decision-making model for Disaster Recovery Planning of Transportation Network (DRPTN) as *a prescriptive decision model, constructed to respond to an extreme hazard that i) exhibits structural damages on the transportation network's components. ii) Directly causes major operational disruptive impacts on the traffic functionally of the network or part of it and iii) can be alleviated only by physical construction interventions such as repair, and reconstruction operations.* The existing studies on DRPTN develop decision-making models in which road's components have to be prioritized for reconstruction such that it optimizes predefined objectives (e.g., Lertworawanich 2012; Kaviani et al. 2018; Shiraki et al. 2017). As a tool, optimization modeling is embedded in Decision Support Systems that formulates and solves problems involving (often) multiple conflicting objectives (e.g., Zhu et al. 2019; Xu et al. 2019; Xing 2017). Particularly, in the setting of the transportation network, as a highly critical and intricately interwoven infrastructure, optimized decisions are products of optimization-based decision modeling that recommend solutions responding to the post-disaster failures of a network's elements (Karlaftis 2007; Zamanifar and Seyedhoseyni 2017). While many reviews investigate the application of optimization modeling in different contexts and fields, it is close to rare in disaster recovery context yet ever-growing essential. This necessity lays on the fact that optimization-based decision modeling, as goes for many complex decision analyses, is an error-prone task that chiefly relies on modelers' judgment (Phillips-Wren et al. 2019; Winter et al. 2018; Beven et al. 2015). This inevitable subjectivity could result in committing the error of the third kind to either correctly solve a wrong problem or partly solve the right one (Mitroff and Featheringham 1974). Besides, the criticality and sensitivity of the disaster recovery problem exponentially escalates the consequence of errors in DRPTN models. This criticality and sensitivity are due to the cascading impact of disasters in urban areas that propagates on a wide scale and emerges beyond the damage of physical assets to adversely affecting people, economy, environment, and social systems (Kadri et al. 2004). Another reason is the inherent characteristic of disaster recovery problems due to its *non-observability* as there is sparse matching data of disasters that can be compared with the output of developed DRPTN models for the evaluation purpose (Sargent 1996 and 2011; Day et al. 2009; Kadri et al. 2014). Even if data is partly available, performing a retrospective test to validate a model is a cumbersome task, if not impossible, due to the degree of inconsistency between two datasets of the previous and probable future disasters (Leskens et al. 2014; Celik and Corbacioglu 2010). The non-observability of a problem emphasizes the pressing need of particular care for defining, formulating, and solving prescriptive models that represent critical and sensitive real-life problems. Hence, it is logical to recognize the need for clear identification of possible uncertainty sources and vulnerable parts of DRPTN models that may challenge the validity and quality of the outcome (Buchanan et al. 1998).

To this end, the objective of this paper is to evaluate existing optimization-based DRPTN models' components to identify and discuss the challenges that can provide understanding toward improving the accuracy and practicality of optimization-based DRPTN models. Additionally, since the focus of existing reviews on optimization modeling is mainly on solving algorithms, we performed our analysis based on four phases of optimization modeling as problem definition, problem formulation, problem solving, and model validation (Nocedal and Wright 1999; Horst and Tuy 1996; Williams 2013). This bottom-up approach helps us to review the performance of an optimization model based on its components such as decision factors, choice variables, solving techniques, objective functions, and result analysis methods. Accordingly, the task of problem definition and identifying decision factors is the first phase of optimization decision-making modeling. The second phase is to formulate the problem such that it demonstrates the representative properties of the modeled problem. In this step, analysts set up relations among decision factors and variables and then translate them into mathematical equations. In the problem-solving phase, the selection and implementation of a matching and robust solving approach is the concentration to maintain the quality of the model and the feasibility of outcomes simultaneously. The last phase is to verify and validate the model's output such that one can apply it as a reliable solution to a real-life problem. Accordingly, to analyze the identified papers, we first studied the problem definition of DRPTN models to explore the adopted decision factors of models and approaches toward selecting those factors. In the problem formulation phase, we tried to understand as to how relationships among objectives are set and how this relationship can be contextualized for the problem of DRPTN. Furthermore, we investigated the phase of problem solving in the reviewed DRPTN literature by identifying the rationale for adopting problem solving algorithms based on objective functions, complexity, and convexity of problems. Finally, we studied the model validation phase to identify approaches toward evaluating the performance of the DRPTN models and the developed mathematical algorithms.

As a review strategy, we began with a systematic search to identify relevant publications based on DRPTN definition and accordingly multiple terms that address hazards, disasters, recovery, roads, and transportation networks. We then used the content analysis approach for analyzing the existing literature. Doing so, we first divided and structured the optimization modeling process into four phases. Afterward, we extracted the information from the reviewed texts that address the adopted phases. Once the representative contents of each publication were categorized, we identified the elements of models that were consistent in all publications such as decision factors, solving techniques, number of objective functions, validation efforts, and so forth. We applied two review questions as 1) What methodological elements of DRPTN models could challenge the validity and contextual application of models' outcomes? 2) How the rationales for structuring the four phases of optimization modeling are conceptually supported? Based on the review questions, we developed several comparing matrixes to state the relation between extracted elements that may lead to possible limitations in the methodologies of DRPTN research. We detected and discussed four research improvement areas as the findings of this study which are: 1] developing conceptual or systematic decision support in the selection of decision factors and problem structuring, 2] integrating recovery problems with traffic management models, 3] avoiding uncertainty due to the type of solving algorithms, and 4] reducing subjectivity in the validation process of disaster recovery models. The identified gaps point out important areas of optimization modeling in the context of disaster recovery that could contribute to the improvement of DRPTN models' performance. The paper presents a contextual understanding of the construction process of DRPTN models which provides insights for decision-makers as to what can be expected from the existing models' performance and what uncertainties they could take into account while receiving decision recommendations of an optimization-based DRPTN model. The study could be also useful for decision analysts and scholars who intend to employ optimization modeling in disaster recovery planning applications.

Within the last decade, a number of review papers addressed several disaster management fields in pre-event and post-event phases such as vulnerability, evacuation planning, emergency response, and reconstruction planning. Among those a few were exclusively devoted to the transportation network and its functionality after disruptive events (e.g., Faturechi and Miller-Hooks 2015; Konstantinidou et al. 2014; Abdelgawad and Abdulhai 2009; Dehghani et al. 2013; Galindo and Batta 2013). However, despite outstanding findings, to the best of our knowledge, addressing the recovery and reconstruction phase of the transportation network was not the focus of those studies. Meanwhile, the literature review on optimization programming is relatively common in different contexts. Existing reviews analyze the optimization methods based on their formulation approach, solving technique, the application of solvers in a specific context (e.g., Fernandes et al. 2018; Wu et al. 2018; Udy et al. 2017; Marler and Arora 2004). While there exist valuable information on the application of optimization solving algorithms, we chose to look at optimization programming as a process. This approach is particularly essential for disaster recovery context because the representativeness of the formulation and reliability of a model's outcome depends on an accurate problem structuring and methodological approach within all four phases of optimization-based decision modeling (Belton and Stewart 2010). Additionally, we failed to identify a review that investigates the adaptability and problem structuring of optimization methods within DRPTN models. Nevertheless, such an effort is of great importance due to the increasing application of optimization programming in the DRPTN context and critical result-sensitive characteristics of such problems.

2.3 Optimization-based Decision-Making Models and DRPTN

Optimization is designing or identifying the most favorable choice among a set of alternatives subjected to a set of formalized bounds (Bertsekas 2015). It consists of one or multiple objective functions and a set of variables as well as a defined set of constraints in a finite non-empty subset of a partially ordered space. An optimization model eventually specifies a possible set of non-dominated solutions by varying the selection or order of variables that represent an optimal compromise among objectives (Ehrgott 2005). Variables are alternatives that diverge to optimize objective functions also called choice set or unknowns (Nocedal and Wright 1999). Constraints refer to the applicable limits on decision choices and are responsible for articulating the functional relationships among alternatives. They also allow users to express enforced behavior of a system and indicate certain limitations. A general form of an optimization problem can be shown as $\Phi(k,x) = \{\max\ [f_1(x), \dots f_n(x)] | \Phi\ (k', x)\}$ where $f_i(x)$ is the objective function and $\Phi\ (k', x)$ is known as the constraints. A multi-objective problem in optimization modeling refers to the notion that the optimal solutions for more than one objective are different and changing the values of the decision vector to improve one objective might result in a decrease in the value of other objectives. Accordingly, Pareto optimality expresses achieving a set of ideal solutions that indicates the optimum trade-off among those conflicting objectives.

For solving an optimization model, problem complexity is an important concept. Problem complexity identifies how difficult it is to achieve the optimal solution for an optimization problem. This difficulty is measurable with the required computational resource that a solving algorithm consumes until it terminates on the optimal or near-optimal solution. The resource is usually referred to the running time (time complexity) or the used memory (space complexity). When some problems exhibit close asymptotic behavior in consuming computational resources for obtaining optimal solutions, then they shape a class of complexity. Insights from the computational complexity of problems especially tackling non-convex problems can locate the cumbersome part of the formulation, which indicates where it is possible to aggregate, decompose, or simplify and helps to model the problem effectively (Tovey 2002).

As an inherent property for some classes of optimization problems, every local optima is a global optima. These problems are referred to as convex optimization problems (Bertsekas 2015). Informally, convexity in optimization means that objective functions and feasible sets formed by constraints shape a convex feasible region that ensures the existence of the global minimum. Convexity analysis refers to the evaluation of the geometric feature of the feasible region toward constructing smooth convex objective and constraints functions. Detecting the convexity of the feasible region of the problem provides useful insights to assimilate the complexity of the problem and eventually selecting an efficient solving algorithm (Johannes 2013). As Figure 2.1 illustrates, presuming that the right problem is recognized, we present the optimization modeling as a process with four main phases namely definition, formulation, solving, and validation. The following section introduces the properties of each phase and its importance in the context of DRPTN.

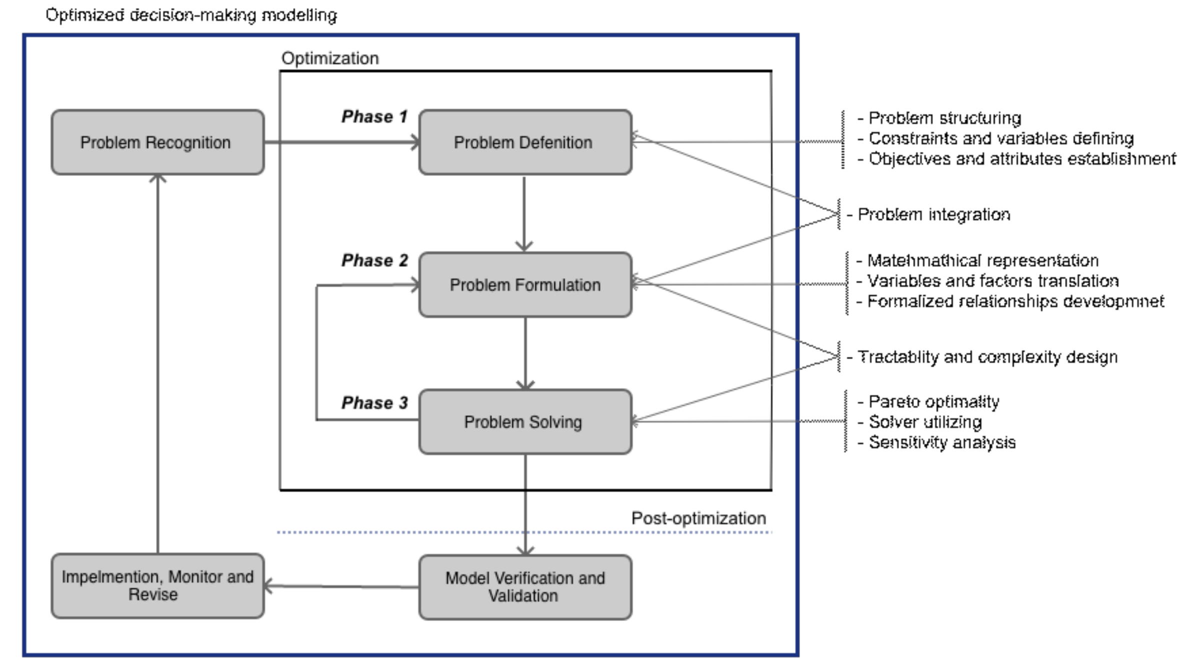

Figure 2.1: Phases of decision-making modeling and steps of optimization programming

2.3.1 Problem Definition

Modeling of a real-scale problem aims at abstracting the perceived system and the problem in one environment (Phillips 1984). It initiates with identifying the problem and selecting its decision parameters as part of problem structuring (Keeney 1992). In optimization-based decision-making modeling, the problem's components are the decision factors, which express the system's function, and decision variables that control the behavior of decision parameters. Among decision factors, attributes evaluate the performance of the system and the distance to the desired state of the system articulated by objectives. Though decision-making models eventually optimize the given objective functions, quality of the resulting outcome depends on *"the completeness of the model in representing the real system"* (Taha, 2007). Meanwhile, representing the real system is highly contingent upon defining decision factors such as objectives and attributes (Belton and Stewart 2012; Keeney and Gregory 2005).

There are many well-posed optimization problems with clearly defined decision parameters such as production efficiency problem, manufacturing problems, blending problems (Zopounidis and Doumpos 2002). However, in the disaster recovery planning context, problems do not often emerge clearly labeled or with fully defined properties. In the aftermath of a disaster, objectives and preferences are dynamic and hardly recognizable (Leskens et al. 2014; NRC 1999). Additionally, effective attributes and even in some cases alternatives are vague as well. Hence, a thorough investigation of the problem definition step as the preliminary phase of the optimization modeling process is vital. Even more so in the context-dependent and critical problem of DRPTN that is highly complex and cannot afford conceptual error in representing the real system due to a broad impact of results on multiple accepts of a big scale society. On this ground, we study the variety of attributes that DRPTN studies developed and analyze the rationale for choosing those attributes.

2.3.2 Problem Formulation

This phase formulates a mathematical translation of the defined problem and establishes sets of relationships among variables and decision factors (Morris 1967). When modelers achieved an equitable set of decision factors in the problem definition phase, in this phase they seek the desired arrangement among them (French 2018; Williams 2013). Additionally, selecting the target set of variables of the problem is a task of this step since those variables are part of possible solutions that ultimately shape the feasible region of the optimization problems (Ehrgott 2005; Lange 2013). Although this step has many interrelations with the phase of problem definition, since both are parts of the problem structuring, yet it cannot proceed unless the outcome of the first step is available. Unlike problem definition during which modelers select decision parameters, in the problem formulation phase, they decide as to how to treat decision parameters. Problem formulation, additionally, deals with integrating the target variable sets and assign values to objective functions to achieve a meaningful and formalized mathematical expression of the intended problem.

In doing so, traffic assignment simulation is a common sub-model for assigning value to traffic decision factors of optimization models in transportation planning. Traffic assignment models simulate the traffic on a network based on origin-destination travel demand to identify the traffic flows distribution on links on which equilibrium is obtained. There are two general approaches for traffic assignment: System Optimum and User Equilibrium (Wardrop 1952). The System Optimum traffic assignment approach assigns the traffic flow to links in order to optimize the ideal possible traffic distribution on the whole network. In contrast, User Equilibrium distributes the traffic flow on the network to reach equilibrium on links based on the utility of routes and the assumption of rationality of drivers (Wardrop 1952). DRPTN optimization problems mainly design the order of variables to optimize the value of traffic assignment models next to other objectives.

In planning for a transportation network, physical assets such as bridges, highways, or links are common choice variables. Administrative or non-physical components are also variables that either represent or impact the performance of the transportation network such as traffic calming strategies, rerouting plans, options of lane management, and travel demand regulations. Problem formulation, in DRPTN, usually adopts the physical components as a variable set to prioritize the recovery tasks of those components that optimize an objective or the trade-off between multiple objectives. These objectives represent different problems after a disaster such as relief distribution, resource allocation, or network design problem. Basically, each problem is associated with its specific choice set variables, which are configured next to the transportation network's components. For example, relief distribution problem adds relief units to the variable of the optimization model or the problem of resource allocation incorporates available work teams and budget into the computation. The integration between those problems eventually constitutes the final variable set as well as the configuration among them to compute the objectives. This integration in DRPTN is critical because, on one hand, the statement of an optimization problem is affected by the nature of relations among decision parameters. On the other hand, a practical multi-facet problem of DRPTN needs to address the goal of modeling by incorporating effective objectives. This motivated us to investigate the problem formulation phase to understand variables and the problem integration within DRPTN models.

2.3.3 Problem Solving

Solving an optimization problem could be the simplest step of optimization modeling because it entails the use of well-defined optimization algorithms and tools (Taha 2007). Nevertheless, selecting an efficient, robust, and fitting technique that promises a reliable optimal solution is a challenging part of solving DRPTN problems. In that context, deterministic and non-deterministic algorithms are the main approaches toward finding solutions for optimization problems. Deterministic algorithms return exact minima points of the solution space. Examples of these algorithms are; Sequential Quadratic Programming, Generalized Reduced, Gradient, and Dynamic Programming. Non-deterministic approaches are heuristic and meta-heuristic population search, evolutionary or trajectory search, and their extensions that lead to methods such as Genetic Algorithms, Simulation Annealing, Particle Swarm, Harmony search, and Tabu Search (for a review see e.g., Blum and Roli 2003). These algorithms provide feasible but not necessarily optimum solutions and cannot submit a mathematical proof of whether the returned configuration is minimal or at least how good it is compared to the optimum solution (Schneider and Kjrkpatric 2006; Talbi et al. 2012). Having that in mind, when the degree of complexity and size of a problem increases, deterministic algorithms consume an unreasonable amount of computational resources. It means solving a big-size non-convex NP-hard problem in polynomial time would be extremely difficult (unless NP=P). In this case, employing a non-deterministic method is a logical choice that relatively easily handles such a problem with the effort that grows polynomially as do the size of the problem. Therefore, while many problems have been solved with deterministic approach, meta-heuristic optimizers are popular attacking engineering and complex problems.

Although the mathematical procedure of solving DRPTN problems with non-deterministic methods is generally correct, the validity of a solvers' outcome cannot be properly examined (Festa 2014; Rardin and Uzsoy 2011) as it operates as a black-box solver and without any further problem-specific adjustments (Rothlauf 2011). Context-independent, general-purpose, or black-box solvers cannot explore the structural properties of the objective function. A feature of these algorithms is that the outcome solution might be inferior to purpose-specific algorithms that solve the same problem (Marti and Reinelt 2011).

This is a major concern when researchers develop sophisticated algorithms to solve mathematically modeled DRPTN problems while the rationale behind the selection of the optimization methods remains unevaluated, especially in the sensitive problem of DRPTN that exact result is vital for reliable planning engaging with human life. Therefore, in the context of DRPTN uncertainty due to the utilizing solving algorithm can be a challenge when multiple objective functions are involved in the modeled problem (Liefooghe 2011; Horst and Tuy 1996; Talbi et al. 2012). Particularly, uncertainties and biases due to the quantification of values or assigning preferences (e.g., in priori decomposition-based approaches) also question the validity of solutions since epistemic uncertainty can easily propagate to the optimization output (Limbourg 2005) even when the model is mathematically correct. Therefore, it is logical to investigate the impact of objective level in DRPTN models on the accuracy of results and rationale behind utilizing solving algorithms in DRPTN models. In this study, the objective level refers to the number of objective functions that a model intends to optimize. Single-objective optimization problems contain one objective function and the bi-objective level problem refers to problems with two objective functions that usually formulate a leader-follower game. Similarly, models that are formulated with three and four objective functions are identified as multi-objective. When a model seeks to optimize more than four objective functions, it forms a many-objective problem.

2.3.4 Model Verification and Validation

Model validation and verification are two concepts toward irrespectively evaluating the reliability of a model's outcome and quality of the solution. Model validity indicates how well the optimal solution of the model is to solve the real-life instance of the intended problem. Model verification, however, demonstrates how well the output represents intended developed mathematical relationships among parameters (Oberkampf et al. 2003; Oberkampf and Roy 2010; Sargent 2011). Validation is a process that attempts for obtaining sufficient confidence (if there can be any) that the solution of the model can be considered valid for its intended application. The classical approach of validation is based on comparing the outcome of the model with the known experimental measurement of the same problem in reality when the input set for both systems are equivalent (Roy and Oberkampf 2011; Sargent 1996).

Validation in the context of DRPTN is challenging because the confidence threshold in models is set relatively high since DRPTN-related decisions are associated with human life and enormous socioeconomic losses. Additionally, disaster recovery problems are highly prone to epistemic and aleatoric uncertainties as well as parametric errors due to the complexity, context-dependency, and time-stretched process of the decision-making. Therefore, the "value of model to user" dictates the demand for maximized model confidence (Sargent 2011). Existing optimization models for disaster recovery problems deliver fast and efficient solutions while they might be limited in representing many of the crucial realities of the modeled system. In such a situation, the validation of models is an imperative phase of the modeling process to evaluate the quality of the model. It answers the question of whether the result can be trusted as bases for making decisions in a critical engineering socioeconomic situation (Babuška et al. 2007). To provide a better understanding of the significance of this question we investigate the validation and verification efforts within DRPTN models.

2.4 Review and Analysis Methodology

2.4.1 Search Strategy

We performed a systematic literature search to find optimization studies that addressed disaster recovery planning for damaged transportation networks. Based on our earlier definition of DRPTN, we established certain exclusion and inclusion criteria to design clear boundaries for the literature search. The four main criteria were, first, the candidate publication studies a component of a transportation network. Second, the system disruption of the study occurred due to a hazard or a large-scale disruptive event. Third, the target of papers is to present a recovery, reconstruction, or repair planning for damaged elements. Fourth, studies use optimization modeling to develop the problem. The search task was according to various terms addressing disaster and transportation network in the abstract, title, and keywords of the publications. We repeated the search task with different terms representing the same concept. For example, addressing the term *disaster*, we performed the search with terms such as "disaster", "hazard", "extreme event", "earthquake", "landslide", "emergency" "flood", and "tsunami". Similarly, for the transportation network, we searched for ''transportation'', "traffic", "bridge", "link", "road", "highway", and "network". Thereafter, we discarded duplicate publications as the outcome of multi-platform searching and sifted the searching process by limiting disciplines as well as exclusion of irrelevant keywords. Selected disciplines were business, management and accounting, computer science, decision sciences, earth and planetary sciences, engineering, environmental science, mathematics, and multidisciplinary.

Reducing errors in finding related publications, we tried to strictly follow our designed benchmarks. Additionally, we agreed not to use multiple screening or filtering steps presented by the used platforms. Instead, we chose to manually investigate the final set of references (n= 910) based on three steps of content analysis to learn whether the publications belong to the scope of our study or not. These steps were irrespectively content analysis of a) abstract, b) abstract, methodology or problem description section and c) full-text of the publications (n=241). Moreover, we also used the snowball method by performing a forward referencing search in the selected papers' reference lists that has led us to identify three additional publications.

2.4.2 Content Analysis

The content analysis is based on analyzing the methodology of DRPTN studies following the phases presented in sections 2.3.1. to 2.3.4. We evaluated the studies with respect to possible sources of uncertainties and conceptual vulnerabilities in the formulation, problem structuring, problem solving, and validation process of DRPTN decision-making models. For this purpose, we performed a directed content analysis and measured the number of studies for all extracted information based on Figure 2.2. We framed two review questions to approach the publications as 1) What methodological elements of DRPTN models could challenge the validity of models' outcomes? 2) How the rationales for structuring the four phases of optimization modeling are conceptually supported? Figure 2.2 shows the detailed steps of the content analysis framework that we describe in the rest of this subsection.

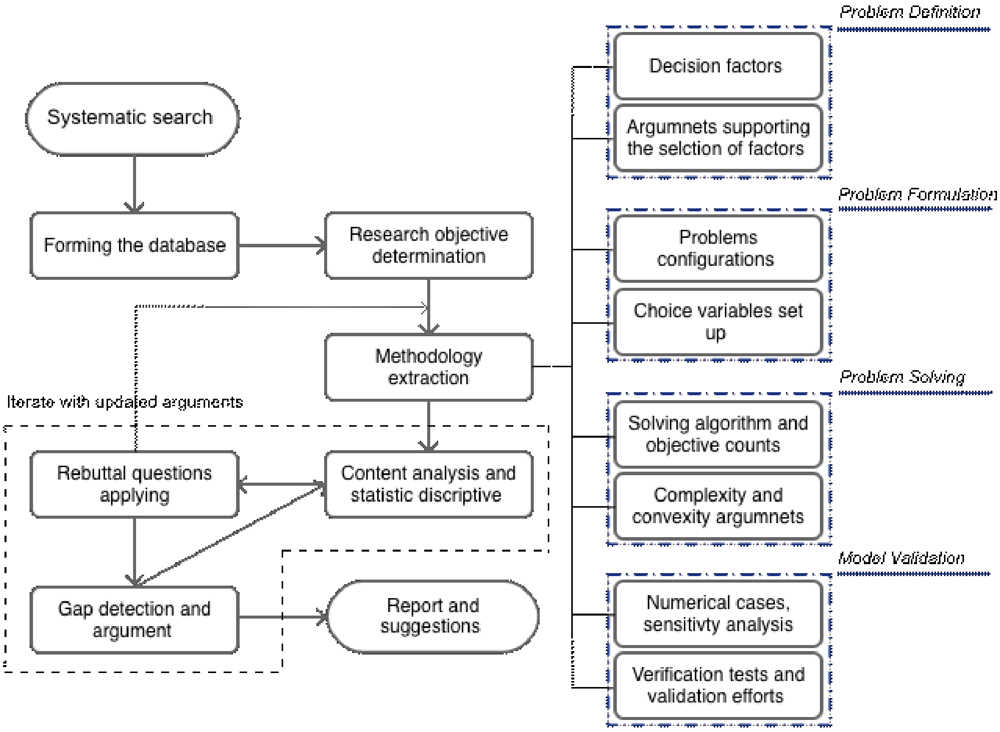

Figure 2.2: The systematic review and gap analysis flowchart for the literature of DRPTN

In the first step, we extracted the elements of the methods applied to our content analysis strategy and the framework of optimization decision-making process introduced in section 2.3. Doing so, we analyzed various components of methodologies such as decision attributes, formulation approaches, solving methods, convexity and computational complexity analysis, arguments supporting the selection of solving methods and the selection of attributes as well as model validity and verification arguments. The second step focused on performing multiple identification and grouping of optimization components including objective counts, attribute types, employed traffic performance metrics, problem integration types, types of solving algorithms, and types of variable sets. For example, we categorized the attributes within three main classes of emergency, traffic, and economic. Accordingly, the traffic factors include attributes that represent the performance of the transportation network such as travel time, capacity, or density. Emergency factors are attributes that respond to the social and individual urgent needs after disasters and demonstrate the performance of emergency response operations such as relief distribution, housing, or population. Lastly, economic factors represent the budget and cost-related attributes incorporated in the planning such as direct or indirect damage costs.

After that, we developed several comparing matrixes to state the relation between extracted elements that may lead to possible limitations in methodologies of DRPTN research as: numbers of objectives and used solving methods, complexity class arguments and used non-deterministic algorithms, formulation approaches and integrated problems, as well as traffic engineering methods and the application of the post-disaster travel demand. Also, the analysis included the corresponding presented theories and methodologies for establishing attributes, selecting solving algorithms, and developing validation approaches in each study. Finally, we analyzed the frequency of the detected gaps to report challenges that are overall in the body of DRPTN literature. Accordingly, the next section presents the results of performing content analysis in the reviewed DRPTN literature.

2.5 Findings

This section demonstrates the findings of the content analysis in each phase of DRPTN optimization modeling process.

2.5.1 Problem Definition

Figure 2.3 shows the attributes that DRPTN models employ. Additionally, Table 2.1 demonstrates the types of attributes and their combinations that are categorized according to whether they focused on emergency, traffic, or economic goals.

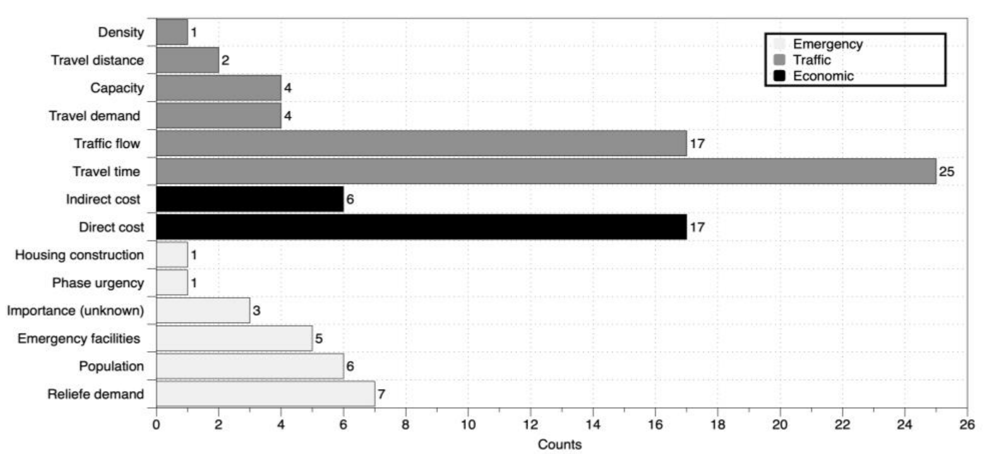

Figure 2.3: Attributes employed in DRPTN as well as their categories.

Table 2.1: Amount and share of attributes in three categories as well as their combination within DRPTN studies (Em: Emergency, Tr: Traffic and Ec: Economic factors)

Factors	Tr	Ec	Em	Em/Tr/Ec	Em/Ec	Em/Tr	Ec/Tr
Counts	39	19	16	5	1	7	9
Share (%)	97.5	47.5	40	12.5	2.5	17.5	22.5

Figure 2.3 and Table 2.1 show that most DRPTN studies establish traffic attributes to measure the technical performance of networks such as mobility and level of service. In some cases, a combination of traffic attributes represents an attribute for network functionality. Figure 2.3 shows that *Travel time* is the most frequent attribute to measure the quality of the traffic service after disasters and *Travel flow* appears in 41% of the studies. Furthermore, two studies (5%) adopt *Travel distance* and five studies (10%) incorporate *Travel demand* and link *Capacity* to measure the achievements of their objectives. With respect to economy attributes, in the whole, 19 studies (47.5%) consider budget-related attributes such as *Direct cost*, which simply refers to the repair cost of transportation components. Six publications (15%) additionally apply *Indirect cost* which in four studies was associated with the direct cost. *Indirect cost* represents the economic disruption due to network failure or secondary costs due to the travel delay. In total, nine studies (22.5%) combine economic and traffic attributes in their models.

Emergency attributes address critical civil needs after disasters or represent metrics that can influence the risk of fatality. For example, *Relief demand* as a major attribute in this category in seven studies (17.5%) refers to traffic nodes to which emergency supply should be distributed. Five studies (12.5%) incorporate the attribute of *Emergency facilities* for links that provide access to those nodes. Six studies (15%) consider *Population* in a traffic zone or *Population* that is served by links to addresses an emergency aspect of the post-disaster situation. Furthermore, 16 studies introduced emergency attributes and five studies (12.5%) incorporate attributes to measure the social impact of disasters on an urban area. Finally, based on Table 2.1, five papers (12.5%) develop the attribute sets with all three categories of decision factors.

Lastly, we analyze the content of DRPTN studies to identify information or approaches that support the selection of attributes. In this regard, 22.5% of the studies provide conceptual arguments to theoretically support this selection or identification. For instance, Feng and Wang (2003) provide a section to identify objectives of the planning, recovery characters, resource constraints, and decision-making process to accordingly justify the selection of the attributes. In another case, performance attributes by Unal and Warn (2018) *"… were selected to be representative and to facilitate the restoration design based on available data and reasonable computational efforts"* and was supported by specific details for each parameter and importance of the selection.

2.5.2 Problem Formulation

To investigate the formulation approach of DRPTN optimization problems we analyzed the integration of objectives, sets of choice variables as well as objective value assignment approaches in traffic flow distribution models. Table 2.2 shows the choice variable sets of optimization DRPTN models.

Table 2.2: The alternative variable sets of optimization models within DRPTN

Variables	Count	(%)	Note
Components	15	37.5	Bridge, railway, link. route, segment, node
Components and resources	11	27.5	Integration of two sets of alternatives
Sequence of recovery of components	7	17.5	Including sets that are combined with resource choices
Set of components	3	7.5	Strategic or zone-based solution set
Sequence of components and resources	3	7.5	Links and contractors/ work troops
Sequence of assigning resources	1	2.5	Relief units

Within the transportation network's components, DRPTN models regard bridges, railways, routes, segments, links, and nodes as variables. These physical components form the alternative set of 97.5% of models, of which 25 studies (63%) integrated transportation network's components with other variables. Table 2.3 shows the integration of objectives and consequently sub-problems within DRPTN.

Table 2.3: Integration of post-event problems with the recovery problem

Task	Count	(%)
Recovery and network design	11	27.5
Recovery and task scheduling	9	22.5
Recovery and resource allocation	8	20
Recovery	8	20
Recovery and relief distribution	4	10

DRPTN models identify resources such as budgets, work troops, and contractors, but always in combination with physical components (except for one study that uses resources independently). 11 studies (27.5%) focus on sequences of alternatives to optimize recovery activities with respect to all possible orders among alternatives. Furthermore, three studies (7.5%) adopt sets of components as the variables defined by selected recovery strategies or a network zone.

Four studies (10%) formulate a model of relief distribution and recovery problem with integrating variables and objectives of both problems. This problem integration prioritizes the recovery tasks that timely meet the post-event needs or optimizes the aid distribution process by solving a network routing problem. Nine studies (22.5%) formulate tasks of scheduling and recovery problems in one optimization model to assign the recovery tasks to contractors and optimize the traffic performance of a network against cost or duration of the recovery. This formulation also optimizes multiple metrics of the network subjected to scheduling constraints such as material or machinery limitations. Resource allocation and recovery problem integration (8 studies, 20%) optimizes the sequence of recovery activities for minimizing the budget or reconstruction duration while maximizing a technical metric of the network. Also, some models assign resources to a sequence of recovery projects in which a compromise between technical objectives of the network and reconstruction cost can be found. 11 studies (27.5%) formulate the integration of network design problems and recovery problems to prioritize recovery tasks according to the network traffic load. These studies propose the use of traffic assignment on a degraded network to identify the importance of specific links. In addition, the network design problem can indicate the optimized recovery order that reduces the travel time for emergency vehicles.

Finally, 23 studies (57.5%) formulate the decision models based on the output of traffic assignment models that assign quantified value to the objective functions. Therefore, we investigated the traffic assignment approach within DRPTN models, to understand how DRPTN models are formulated to address post-disaster travel demand of the network. Accordingly, two studies (5%) modify the regular travel demand for the post-disaster condition addressing limitations in the functionality and accessibility of the network. Additionally, except for one paper that considers the System Optimum approach, User Equilibrium traffic assignment is the dominant approach for assigning traffic flow to the network.

2.5.3 Problem Solving

75% of the DRPTN models (30 studies) use non-deterministic algorithms in the problem solving phase such as Genetic Algorithm, Simulated Annealing, Tabu search, and Ant Colony. To understand the rationale of selecting non-deterministic algorithms and the impact of this selection on the quality of outcomes we investigate the objective level of optimization problems that are solved by non-deterministic methods. Additionally, we analyze the arguments that support selecting non-deterministic methods to solve the optimization problems. Figure 2.4 shows the relation between objective numbers and the rate of studies that used non-deterministic methods for solving the intended problems in each class of objective count.

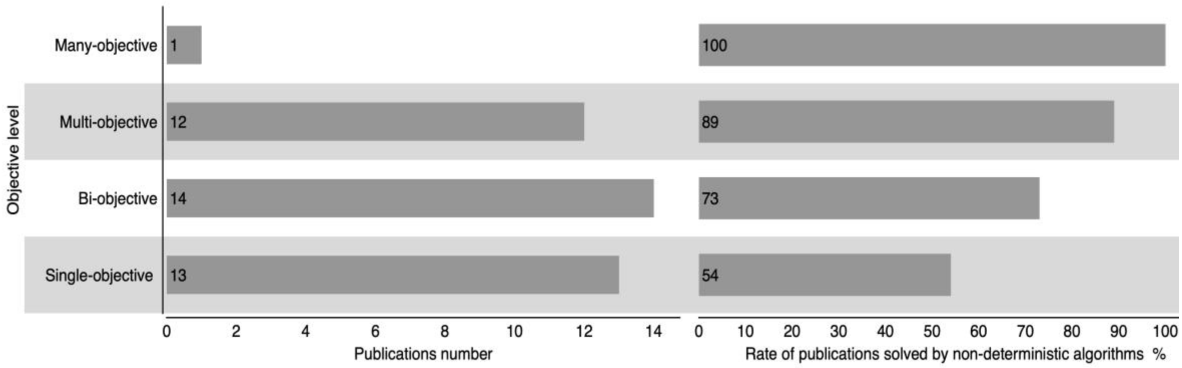

Figure 2.4: The use of single, bi, multi, and many objectives formulation in DRPTN research and percentage of used non-deterministic methods in each objective level.

Non-deterministic algorithms solved 54% of the problems with one defined objective function. Similarly, 73% of the problems with two and 89% of the problems with three and four objectives are solved by non-deterministic methods. Figure 2.4 also shows that problems with one and two objective functions reach 67.5% of the whole DRPTN optimization models and one study developed the optimization model with more than five objective functions. Furthermore, Table 2.4 provides an overview of the rationale that DRPTN studies reported for choosing non-deterministic optimization methods.

Table 2.4: Description and amount of discussions over applying non-deterministic algorithms in optimization problems.

Count	%	The argument for utilizing the non-deterministic methods
15	50	No discussion presented
7	23.3	NP-hard according to characteristics discussed by other sources
5	16.7	Due to computation cost
2	6.7	Computation complexity discussed
1	3.3	Avoiding Braess's paradox (Braess 1968)

Nine papers (30%) address the complexity of the problem. Two of those studies (6.7%) fully discuss the class of complexity of their optimization problems and seven studies (23.3%) identify a known Hard problem within the original problem which results in an NP-Hard or Complete problem thus accordingly derive the methodology toward utilizing non-deterministic methods. Furthermore, three publications (10%) point out the convexity state of their problem although without a report of an investigation over visualized geometric of the search space or computing the Hessian matrix for the second-rate derivative of the objective function. Additionally, five studies (16.7%) mention the computational cost of solving methods as the reason for selecting non-deterministic algorithms, although no representative computational indication could be identified.

2.5.4 Model Validation

In the validation phase of the optimization decision-making models, some DRPTN studies provide approaches and arguments to assess the quality of algorithms and models while in the majority of cases we failed to identify explicit argument on the validation phase of the developed models. Table 2.5 and Table 2.6 demonstrate how reviewed DRPTN studies evaluate the performance of algorithms and validate the solution of models and to what extend studies did not offer a direct argument referring to the validation phase of DRPTN models.

Table 2.5: Efforts and arguments toward verifying and validating DRPTN models.

Arguments on validation of the models		
Case	*Count*	*%*
Numerical case for validation	8	20
Validation is left for future studies	4	10
No specific argument is provided	28	70

Table 2.6: Efforts toward verifying solving algorithms of DRPTN models

Efforts on evaluating the performance of the algorithms		
Case	*Count*	*%*
Numerical example	10	25
Sensitivity analysis	11	27.5
Algorithms computational performance	18	45
Algorithms verification tests	8	20
No effort identified	11	27.5

Results show that eight publications (20%) represent their numerical examples as a validation approach for the developed model. Also, ten studies (25%) provide numerical examples to conclude the performance or quality of the developed algorithm. For example, a study states that the reason for providing a numerical example is "to *verify the feasibility and applicability of the method"* and claims are made that […] *it also indicates that this method is clear, efficient and adaptive and it can provide theoretical foundation and technical evaluation"* (Yuan et al. 2014). Another case highlights that the numerical example *"…proves the validity of models and algorithms, provided a scientific foundation for the government to make reasonable rush-repair scheduling when the disasters occur"* (Zhang and Lu 2011). On the other hand, some studies directly point out that the presented application example "*... is to illustrate the use of programming formulation …*" (Orabi et al. 2010) or to only "…*evaluate the algorithm's performance*…" (Wang et al. 2011) within the model. For example, Sato and Ichii (1995) present a numerical example to test the efficiency of the solving algorithm and Duque and Sörensen (2011), el Anwar (2016), or Hackl et al., (2018) emphasize that experimental future works are required for validation of the model.

Furthermore, 18 studies (45%) evaluate the algorithm's computational performance. Additionally, eight studies (20%) employ standard verification tests to evaluate the mathematical performance of their models such as consistency tests, simplified testing, output comparison with similar models, and comparison with all permutated results (in small size problems). Finally, 11 publications (27.5%) analyze the sensitivity of variables and weight vectors aiming at assessing the performance of models.

2.6 Discussion and Suggestions

Based on the findings of the previous section, we provide arguments for the identified challenges and opportunities within each phase of the DRPTN optimization modelling process.

2.6.1 Problem Definition

The broad set of attributes within DRPTN offers divers and exhaustive representations of the real system which itself is diverse and stochastic. At this stage, practice can benefit from various problem definitions DRPTN literature provides to address different and specific real-world problems. Equally important, DRPTN models have the potential for improvement in enhancing the completeness of the attributes set. One of the reasons is the absence of highly effective attributes in the decision factor sets of some DRPTN models. For instance, although the transportation network disaster recovery is a technical problem, it serves a social system (Nigg 1995; Lubashevskiy et al. 2017). Nonetheless, only five studies incorporate social vulnerability or an indicator that measures the social impact of recovery operations. Additionally, the expected outcome of a disaster recovery model in practice is to alleviate the calamitous impact of disasters on societies given its sociotechnical aspects. Nevertheless, the main goal of DRPTN studies is set to improve only the technical performance of the road network, since 95% of studies incorporate traffic attributes and 50% of them introduced their model only based on traffic attributes. Furthermore, only five sources (12.5%) include all three clusters of decision factors and seven studies (17.5%) introduced a combination of traffic and emergency factors in their formulation.

Additionally, the interaction of a transportation network's components with other critical infrastructure networks (lifelines) is a widely acknowledged critical decision factor in disaster management (Zhang 1992; Cavalieri et al. 2012; Kadri et al. 2014). Nevertheless, we could not find this factor in any of the reviewed studies as an attribute toward optimizing recovery activities. Lifeline interaction is an important attribute for prioritizing the recovery of links since early-stage damage control in other interconnected infrastructures such as the gas delivery network or power lines is essential to avoid secondary, technical, and cascading hazards. Similarly, only 12.5% of the studies included the level of access to critical facilities, which shows that "accessibility" and, in particular, access restoration to service providing nodes such as hospitals, fire stations, strategic points, control centers, or shelters have not been considered sufficiently yet.

A worth noting finding is that in the majority of the reviewed DRPTN studies (31 studies, 77.5%), we could not identify a systematic approach or a conceptual argument to support the incorporation of attributes in the developed decision-making models. This argument is also consistent with the identified challenge by some studies in different fields (Ha and Yang 2018, Tiesmeier 2016, Fekete 2019). However, we are not able to pinpoint the cause, yet, the absence of incorporation of highly effective attributes such as accessibility and social factors within the attribute set of DRPTN models might be the result of the absence of a formal or informal effort to identify effective decision factors.

To control subjectivity and reduce conceptual errors in establishing decision factors, we suggest the development of a systematic framework toward the selection of decision factors in the DRPTN context. To avoid the error of the third kind, it is critically important that such efforts recognize the collectivity of the disaster recovery problem. It is a necessary task that future studies address the identification of complete and collective sets of decision factors or establish accredited evaluation criteria for such a set. Accordingly, a broad descriptive and qualitative analysis of the problem in the initial steps of research and dedicating more time and effort into the problem conceptualization and problem structuring is inevitable.

2.6.2 Problem Formulation

DRPTN studies addressed essential post-disaster problems by integrating different objectives in one decision environment such as relief distribution, route planning, and resource allocation. As a whole, DRPTN studies cover many variables of the post-disaster setting. Meanwhile, DRPTN models formulate representative properties of the post-event network performance regardless of administrative variables. Additionally, the problem formulation of DRPTN models might be challenging in terms of contributing to post-disaster traffic quality in surviving networks with the recovery schemes. This interpretation is apparent based on Tables 2.2 and 2.3, as we could not identify studies that integrate disaster recovery planning and traffic management problems. Nor could we identify a study that adopts traffic management measures such as redistribution of the traffic flow, rerouting, signals management, lane reversal, temporary shoulder capacity, etc., as an administrative variable set of the DRPTN optimization problem.

Regarding the representativeness of DRPTN models in the formulation phase, the status quo of DRPTN studies is using the assumption that post-event traffic flow follows a sub-pattern of the existing pre-event traffic flow along some degree of network geometric restrictions (damaged nods or links). This assumption is understandable due to the high degree of uncertainty and complexity in predicting the route choice of travelers after a disaster that within DRPTN exists a lack of interest in estimating the post-disaster traffic condition of networks since User Equilibrium is the most popular approach within DRPTN models. However, this might be a too simplified assumption since, on one hand, User Equilibrium philosophy is based on the reflection of the optimal state of each traveler according to his or her perception in a normal condition and perfect information environment. In addition, according to Braess's paradox (Braess 1968), the equilibrium is not necessarily relaxing in the ideal state of the network. On the other hand, in the significant information lack condition of the post-disaster environment (Day et al. 2009), the route choice utility (Dobler 2011), serviceability of the system (Chang and Nojima 2001) and even users of the network (Iida et al. 2000) are radically different from the pre-event condition. On this ground, User Equilibrium cannot realistically represent many features of traffic flow in the post-event distributed network since several fundamental assumptions of this approach are violated in the post-disaster traffic behaviors. Accordingly, the findings suggest the challenge of formulating DRPTN models in assigning representative values to objective functions as well as integrate traffic management variables with recovery options.

To improve the DRPTN formulation, applying the User Equilibrium approach for the post-disaster phase can be revised by manipulating variables and the problem integration. Doing so, we suggest shifting the role of traffic assignment from a post-event unknown variable to a known target value, i.e., design the optimization problem such that the model finds the optimized order of variables to reach the ideal given state of the network in the Service Optimum approach. This formulation also entails including traffic management measures as an auxiliary alternative set next to the recovery activities. Using integrated traffic management and recovery planning, planners can assist and direct the users' route choice in the post-event phase. This formulation approach optimizes travel demand of the ideal traffic flow distribution by designing a new network plan based on the surviving network, recovery options, and updated administrative regulations (e.g., lane reversal, demand regulation signal management). It can indicate how external interventions by planners after a disaster (recovery of links and traffic management) lead the network toward reaching the optimum equilibrium based on the Service Optimum traffic assignment approach.

2.6.3 Problem Solving

The incorporation of non-deterministic algorithms within the problem of DRPTN in many cases overcomes the challenge of solvability of DRPTN problems. In fact, DRPTN studies could very effectively harness the advantages that non-deterministic methods offer. Therefore, it is impossible to ignore the benefits of fast and feasible solutions of non-deterministic algorithms, however, results also suggest the challenge of conceptual and computational support for selecting the solving method as well as the absence of complexity and convexity analysis before choosing the algorithms. Figure 2.4 shows the increase in employing non-deterministic algorithms when the number of objectives rises. Accordingly, a compromise between certainty and effectivity is apparent within DRPTN models. The more objectives do models incorporate, the less certain the final solution is. On the contrary, the more solving algorithms try to yield an accurate mathematical outcome; the model can cover fewer objectives. Thus, it might exhibit a lack of inclusion to address various aspects of a post-disaster condition. The compromise between certainty and effectivity arises since; a) subjectivity and errors within the process of selection and quantification of decision parameters and b) the urge for use of non-deterministic algorithms due to the complexity of a problem, both cardinally grow with the number of objectives (Vianna and Vianna 2013; Limbourg 2005). This is a challenge for the quality of multi-objective optimizations when a result-sensitive context-dependent problem is solved with a context-independent method with no guarantee of returning optimal results at the global level (Ishibuchi et al., 2008). This challenge is highlighted when 73% of bi-objective and 54% of single-objective problems have been solved by non-deterministic algorithms even though the exact methods are generally valid for single and bi-objective optimization problems up to a large size (Vianna and Vianna 2013; Liefooghe 2011). Consequently, although the increase in objective numbers provides a more contextually exhaustive and effective model to cover different dimensions of a disaster recovery problem, it also comes at its impact on the certainty of the algorithm's solution. Therefore, given the critical engineering socioeconomic nature of DRPTN problems, the right balance between exactness of result and inclusion of the model is a critical consideration that might require broader attention to the problem-solving phase of DRPTN optimization modeling process. To reduce uncertainty in solving disaster recovery problems, it perhaps would make more sense to utilize non-deterministic methods only for optimization problems with multiple objectives and constraints that even their approximation apt to be a cumbersome task.

Besides the absence of convexity analysis, it is believed that *"the complexity class of an optimization model dictates the nature of the solving method" (Taha 2007).* Yet, 53.3% of studies chose the solving method regardless of complexity investigation of the problems and only two studies present a detailed discussion on complexity analysis of the problems. Moreover, although it is commonly understood that when a problem is NP-Hard then non-deterministic methods are the method of choice, the fact is ignored that many NP-Hard problems can be still solved relatively fast with standard mathematical methods (Rothlauf 2011). Therefore, it is logical to consider both complexity class and convexity analysis of DRPTN problems before choosing the solving algorithm since when an optimization problem formulates a convex problem, it is very likely solvable deterministically and efficiently (Boyd and Vandenberghe 2004; Grötschel and Holland 1991). On this ground, while solving a critical result-sensitive problem of DRPTN, an important consideration is that approximation is secondary to the deterministic approach as long as an exact solution is achievable. However, complexity class and convexity analysis of the DRPTN models have not been sufficiently emphasized. Among 50% of the reviewed studies, we failed to spot conceptual or computational justification that supports the application of non-deterministic algorithms for a specific problem, even though the size of the problem, in most of the cases, was relatively small and the number of objectives in 67.5% of cases was not exceeding two. Therefore, we suggest that future research evaluate the complexity class and convexity state of the problems of interest before choosing a solving method, As Rockafellar (1997) highlighted, *"The familiar division between* *linearity and nonlinearity is less important in optimization than the one between convexity and non-convexity"* (Rockafellar 1997). Another suggestion is to consider formulation approaches which likely form a convex solution space such that exact methods can solve the problem. As an instance, we can highlight the work of el-Anwar et al., (2016a and b) which formulates a mix-integer optimization problem with a convex cone in the DRPTN context and could efficiently improve the near-optimal solution to the optimal solution.

2.6.4 Model Validation

Despite the non-observability of DRPTN problem, the fact that 72.5% of studies conducted efforts to systematically evaluate the outcome of the models indicates that within the field of DRPTN the awareness is established that the DRPTN problem is highly result-sensitive thus cannot afford inaccuracy in the solution and requires a relatively high level of confidence. At the same time, results point out a potential improvement area in validating disaster recovery models. That is because, based on the classical definition of the model validation, (which relies on the comparison of a known solution to the model's outcome), efforts toward validation of DRPTN model are limited to 30% of total DRPTN studies and in 70% we were not able to identify explicit argument to support the validation phase of DRPTN models. Alternatively, we observed that eight studies (20%) provide hypothetical numerical examples to validate their models. However, an illustrative example might not provide sufficient evidence to conclude the validity, quality or applicability of the entire model because it is tested within a simplified network and based on several uncertain assumptions, stochastic input data, subjective values and preferences, scenario-based damage states, and static traffic distribution. Scenario-based numerical case studies (with real-world data) can provide some level of confidence in the mathematical configuration of algorithms and are beneficial in the sense of invalidating the model that initiates the advancement of the model construction in each invalidation process (Popper 1987). Using terms such as "effective", "validated", "accredit" for evaluating developed models based on internal properties of a model can yield misleading expectations from the model for future research and users of a publication in the sensitive critical context of DRPTN (Konikow and Bredehoeft 1992).

Furthermore, 11 studies (27.5%) conduct a sensitivity analysis to evaluate the performance of models. Sensitivity analysis is indeed necessary to evaluate the input-dependency of the model as an observation over the internal behavior of the objective function to a supervised change in variables or weights. However, this observation, might offers very little in terms of insight or foresight about the validity of models to indicate its reliability to be used for a real-world instance of the indented problem (Oberkampf et al. 2003; Babuˇska and Oden 2004; Scandizzo 2016). Because sensitivity analysis neither evaluates the validity of the information fed into a model nor assesses the validity of the defined conceptual relationship among the models' parameters. Nevertheless, sensitivity analysis can sophisticatedly determine the degree of robustness of the model, logical relationships, or verify the algorithm. Therefore, although performing sensitivity observation is essential for DRPTN models, it should not be used interchangeably as a mechanism for the model validation in the DRPTN context.

A pressing need for the DRPTN field is to develop frameworks and approaches within the modeling process that provide a level of confidence in DRPTN models and pinpoint clear benchmarks within the validation process. One of these measures is to distinguish between subjective and objective parts of the models and control the subjectivity in the steps of the model construction. Another suggestion is to develop a set of critical conditions, tests, and boundaries in an attempt to refute DRPTN models or to quantify the uncertainty associated with the result of the model. Moreover, producing accredit synthetic observed data can also facilitate the "comparison of a known data to the known solution" that allows obtaining a satisfactory degree of credibility of models. This approach provides data from a simulated real world that can be compared to models' predictions. It, therefore, worth initiating efforts toward simulating a comprehensive visualized multi-dimensional, multi-disciplinary, agent-based post-disaster environment that can capture the complexity of the system and allow users to directly evaluate the consequences of different optimized recovery strategies.

2.7 Summary and Conclusion

As a summary, first, we observed that DRPTN studies provide diverse sets of attributes in different categories, however, in a significant amount of cases, no conceptual underpinning has been presented to justify or support the selection process of the model's attributes. Therefore, it is essential that future studies propose systematic bias-reduced methods and methodologies toward establishing the attribute set of DRPTN problems and conduct a solid problem structuring. Second, despite successful divers formulations of the recovery problem, we could not identify an integration of traffic management and the disaster recovery problem and including traffic management options as a variable set of the decision model next to recovery projects. Hence, we proposed to integrate variables of route reopening and traffic control measures to reach the optimized performance of the transportation network. Third, we concluded that DRPTN problems require a computational, conceptual, and context-dependent justification for the selection and application sense-making of the solving methods. Therefore, we suggest devoting more effort to the identification of local characteristics of the problem with respect to complexity and convexity as a technical justification of utilizing deterministic and non-deterministic methods. Obviously, aiming at global solutions in the DRPTN context, if there were any, would promote the reliability of the model. In the last section, the study identified the major focus on verification of the optimization algorithms. Developing a systematic approach to provide a degree of confidence in the quality of non-observable models' solution remains a compelling direction for future works. Accordingly, the field of disaster recovery of infrastructures is calling for high-resolution simulations of the urban system in a microscopic level that facilitates modeling the individual decision-making process, within its sub-models and assimilates the user-user and user-system interactions in the post-disaster scenarios.

Finally, we pose this question that whether we need more novel, fast, and feasible optimization algorithms regardless of their conceptual and methodological strength in supporting the rationale of models' elements. Rather, research directions that can introduce science-developed-but-practice-oriented models which provide error-minimized practical results for operational levels. Perhaps what the field of DRPTN needs is not a new optimization approach or solving technique but conceptual descriptive models and systematic frameworks that stand as a solid foundation for models' construction and structuring (Landry et al. 1983) in problem definition, solving and validation phases to avoid a method-rich but methodology-poor phenomenon in the optimization-based DRPTN context.

2.8 References

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Chapter III

A METHODOLOGY FOR SELECTION OF ATTRIBUTES

"If a tractable model is obtained, enrich it. Otherwise, simplify."

William T. Moriss, On the art of modeling, (1967).

3 A Methodology for Selection of Attributes

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3.1 Summary

This paper proposes a framework to systematically evaluate and select attributes of disaster recovery decision models. In doing so, we formalized the process of attribute selection as a sequential screening-utility problem by formulating a prescriptive decision model. The aim is to assist decision-makers in producing a ranked list of attributes and selecting a set among them. We developed an evaluation process consisting of ten criteria in three sequential stages. We used a combination of three decision rules for the evaluation process, alongside mathematically integrated compensatory and non-compensatory techniques as the aggregation methods. We implemented the framework in the context of disaster resilient transportation networks to investigate its performance and outcomes. Results show that the application of the framework acted as an inclusive systematic decision-aiding mechanism and promoted creative and collaborative decision-making. The

Contributions: *The first author developed the idea and the framework as well as related mathematical models. Furthermore, he established the discussions based on the framework's performance, analysis of results, and drafting the paper. The second author proofread, and commented on the structure and communication of the paper. The second author also participated in the revision of the paper.*

properties of the resulting attributes and feedback of the users suggest the quality of outcomes compared to the retrospective attributes that were selected in an unaided selection process. Further analyses are required to discuss the performance of the produced attributes. Both research and practice can use the framework to conduct a systematic problem-structuring phase of decision analysis and select an equitable set of decision attributes.

3.2 Introduction

Decision analysis is used for planning and solving problems concerning environmental challenges, which often integrate multiple objectives and decision attributes. When responding to risks in environmental systems such as climate change and natural hazard-induced disasters, several objectives and attributes are involved covering multifaceted characteristics of a modeled problem. Identifying the underlying decision attributes is an essential, preliminary step in the decision-making modeling process (Keeney 2007; Belton and Stewart 2012). However, in both practice and research, systematic approaches towards the selection of attributes are either rare or inadequately applied which hinders the identification of contextual, representative, and complete attribute sets (Dale et al. 2015; Niemeijer and de Groot 2006, Tiesmeier 2016). Attributes are often selected without the contextual justification or formal approach needed to shift speculative intuitions to rational judgments (Tiesmeier 2016). This issue has been shown in many decision-making contexts, including Disaster Recovery Planning of Transportation Network (DRPTN) (Zamanifar and Hartmann 2020). DRPTN is a decision-making context in which optimized recovery operation plans are identified. These operations respond to the disruptive impact of hazards to restore an expected performance of a transportation network with repair and reconstruction operations. The extent to which the outcomes of DRPTN decision models are effective and reliable relies on the quality of attributes integrated into the decision modeling process. Therefore, selecting tenable decision attributes is critical for complex and sensitive disaster recovery problems due to the socio-economic and environmental consequences of decisions (Sandri et al. 2020; Beling 2013). However, a gap in conceptual or systematic support for the selection process of DRPTN attributes exists. Based on this premise, the current paper is a response to the call of several studies for an approach that allows a systematic and transparent selection process of contextual decision attributes (Zamanifar and Hartmann 2020; Ha and Yang 2018; Tiesmeier 2016; Vaidya and Mayer 2016; Dale et al. 2015). On this ground, we propose a framework in the form of a decision aid mechanism that supports and facilitates the selection of attribute sets. In doing so, we formalize the process of attribute selection as a screening-utility choice problem, since "the problem of choosing between various formulations can itself be represented as a complex decision-making problem" (Mitroff and Featheringham 1974). As part of the developed framework, we formulated a prescriptive multi-criteria decision model. The model incorporates ten criteria as the evaluation factors based on the literature of Multiple-Criteria Decision Analysis (MCDA) and a combination of compensatory and non-compensatory techniques as the aggregation and evaluation method. We used this model in three sequential stages of evaluation to assist decision-makers (DMs) in assessing the performance of both attributes in isolation and attributes in sets. Once the framework was developed, we tested it in a real case problem of disaster recovery planning and analyzed the results together with the application process of the framework.

Although the framework (supposedly) possesses the capacity to be generalized to various decision contexts, mainly one that addresses complex environmental planning problems, we chose to explore its performance in the context of recovery planning of transportation networks after environmental hazards. On this ground, we collected decision attributes from the literature of DRPTN and experts' opinions as the input of the model. Then, we held a workshop with experienced emergency managers as the DMs for conducting the evaluation of inputted attributes following the flowchart of the framework. Results suggest that the framework is capable of facilitating a degree of supervision over the selection process and promoting critical and creative thinking. DMs were able to systematically evaluate attributes and collaboratively produce a ranked list and a set of attributes. The implementation of the developed framework revealed satisfactory application from the users' point of view. Based on the entropy information analysis of evaluation factors, DMs of the case problem were more inclined to select “understandable” and “certain” attributes for the at hand disaster recovery problem. We employed several analyses, including typological examination of the set, properties of the selection process, and the feedback of experts, to investigate the quality of the attributes while further experimental evidence is required to support the attributes’ performance.

3.3 Knowledge Gap and the Necessity

As a representation of values in a decision context, attributes clarify the meaning of objectives and measure the consequences of different alternatives (Keeney and Gregory 2005). The attribute set of a decision model represents essential problem-related characteristics and the behavior of the modeled system (Keeney and Gregory 2005). The degree to which this representativeness is preserved within attributes indicates the directness of attributes. A primary purpose for establishing a set of attributes is to disaggregate a complex decision problem into more analytically tractable components while maintaining the representativeness and collectivity of the modeled problem as direct as possible. Therefore, a well-thought-out attribute set can increase the likelihood of representativeness, directness, and completeness of a decision model. Despite the critical and fundamental role of attributes in decision analysis, the inadequacy of problem structuring and efforts for attributes identification in the decision modeling process is well documented (see, e.g., von Winterfeldt and Fasolo 2009; Tiesmeier 2016; Belton 1999). Maier and Stix (2013), Belton (1999), and Keeney and Gregory (2005), among others, raised awareness that far too little attention has been paid to the manner in which a list of attributes and their contextual structures are obtained. Specifically, much of the literature on decision analysis neglects the role of problem structuring and thorough investigations on attributes as the primary task for structuring a decision-making model (Franco and Montibeller 2010). Similarly, in practice, Girod et al. (2003) observed that during three workshops involving experts engaged in the decision-making process of an engineering design, less than 8% of the time was used to identify the criteria for the targeted problem (Girod et al. 2003). Thus, it is hardly clear to what extent the model recommended solution holds for the real system

(Corner et al. 2001). This issue is crucial for Decision Support Systems (DSS) in disaster recovery and environmental models that seek to present decision-making methodologies associated with tremendous socioeconomic loss or gain (Goujon and Labreuche 2015; McDaniels et al. 2015).

A destructive or disruptive event in urban area that hinders access within a transportation network or adversely influences the safety and efficiency of a network's mobility, to any extent or period that exceeds the affected community's socioeconomic tolerance and coping capacity, can be perceived as a disaster. Consequently, the concept of resilience is employed to mitigate, postpone, or eliminate the likelihood of a hazard transforming into a disaster. Resilience is "the 'shear zone' between (dynamic) adaptation and (static) resistance" (Alexander 2013). More specifically, disaster resilience in the transportation network context refers to plans and actions that improve the recovery potential of network performance and adapt to the network's failure during and after a disaster. Non-resilient transportation infrastructure leads to significant economic loss, threatens society's health and well-being, and exacerbates the consequence of hazard exposure and vulnerability (Kurth et al. 2020; Koks et al. 2019). To increase resilience, developing reliable disaster recovery planning is essential to meet the restorative, rapidity, redundancy, and resourcefulness properties of resilient infrastructures (Bernau 2003; Liu 2020). Recovery planning of a transportation network is an essential characteristic for a disaster resilient community, usually formulated as a decision model to rank or optimize links or recovery operations (Zhang et al. 2017; Aydin et al. 2018; Rouhanizadeh and Kermanshachi 2019). To improve disaster recovery planning, one must establish a set-up in which DMs can make informed decisions concerning the attributes integrated into the disaster recovery decision model. Therefore, it is of utmost importance that disaster recovery models harness the benefit of properties of a desirable attribute set while engaging with such ever evolving and critical problems (Pearson et al. 2018; Quigley et al. 2019).

Studies have pointed out the role of MCDA in the decision modeling processes used for risk assessment, resilience, and recovery planning (e.g., Cegan et al 2017; Rand et al. 2020; Manyaga et al. 2020). Keisler and Linkov (2014) highlight the utility and favorability of MCDA, such as linear additive scoring models in decision recommendations for environment models. Rand et al. (2020) argue that disaster recovery planning requires decision models and decision support systems for informed decision-making since the recovery of infrastructure is coupled to at-risk communities' resilience. While the application of MCDA in prescriptive decision models is evident, it has also been vastly employed for problem structuring, identifying decision values, or relevant metrics under the guide of frameworks (e.g., Fox-Lent et al. 2015; Convertino et al. 2013; Linkov et al. 2018). For example, Linkov et al. (2013) developed the Resilience Matrix framework to identify metrics where performance scores for critical functions related to disaster resilience of a defined system can be calculated. Keeney and McDaniels (1992) highlight that a key component in decision analysis is the use of facilitation to identify values and frame the multi-criteria problem (Keeney and McDaniels 1992). Moreover, Keisler and Linkov (2014) also argue that the value of interventions in decision analysis is not only in the scoring and rating of alternatives but the ability to facilitate discussion and articulating viewpoints and decision values. They further point out a need for tools and approaches to allow analysts to measure and discuss the desirability of hypothetical alternatives. This paper seeks to offer a facilitation process that helps DMs process values in a certain decision context and to more reliably select decision attributes. The necessity of this facilitation escalates when the decision context embeds disaster resilience and recovery planning.

Whilst the critical importance of attributes is generally recognized, it is still insufficiently addressed in the disaster risk management context. DRPTN studies have introduced a wide range of attributes to optimize or rank recovery operations of lifelines, whilst only 22.5% of studies have illustrated how the problem of DRPTN is structured or decision attributes are selected (Zamanifar and Hartmann 2020). Even with highly visible decision processes, insufficient thought is typically given to the identification and choice of attributes (Keeney and Gregory 2005), while in the context of DRPTN, variables and factors are often inherently uncertain. This challenge is not limited to the disaster management field, but has been shown in other contexts too. For instance, Desmond (2007) outlines that there is a lack of methodology to assist in identifying attributes or alternative sets in the strategic environmental assessment field. Similarly, Ha and Yang (2018) share the same point of view and recognize this gap in the infrastructure performance assessment domain. They highlight that studies lack a systematic approach capable of processing and incorporating adequate information, such as decision factors, into the decision problem. Furthermore, Niemeijer and de Groot (2006) argue that the selection process of attributes is mainly subject to arbitrary decisions and called for a clear process for selecting attributes, whilst Lin et al. (2009) believe that attribute selection processes in most cases are insufficiently systematic and transparent. Tiesmeier (2016) identifies the same shortcoming in the real estate domain, reported incomplete lists, as well as high inconsistency across studies while identifying attributes. He underscores that very few studies fully justify the adoption of the chosen attribute systems. Moreover, Ma et al., (2017) highlight that answering the question of how to select the optimal decision attributes is a compelling future research direction and a critical process for many domains that use decision analysis. Fekete (2019) takes a similar stance and emphasizes the demand for guidance on attribute selection in disaster social vulnerability context. Overall, many decision-making models fall short in benefiting from a reproducible and transparent model that assists analysts in selecting decision factors (Tiesmeier 2016). That is, the task of attribute identification itself remains a challenge that has not been adequately met (Vaidya and Mayer 2016; Dale et al. 2015) which has led to a call for a systematic guide as a reliable decision aid framework to select attributes of decision problems.

3.4 Current Approaches towards the Selection of Attributes

Excluding the arbitrary selection of attributes, studies choose attributes based on expert opinions, literature, or a combination of the two. The expert-based approach refers to drawing out information from stakeholders, actors, and DMs to articulate important decision factors in a specific context (e.g., McIntosh and Becker 2020; Elboshy et al. 2019; Mirzaee et al. 2019). The expert-based approach has the benefit of being based on the experiences of experts who possess the knowledge related to the values of the decision context (assuming that the desired properties of stakeholder analysis, interviews, inclusion criteria of interviewees, and aggregation methods are met). However, on the one hand, it falls short in including existing literature and might fail in providing a complete list of attributes. On the other hand, expert opinions are assumed reliable sources for providing preferences and values in a decision-making process as long as they possess adequate decision-relevant knowledge, experience, or stake (Bond et al. 2008). Nevertheless, numerous empirical studies suggest that individuals' striking inability to understand their objectives, values, and preferences, and their markedly deficiency in communicating them is a plausible consideration (Bond et al. 2008; Barron and Barret 1996; Kahneman et al. 1982). Thus, expert-driven attributes could be a product of bias and error-prone efforts in a limited amount of time and lesser in-depth thinking on a specific problem (Girod et al. 2003; Tiesmeier 2016). In order to shift towards a less interview-intensive and intuitive approach, some studies used the available literature to identify and select the attributes of a decision problem (e.g., Herrera and Kopainsky 2020; Merad et al. 2019; Yu and Solvang 2017). Although selecting attributes based on existing literature is an accepted approach, critique holds that literature might disregard some aspects of a problem due to its limitations in accessing comprehensive data, simplifying assumptions, and communication. When one adds the challenge of dynamic nature of problems, temporal limitation of empirical studies, and the contextual inconsistency of literature-recommended attributes, therefore, sole reliance on existing literature might not sufficiently ensure an exhaustive and error minimized approach for selection of attributes. To shape a more complete, up-to-date, and practical set of attributes, the third approach is a combination of expert opinion and previous literature within the field (e.g., Walpole et al. 2020; Caruzzo et al. 2020; Kassem et al. 2016). While this approach maximizes the exhaustiveness of the inclusion of attributes, it yields a broad list of attributes from which some must be selected intuitively. Nevertheless, objectively supervise this intuition to select a viable attribute set remains a challenge. Thus, a prescriptive model as a decision intervention is needed to formulate and solve the choice problem of the selection among a finite number of alternatives.

To overcome this challenge, the model-based approach has been introduced as an alternative to systematically select effective attributes that cover the concerns and values of the problem under consideration. Accordingly, a few studies provide model-driven attributes by formulating the selection process of attributes as a choice problem (Cinelli et al. 2020; Höfer et al. 2020; Otto et al. 2018; Axel et al. 2017; Dale et al. 2015; Convertino et al. 2013). Regardless of the source of the alternative pool, these studies evaluate candidate attributes based on properties of the desired attribute and apply a systematic process to select the attribute set. Properties of the desired attribute are factors that evaluate the merits of an attribute such as unambiguous, operational, and direct (see, e.g., Keeney 1992). Our work extends this strand of approaches with some innovation in the formulation approach, capability, and generalizability of the application. First, as a general guide for constructing a framework that seeks to prescribe a decision, we followed the recommended structure of the prescriptive decision analysis. Prescriptive decision analysis is an intervention process to model a rational choice with the recommended steps of problem structuring, preference elicitation, evaluation/aggregation, and solution handling (Clemen 1996; Kenney 1982). Second, we introduced three stages of evaluation that lead us to three decision regions and subsequently three decision rules. The multi-stage evaluation process allows the incorporation of ten evaluation factors without the urge of introducing hierarchy into the criteria system or increasing the complexity of the modeled problem. This architect of the evaluation environment also leads to a thorough yet cognitively manageable evaluation process. Third, the built-in screening evaluation stage grants the inclusion of candidate attributes from various sources such as literature and expert opinions. Fourth, the developed decision model not only evaluates attributes but also evaluates sets of attributes in the third decision region. Fifth, we proposed a comprehensive and illustrated framework to support the implementation of the decision model that can be used for future research and practice as well as by those who are not necessarily an expert in decision analysis. Therefore, the added value of this research is:

1. Formulating the process of selecting attributes of the DRPTN problem as a prescriptive decision model to aid the attribute selection process and DMs' knowledge acquisition;

2. Exploring the performance of integrating compensatory and non-compensatory decision rules and introducing a new application for this integration;
3. Presenting a tractable and user-friendly framework to assist systematic multi-stage evaluation and selection of tenable decision attributes of disaster recovery planning problems.

The framework aims to systematically process the DMs' inputs to contextual decision values and assist them in selecting an effective, operational, and complete set of decision attributes. The contribution of this paper is the proposed framework and the embedded decision model. The practical implication of results is to help decision analysts to make an informed choice and tenable decisions within the construction of a decision-making model. Therefore, scholars who develop multi-objective or multi-attribute decision models can use this framework in the problem-structuring phase of their modeling process.

3.5 Evaluation Factors and the Decision Environment

As decision criteria, we adopted existing evaluation factors of attributes, or "properties of a good attribute" (Keeney 1992), by conducting a review in MCDA problem structuring literature. Based on the recommendation of Franco and Montibeller (2010), these evaluation factors are adopted to address whether attributes are operational and relevant to the decision context, the way they measure the performance of alternatives, and how they are aligned to the objectives. In the literature, except for Roy (1996), the properties of an attribute and a set of attributes are not distinguishably discussed. Therefore, we took into account the "properties of a good set of attributes" by identifying the factors that address the characteristics of an attribute set. We also interpreted "measurability" to "certainty of measure" to tailor a set of evaluation factors for our particular problem, since we had good reasons to believe that after a disaster, the certainty of the measuring associated with an attribute reduces the uncertainty of the value of an objective. Table 3.1 shows ten adopted evaluation factors, where seven count for members of an attribute set while three factors evaluate sets of attributes.

Table 3.1: The evaluation factors for members of an attribute set and sets of attributes suggested by MCDA literature

Evaluation factors	For members	For set	Suggested by
Coherency with objectives	◆		Belton 1999; Majumder 2015; Gregory and Falling 2002
Operational	◆		Baker et al. 2001; Belton 1999; Dodgson et al. 2009; Belton and Stewart, 2012, Keeney, 2007
Discriminative	◆		Baker et al. 2001; Gregory and Falling, 2002
Understandable	◆		Keeney 2007; Belton and Stewart 2012; Roy 1996
Direct	◆		Belton and Stewart 2012; Majumder 2015
Certainty in measure	◆		Gregory and Falling 2002; Majumder 2015
Representativeness	◆		Roy 1996; Baker et al., 2001; Dodgson et al., 2009; Belton and Stewart, 2012; Keeney, 2007
Completeness		◆	Belton and Stewart, 2012; Dodgson et al., 2009; Roy, 1996; Baker et al., 2001
Non-redundant		◆	Belton and Stewart, 2012; Dodgson et al. 2009; Baker et al. 2001; Roy 1996; Gregory and Falling 2002
Concise		◆	Belton 1999; Majumder 2015; Gregory and Falling 2002; Baker et al. 2001

Evaluation factors are divided into three decision regions based on whether they evaluate the performance of individual attributes or a set of attributes, and whether they address the property of necessary or sufficient conditions of the desired attribute. That led us to three decision regions for which we assigned each a known decision rule: compensatory, non-compensatory, and optimal. The reason for designing a multi-stage evaluation strategy is to take into account both the properties of evaluation factors and properties of alternatives of this specific problem. Therefore, while in the first two regions, attributes are evaluated individually, in the third region, they are evaluated as a set. For the properties of evaluation factors, the first region includes factors that are necessary for attributes to meet. Hence, compromise among factors is not desired which justifies the use of non-compensatory decision rules. The second decision region includes factors that can compensate for each other, which makes using a compensatory decision rule reasonable. In the third decision region, the optimal performance of three evaluation factors is the target of the evaluation. Additionally, designing separate decision regions allowed us to reduce the complexity of the evaluation process and avoid possible errors and biases that could come with a hierarchized criteria structure such as systematic spitting bias (Hämäläinen and Alaja 2008) influence of the type of asymmetry in a hierarchy (Marttunen et al. 2017), and larger variance in weights (Jacobi and Hobbs 2007). Breaking the evaluation into three discrete stages resulted in a more cognitively manageable process when assessing alternatives' performances with the maximum number of evaluation factors in each region not exceeding four (Cowan 2010). Figure 3.1 demonstrates the decision regions and corresponding decision rules of the model.

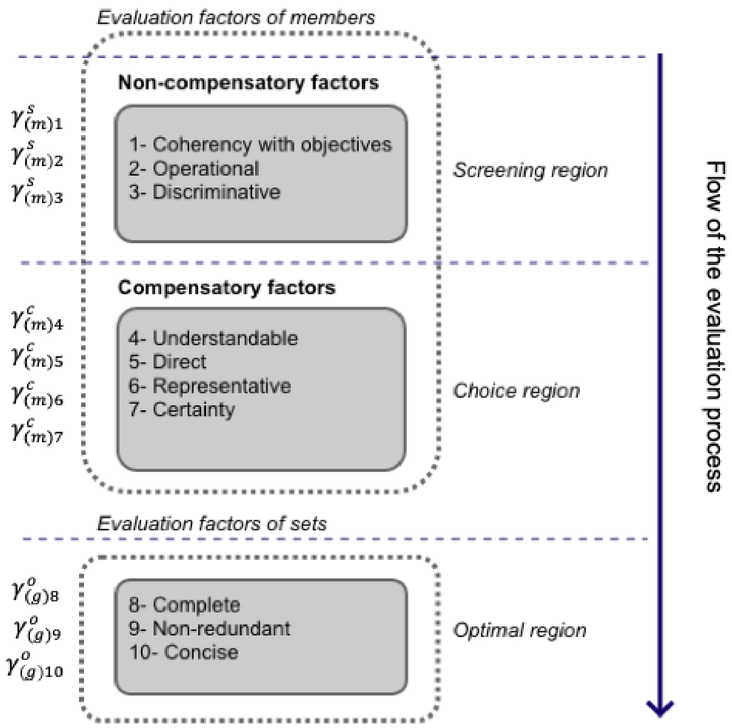

Figure 3.1: The structure of evaluation factors, notions, decision regions, and decision rules for members and sets

The evaluation begins with the screening region, as the filtering phase of the decision process with a non-compensatory decision rule. Thus, alternatives, which fail to satisfy the factors of this region, will be either removed or considered for redefinition. We postulate a genuine interest in the first three evaluation factors which we call concrete factors. Therefore, the screening region excludes attributes that; 1) are not relevant to the decision context (coherency with objective; 2) are not commensurable in a consistent manner and with a reasonable amount of effort (operational); and 3) are not clearly distinguishing among all alternatives to perform a comparison (discriminative). By establishing a screening region, we ensure that concrete factors are not ignored in compensation for other evaluation factors. Attributes that meet the three evaluation factors of the screening region move into the choice region. The choice region operates with a compensatory decision rule, therefore, a compromise among evaluation factors in this decision region is desired. The choice region evaluates the attributes based on the four criteria including 1) "understandable" when it has a clear and unambiguous definition; 2) "certainty" when it yields a certain measured value for the objectives; 3) "directness" when it directly measures the primary objective of the decision problem; and 4) "representative" when it represents the essential characteristics of the system. The third group of factors evaluates "sets of attributes" based on the optimal decision rule. The optimal decision rule can be regarded as the optimized outcome for a set of attributes that capture the maximum key aspects of all objectives (completeness) with optimized size of the attribute set (concise). In addition, the set should not contain a double-counting attribute (non-redundancy), which can be expressed as the constraint of the optimal region (Zamanifar and Hartmann 2021).

3.6 Methodology and the Developed Framework

This section presents the methodology toward developing the attribute selection framework, the framework itself, and methods used for implementing the framework. Table 3.2 demonstrates the adopted methods in the frame of the prescriptive decision analysis. While the problem structuring phase was presented in section 3.5, this section discusses methods and their applications of the remaining tasks of our research design.

Table 3.2: An overview of the adopted methods and tasks for developing the framework

Purpose	Task	Method
Problem structuring	Adopting evaluation factors	Content analysis
	Defining decision regions and assigning decision rules	Based on the property of factors and alternatives
Preference elicitation	Identifying the relative importance of compensatory evaluation factors	Cardinal-ranked based weights
Problem solving	Combination and extension of compensatory and non-compensatory MADM techniques	- Multi-attribute value theory - Elimination by aspect
Implementation and solution handling	Collecting data	- Systematic review - Questionnaire
	Implementing methodology	Workshop with decision-makers
	Analyzing data	Proposed methodology
	Analyzing results	- Performance observation and feedback survey - Retrospective comparison - Typology of selected attributes - Shannon information entropy

3.6.1 Preference Elicitation

Imprecise weight elicitation is based on ordinal and cardinal values that DMs approximate regarding the relative importance of criteria. Ordinal information refers to the rank of criteria based on their importance, while cardinal information represents the relative range of intervals among assigned ranks. Ordinal methods such as Rank Ordered Centroid (ROC), Rank Sum (RS), and Rank Reciprocal (RR) (for a review, see, e.g., Roszkowska 2013) convert the rank of criteria to (surrogate) numerical weights. Unlike the approaches based on semantic and numerical scales, weight approximation methods assume that compelling DM to express their exact perceived values is cognitively demanding and refrain from obtaining viable preferences (Barron 1996; Alfares and Duffuaa 2008). For example, Barfod and Leleur (2014) argue that DMs are more comfortable and confident with ranking the attributes rather than communicating their preferences by verbal scales. Roszkowska (2013) highlights that for a group of DM is easier to agree on rank-based sorting of items than to assigning precise numerical values. However, the critique also exists that preference elicitation following ordinal methods encounters information loss since these methods do not inquire or make use of information regarding the magnitude or intensity of preference among sorted items (Danielson and Ekenberg 2016). Rank-based methods generally rely on the centroid of ordered factors and do not require any further input from DMs on the preference difference between ordered pairs of factors. Some studies also report the victimized weight for lower-placed criteria due to large discrepancy between the highest and lower sorted criteria, suggesting the need for methods that incorporate cardinal information into the weight approximation process and generate "smoother" weight (Roberts and Goodwin 2002; Huang et al. 2011; Belton and Stewart 2002)

Building upon the existing weight approximation approaches (Kárný 2013; Salo and Hamalainen 2001; Barron and Barret 1996), we designed a rank-based tool to allow experts to communicate their cardinal and ordinal preference related to the relative importance of four compensatory evaluation factors. The reason that we customized a weight approximation approach instead of pure ordinal methods was first to avoid extreme weights that significantly marginalize the weight of lower factors (Belton and Stewart 2002), second to prevent equalizing impact on upper factors (Kunsch and Ishizaka 2019), and third to utilize the available cardinal information that ordinal methods often do not take into account (Danielson and Ekenberg 2016).

We used the input of six MCDA experts to suggest trade-offs among the evaluation factors that represent criteria of a good attribute. In order to recognize participants as experts, we considered the fulfillment of three criteria consisting of research engagement in the MCDA field, current involvement in the field through MCDA-related publications in the last five years, and post-graduates holding academic research assistant positions. Since the properties of attributes in the decision-making context have been widely discussed in decision analysis and MCDA discipline, we chose to acquire the input of academic experts within this field. Experts provided ordinal information for evaluation factors by ordering them from the most important to the least important on a vertically 2D visualized slider. They then adjust the distance among the sorted evaluation factors on the slider to express their cardinal preference information. Therefore, while experts can communicate the ordinal preference by ordering the factors, they can also regulate the intervals among each pair of sorted factors expressing the pairwise preference intensity. No numerical scale has been presented for experts on the slider and visuospatial scale was the interface for regulating the distances. The mathematical model that interprets the defined rank and intervals into numerical weights can be formally articulated by the following:

The input value for an evaluation factor i is $d_i \wedge d_1 = 0$ where d is Euclidean distance of factors assigned by experts to the Cartesian origin O of the vertically visualized slider. Each evaluation factor is presented to experts as an item on this slider, while the first factors always remain at the origin O. The assigned location of each item represents experts' ordinal preferences. Since the most important factor is set as an item in the highest point of the slider, it is then logical to assume $\acute{d}_1 \geq \acute{d}_2 \geq \acute{d}_3 \geq \cdots \acute{d}_n$ for $\forall i \in n$, $9 \geq n \geq 2$ where $\acute{d}_i$ is the revisited distance of factor i to a new origin that increases as do the preference of factors. This assumption allows for converting the growth of the distance from the origin equal to the growth of preference. Therefore, for n=4 evaluation factors of the choice region, we have $d_1 \leq d_2 \leq d_3 \leq d_4$ which represents $d_1 \succcurlyeq d_2 \succcurlyeq d_3 \succcurlyeq d_4$. Now following the equations below, the relative importance of factors can be calculated:

$$v_o = \frac{\sqrt{\sum_i^n (d_i - \bar{d})^2}}{(n-1)-k} + d_{max} \quad (1)$$

$$\acute{d}_i = |(d_i - v_o)| * \ln|(d_i - v_o)| \,; \forall i \quad (2)$$

$$w_i = \left(\acute{d}_i \Big/ \textstyle\sum_1^n \acute{d}_i\right) * 100, (i = 1, \dots n) \quad (3)$$

$$w = w_1\, \gamma^c_{(m)4} + w_2 \gamma^c_{(m)5} + w_3 \gamma^c_{(m)6} + w_4\, \gamma^c_{(m)7} \,, \textstyle\sum_1^n w_i = 1 \,, d \in \mathbb{R} \,, w_i \neq 0 \quad (4)$$

where $\bar{d}$ is the mean value of all distances from origin O. v_o is the virtual origin point of the weight vector as a base for calculating the revised distance, d_i is the initial distance for each interval that experts assign, k is the number of evaluation factor with equal ordinal preference (if there is any), n is the number of factors, $\acute{d_\iota}$ is the revised distance of each interval value to the v_o, and w_i is the calculated weight of ith factor when $\sum_1^n w_i = 1$. We incorporated the exponential effect in Eq. 2 to prevent equalized weights while allowing the weight vector to count for both ordinal and cardinal preference input of DMs. Haung et al. (2011) point out that the non-linear distances between single dimension scores and ratios should produce smoother trade-offs. In addition, we know of no study that suggests preference of individual related to a sorted list of objects is distributed uniformly (see Robert and Goodwin 2002). With this approach, we could shift the weight vector toward a flatter shape and, in the meantime, prevent significant discrepancy between the weight of the first and last factors.

By using the input of experts regarding the order and interval among four compensatory evaluation factors, the weight factor can be delivered in the format of Eq. 4. Experts ranked the four evaluation factors as the following: $\gamma^c_{(m)5} \succcurlyeq \gamma^c_{(m)6} \succcurlyeq \gamma^c_{(m)4} \succcurlyeq +\gamma^c_{(m)7}$. The cardinal preferences could not be stored due to a lack of storage capacity for the input information. Assuming that the preference for all factors is judgmentally independent, the preferential model of the four evaluation factors of the choice region, including *understandable*, *representative*, *direct*, and *certain*, ($\gamma^c_{(m)4}$, $\gamma^c_{(m)5}$, $\gamma^c_{(m)6}$, $\gamma^c_{(m)7}$) can be shown as the weight vector $w = 20.68\,\gamma^c_{(m)4} + 36.56\,\gamma^c_{(m)5} + 27.44\,\gamma^c_{(m)6} + 15.32\,\gamma^c_{(m)7}$.

3.6.2 Models of Transition and Aggregation

Both compensatory and non-compensatory approaches have their own application and advantages; hence, a contrast between them is not meaningful. Nonetheless, there are decision contexts in which employing either of compensatory or non-compensatory decision rules alone cannot meet the characteristic of the modeled problem. Non-compensatory aspect-based methods rely on a sequential elimination approach based on sorted criteria that usually leads to a straightforward selection of the most preferred alternative. Non-compensatory methods are widely used in normative decision theory (see, e.g., Gigerenzer and Goldstein 1996) since they are consistent with the concept of bounded rationality. However, aspect-based non-compensatory methods overlook the existence of some criteria and a part of the available information in the decision context is often regarded as irrelevant (Rothrock and Yin 2008). This is because most of the information collected on alternatives will not play a role in the evaluation process (Munda 2005). Therefore, they are limited in application to conditions when non-compensatory is the desired rule of the entire decision context. Meanwhile, compensatory methods cannot be applicable when some criteria are infinitely more important than others. With this preferential model, compensatory methods could lead to an undesirable outcome as the choice might fail to meet the minimum level of desirability in one or more criteria. Consequently, compensatory methods might not be efficient when a part of the decision context does not accept trade-offs among some of the criteria. Both compensatory and non-compensatory methods, when they are used individually, assume that the same decision rule holds for all criteria. Therefore, for some problems, they are unrepresentative of the decision strategy they seek to represent. For the benefit of our framework, we combined the application of compensatory and non-compensatory methods and designed two decision regions for appraising isolated attributes within a single decision system. Integrating compensatory and non-compensatory decision rules maximizes the amount of incorporated information and allows its specificity within the modeling procedure. The first decision region performs in a perfectly non-compensatory fashion, while the second decision environment allows for a compensatory interaction among the factors. The first decision region is absolutely preferred to the second decision region which we mathematically formulated as part of the transition between two regions.

For the non-compensatory region, we adopt the axioms presented with the lexicographical choice concept (Tversky 1972) and formulated it to an aspect-based screening condition as it is formalized in Eq. 1. For the choice region, we directly used the well-known Multi-Attribute Value Theory (MAVT) (Keeney and Raiffa 1993) and contextualized it to the local variables of our decision context shown in Eq. 2. In doing so, the following mathematical expression represents the integration of compensatory and non-compensatory decision rules. The condition expressed in Eq. 1 indicates that alternative A is preferred to B when two alternatives have equal performance on a set of factors in a binary format while there exists at least one factor that alternative B is not satisfying. This means, for an attribute to proceed to the choice region, it needs to satisfy each of the three non-compensatory evaluation factors. Accordingly, for the first three evaluation factors (*coherent with objective*, *operational*, and *discriminative*: γ_1^s, $\gamma_{2,}^s \gamma_3^s$) of the screening region: Let $\Gamma_s = \{\gamma_1^s, \dots, \gamma_i^s\}$, $\forall_i \in \{1, \dots, h\}, h \geq 2$ be the finite set of already known *Concrete factors* of our screening region(s) which is denoted by *s*. Now, suppose there exist a nonempty finite set called ϑ that $\vartheta_{\ \gamma_i^s}$ represents the importance degree among factor γ_i^s where V represents the preference of DMs on a factor and $V_{\ \gamma_1^s} = V_{\ \gamma_2^s} = \ V_{\ \gamma_3^s}$. Moreover, let $\Delta_1 = \{\delta_1^s, \dots, \delta_j^s\}$, $\forall_j \in \{1, \dots, m\}, m > 2$ and a positive integer define the set of competing alternatives and Ψ_{ij} denotes the binary value of ith factor to jth alternative where $\Psi_{ij} \in \{1,0\}$. Now consider δ_j^s and $\delta_{j+n}^s \in \Delta, \forall n > 0$ then δ_j^s is lexicographically preferred to δ_{j-n}^s if, and only if:

$$\begin{cases} \Psi_{ij}^{\delta_j^s} \text{ equals 1 for all } \Gamma \ = \{\gamma_1^s, \dots, \gamma_i^s\} \\ \qquad\qquad\qquad \text{and,} \\ \exists \gamma_i^s \ \in \ \Gamma \text{ that } \Psi_{ij}^{\delta_{j-n}^s} \text{ equals 0.} \end{cases} \tag{5}$$

Meanwhile, for the choice region with compensatory decision rule, we aggregate four evaluation factors of *understandable*, *representative*, *direct*, and *certain* ($\gamma_{(m)4}^c$, $\gamma_{(m)5}^c$, $\gamma_{(m)6}^c$, $\gamma_{(m)7}^c$) with formulating MAVT for our problem. The transition from the screening region to the choice region can be shown: again, let $\acute{\Gamma}_c = \{\gamma_1^c, \dots, \gamma_i^c\}, \forall_i : \{1, \dots, k\}, k \geq 2$ an integer for the new discrete finite set of *Choice factors* of the choice utility region (c) which is denoted by c such that $\acute{\acute{\Gamma}}_c \cap \Gamma \acute{=} \{\emptyset\}$, $\wedge \acute{\Gamma}_c \succ \acute{\Gamma}_s$. Moreover, accept $\acute{\Delta}_2 = \{\delta_1^s, \dots, \delta_j^s\}, \forall_j \in \{1, \dots, m\}$, $m > 2$ as the choice set that already satisfied the set of Γ_s in the screening region such that $\acute{\Delta}_1 \subseteq \Delta_2$. Additionally, assume preference weight among factors follow $0 > V_{\ \gamma_1^c} > V_{\ \gamma_2^c} > \dots > V_{\ \gamma_i^c}$, then, without loss of generality, the utility of each alternative is:

$$U_i\big(\delta_j^c\big) = \sum_{i=1}^{n} \omega_i \,.\, \acute{\Psi}_{ij}(\delta_j^c), \qquad i = 1, \dots, n, \tag{6}$$

Where $U_i\big(\delta_j^c\big)$ is the scaled utility function of alternatives, $\acute{\Psi}_{ij}$ denote the performance of attribute $i \in \acute{\Delta}$ on alternative $\delta_j^c \in \acute{\Gamma}$ as a single attribute value function, $\big(\delta_j^c\big)$ is the performance of alternative j for attribute i and ω_i is scaling factor projecting the importance weight of attribute i, $\sum_{i=1}^{n} \omega_i = 1$. For further investigation on the axiomatic background of the Eq. 6, one can see the original work of Keeney and Raiffa (1993).

3.6.3 The proposed Framework

We designed the framework based on the evaluation factors, their preferential model, and the decision rules as well as the adopted transition and aggregation logic. It consists of nine steps which acts as a decision aiding toolkit for selecting attributes of DRPTN problems. Figure 3.2 provides a detailed flowchart and the process of applying the proposed framework.

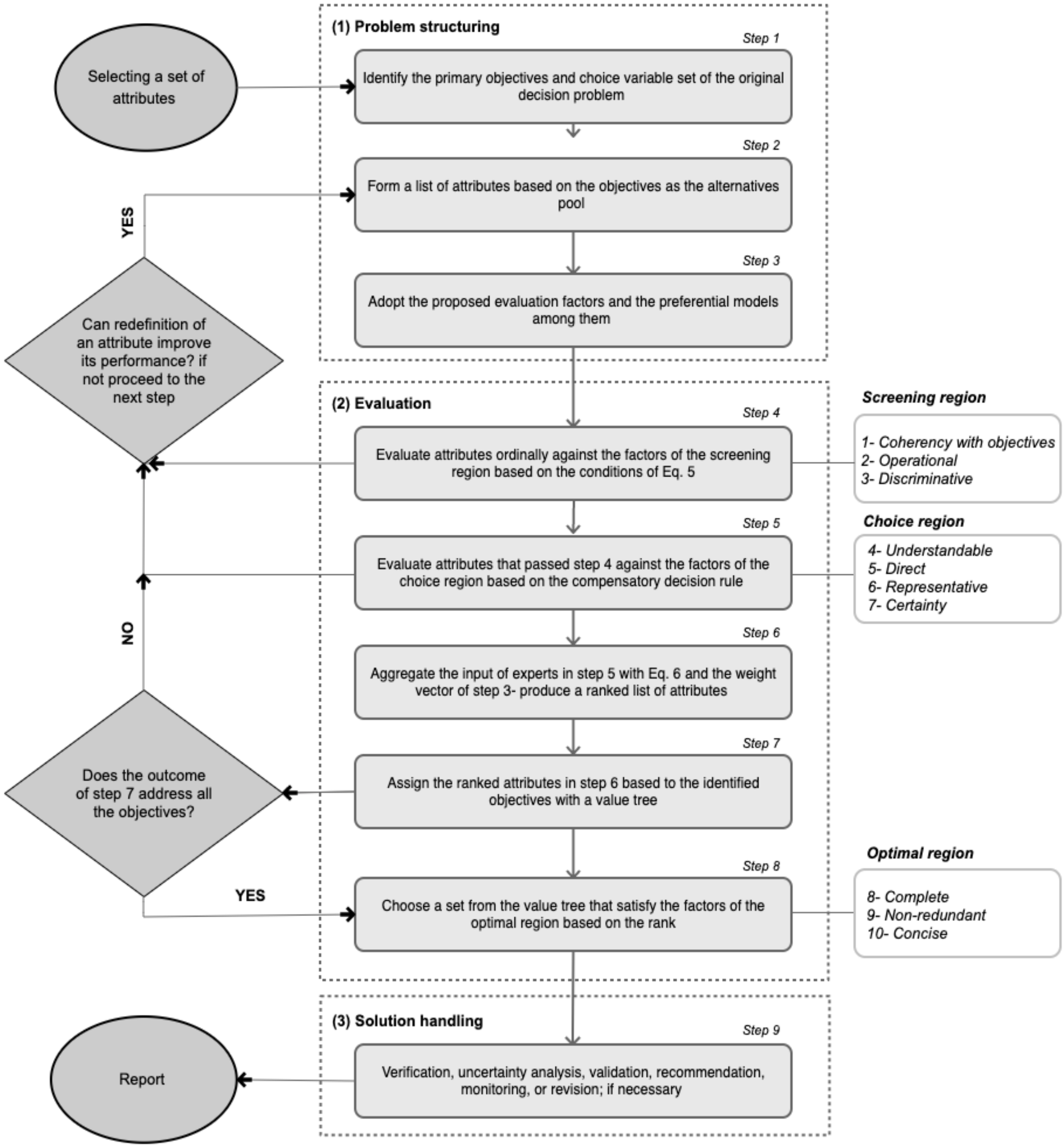

Figure 3.2: The consecutive algorithm of the framework for the selection process of an attribute set

The implementation of the framework begins with identifying the primary objectives of the original problem. The original problem refers to the problem for which the framework intends to select attributes. Since the framework embeds a choice model, the task in the second step is to develop a set of alternatives. The alternative pool is a set of candidate attributes as the input of the model for the evaluation process.

Regardless of the approach used in constructing such a set, it is essential to establish an expanded and complete set of attributes from diverse sources such as literature, experts, stakeholders, actors, and decision-makers to obtain a "reasonably complete" list of attributes (Keeney 2007).

The third step is adopting the ten evaluation factors for the three evaluation stages as well as the relative importance among the four evaluation factors of the choice region. In step four, Eq. 5 indicates that alternatives for which the necessary condition of all three screening factors is not held must be ruled out or redefined. Within the fifth step, the remainders of alternatives enter the choice region in which users can assign a numerical value for attributes' performance in relation to satisfying compensatory factors. Once each alternative has received the scores of the previous step, in step six, an additive aggregation method (Eq. 6) is recommended to rank the alternatives under the compensatory decision rule. During the evaluation, users can redefine or suggest new attributes to satisfy the screening evaluation factors or improve the performance on the choice evaluation factors, under the condition that the evaluation process iterates from the second step.

Concept mapping of ranked attributes is the aim of the seventh step, by assigning each ranked attribute from the previous step to its representing objectives. In accordance with Keeney's recommendation (Keeney 1992), we suggest the generic value tree as the concept mapping approach to aid in identifying the completeness of the attribute set. The last step inherits the ranked list of attributes from screening and choice regions that are classified within the organization of the conceptual value tree of the defined objectives. In this step, the task is to evaluate sets of attributes based on completeness, size, and non-redundancy. Using the value tree, the completeness of the set can be monitored with regards to covering all objectives. In the optimal region, the minimum size of the attribute set that satisfies the completeness of the set and does not contain a double-counting attribute is the selected attribute set. If the resulting ranked attributes of step seven could not cover all the objectives of the value tree, expanding the alternative pool is necessary.

3.6.4 Methods of Implementation

For obtaining a degree of validation and investigating the performance of the framework, we conducted an experiment to test the implementation of the framework in the context of mid-term disaster recovery planning of the Tehran transportation network. We sought to select an attribute set for optimizing the performance of the network recovery process after a major earthquake. In doing so, we collected data from literature of DRPTN and disaster recovery experts to obtain a list of candidate attributes as the input of the framework. A systematic literature review of 46 papers allowed us to extract 34 attributes from DRPTN publications. Additionally, we collected ten additional unique attributes from 23 decision-makers of crisis management organizations in Tehran using a paper-administrated survey. Thereafter, we organized a workshop and followed the steps of the developed framework that is presented in section 3.6.3. We acquired the input of a focus group that includes four senior members of a group of city planners and emergency managers who had previously developed the disaster recovery planning of the Tehran transportation network. Before the evaluation session, we explained the structure and function of the framework and discussed the problem by presenting a brief disaster scenario as well as detailed descriptions and definitions of the evaluation factors. For the sake of consistency with a real-life instance of the DRPTN, we accepted the previously defined objectives for the same problem that the focus group had formulated. The objectives were maximizing accessibility and mobility as the properties of the network, and maximizing recovery effectivity and recovery efficiency as the properties of the recovery process.

At first, DMs evaluated the alternatives based on the three non-compensatory evaluation factors of the screening region and assigned a binary value of 1 or 0. Following the non-compensatory decision rule shown in Eq. 5, alternatives were screened and transmitted to the choice region. In the next step, DMs used a direct rating on a local scale of 0 to 10. The group was also free to redefine the attributes that have not satisfied the evaluation factors of the screening region. DMs deliberated on the score of each attribute and communicated it verbally once a consensus was reached. This process varied for different attributes. Sometimes disagreements required more extended discussion to be resolved, particularly in the presence of an opposite voice, and in other cases, the value assignment process was relatively fast. In the screening region, three attributes have been excluded using a majority vote where no consensus could be reached. We observed that conflicts mainly occurred in the screening and optimal region, while the evaluation process in the choice region encountered some relatively minor disagreements resulting in less controversial discussion. In both screening and choice regions, critical issues were resolved by allowing experts to redefine or improve attributes that failed to meet non-compensatory evaluation factors. As subject-matter experts, participants had prior experience analyzing possible attributes for disaster recovery planning of Tehran transportation network and emergency network planning. Once the scores had been documented, we used the weight vector presented in 3.6.1 and Eq. 6 to aggregate DMs inputs and solve a utility choice problem that resulted in a ranked list of attributes. Consequently, we used a conceptual value tree of objectives to assist DMs in assigning each ranked attribute to the representative objectives. In the last step, DMs selected a set among ranked attributes which satisfied the optimal region's three factors and constituted the recommended set. The evaluation session took 3:07 minutes, while the total time of the subject-relevant discussion was 2:42 minutes.

Finally, to analyze the performance of the framework and the resulting attributes of the case study, we began by investigating the typology of the selected attributes according to Keeney’s recommendations (Keeney 1992). Keeney characterized attributes as three different types: Natural, Proxy, and Constructed. Natural attributes directly measure the degree to which an objective is met and can be counted or physically measured. Proxy attributes share features of natural attributes but are less informative and do not directly indicate the achievement of an objective. Constructive attributes are developed when there are no natural attributes for the objective of the concern. The certainty and accuracy of these attributes might be less than Natural attributes with respect to measuring the objective, but their presence is essential in the absence of natural attributes (Keeney 2007). Secondly, we determined the source of inclusion of attributes in different stages of the evaluation process and in the ranked list of attributes to understand how the population of the attributes in each stage is distributed. Thirdly, we compared the resulting attributes of the framework to the list of working attributes previously selected by the participating experts for the same planning in the case area. Fourthly, we used the Shannon information entropy approach (Shannon 1948) to understand the distribution of information and its specificity in the choice region among compensatory decision factors. Shannon entropy information analysis has been used for sensitivity analysis, analysis of information distribution in criteria system, or assigning quasi-objective weights to criteria in MADM (e.g., Qi and Guo 2014; Wu et al. 2011; Liu and Chen 2018). This analysis was initially introduced within the information theory context to estimate the degree of disorder and randomness in the original data using probability theory (Penjani Hopkins and Erden 2020). Entropy, in information sensitivity context, is an index representing the discrimination ability of the information that is assigned to the value of alternatives for a certain criterion, assuming that the diversity of assigned information to alternatives based on a criterion has a linear association with the specificity of that criterion. Entropy information analysis follows a set of straightforward calculations based on a decision matrix R in which alternatives are scored against criteria. Assume there is a set of m alternatives and a set of criteria with n member in a decision matrix, where x_{mn} represents the performance of ith alternatives on jth criterion ($i = 1, 2, \dots, m$; $j = 1, 2, \dots, n$) as below:

$$R = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{7}$$

The entropy value and relative weights of criteria can be calculated following a series of steps (Penjani Hopkins and Erden 2020; Hwang and Yoon 1981). First, the raw data of performance indices in the decision matrix is normalized using Eq. 8 to bring all values in an identical dimension in case they are inputted under different scales and units.

$$p_{ij} = {x_{ij}} \Big/ {\sum_{i=1}^{m} x_{ij}} \, ; \forall i, j \tag{8}$$

Once the normalized matrix is obtained, we arrive at p_{ij} as the standardized value of a non-negative non-zero index. Afterward, the entropy value (E_j) can be computed following the Eq. 9, where $K = (\ln m)^{-1}$ is a constant to hold the value of E_j between 0 and 1. Meanwhile, $(p_{ij} \ln p_{ij})$ is agreed to get the value of zero if $p_{ij} = 0$ (Lotfi and Fallahnejad 2010).

$$E_j = -k \sum_{i=1}^{m} p_{ij} \ln p_{ij} \,; \forall j \tag{9}$$

Now, $(1 - E_j)$ represents the diversification value for each criterion (D_j). It determines how a set of information content assigned to alternatives is divers based on jth criterion (e.g., performance score, retrospective data, observed measurements, expected value, or similar). The lesser the value of E_j, the greater the degree of differentiation of values assigned to alternatives, which suggests that more information can be derived from the criterion. Similarly, a larger value of D_j, is due to the larger variation of values in the jth criterion's, which is assumed to be associated with information specificity within a criterion. It means the less diversification, the more entropy, and therefore the less information (Penjani Hopkins and Erden 2020). Finally, Eq.10 gives the entropy-based importance for each criterion that determines the information value of criteria based on their entropy:

$$w_j = \frac{(1-E_j)}{\sum_{j=1}^{n}(1-E_j)} \,; \forall j \tag{10}$$

The last analysis on the performance of the framework was issued to obtain the focus group's feedback to two questions: 1) as users, to what degree are you satisfied with the application of the framework, and 2) to what degree do you agree with the improved quality of the framework's outcome compared to the previously selected attributes. We used an anonymously printed-format survey based on a 5-point Likert scale (Joshi et al. 2015) two days after the workshop. Additionally, we performed an unstructured group discussion with open-end questions that lasted approximately 30 minutes immediately after the workshop, allowing DMs to openly communicate the experience of using the framework.

3.7 Result and Synthase

3.7.1 Performance of the Framework in the Implementation Process

We followed the steps of the framework and applied it to the Tehran DRPTN problem. Having 57 candidate attributes as the input of the framework, the screening region filtered 42% of alternatives that failed to meet at least one of the non-compensatory evaluation factors. Therefore, the compensatory evaluation in the choice region began with 33 attributes that formed 58% of the initial alternative pool. Table 3.3 highlights the number of alternatives in each stage of the evaluation process.

Table 3.3: Number and share of attributes in decision regions of the evaluation process

	Number	*Share*	*Examples*
Proceed into the screening region	57	100%	Full list available at: https://doi.org/10.14279/depositonce-10019
Filtered in the screening region	24	42.1%	Lifeline interaction, traveler convince, link geometry, damage complexity
Proceed into the choice region	33	58%	Depot and need points, traffic redundancy, centrality measures, redundancy
Proceed into the optimal region	16	26%	Link topology, capacity, social vulnerability* link delay, recovery efficiency

The outcome of the choice region yielded a ranked list of attributes that was preliminary to organizing a generic value tree based on the primary objectives. In the optimal region, the distribution of eight first ranked attributes to the objectives was required the way that all objectives receive at least one representative attribute. Similarly, DMs assigned the first 11 attributes to the value tree to provide each objective with no less than two attributes. To be able to provide three available choices for all four objectives, assigning 16 first-ranked attributes was required. That supports the transmission of 16 attributes to the optimal region (approx. 26% of the alternative pool). Table 3.4 shows the first 16 attributes assign to four objectives until each objective receives at least three attributes.

Table 3.4: The generic distribution of the first 16 attributes to the respective primary objectives

Objective	Rank 1	Rank 2	Ranke 3	Rank 4	Ranke 5
Maximize recovery effectivity	Travel delay of link * link flow	Impact on Total Network Travel Time	Social vulnerability* link flow	Social vulnerability* zone travel demand	
Maximize recovery efficiency	Travel time improvement per resources	Travel time improvement/ recovery duration	Recovery efficiency		
Maximize accessibility	Access level to the service providing nodes	Centrality measures	East-west and north-south connectivity	Connectivity to other traffic zones	Network topology
Maximize mobility	Link capacity	Annual Average Weekly Traffic	Annual Average Daily Traffic	Traffic density	

Based on the arrangement of the rank attributes on the value tree, the DMs selected six attributes as the recommended set of decision attributes for the DRPTN problem. The set contains the first five ranked attributes as 1) *access level to Service Providing (SP) nodes*; 2) *product of link travel delay and traffic flow*; 3) *travel time improvement per recovery duration*; 4) *travel time improvement per resources*; and 5) *centrality measures* plus *Link capacity* that is ranked as the eighth attribute. The recommended set covers the main concerns of the decision problem based on the primary objectives and is supposed to be complete and non-redundant with optimized size. Table 3.5 provides a brief description of the selected attributes.

Table 3.5: A brief description of attributes of the selected set

Selected attributes	Brief description
Access to service providing places	*The topographical capability of links in providing access to the location of critical facilities and service providing nodes on the network.*
Link capacity	*The ability of each link to carry the traffic as a measure of mobility performance of a link.*
Travel time improvement (TTI) per resources	*The amount of machinery or monetary resources that have to be assigned to achieve a certain improvement in travel time on the network.*
Travel time improvement per recovery duration	*The amount of consumed unit of time to achieve a defined travel time improvement in the network*
Travel delay * link flow	*The travel delay time that closure of a link imposes to a specific O-D trip integrated to the amount of the traffic volume that the link sustains.*
Centrality measure	*Topological importance of a link in a network graph regardless of the traffic flow.*

Table 3.6 demonstrates the properties of each selected attribute of the recommended set and their representing objectives. The calculated utility based on the compensatory factors as well as the rank of each attribute irrespectively indicates the score and ordinal importance of attributes. The selected set consists of four natural attributes, one constructive, and one proxy attribute. The range of the assigned utility of attributes was between 14.22 to 29.67 while the best utility could ideally be 30.3, and 3.03 for the worst utility.

Table 3.6: Rank, calculated utility, representing objectives, and type of attributes of the selected set

Attribute	*Access level to critical nodes*	*Travel delay of link * link flow*	*TTI/resources*	*TTI/recovery duration*	*Link centrality index*	*Link capacity*
Rank	(1)	(2)	(3)	(4)	(5)	(8)
Utility	29.675	29.375	28.912	28.448	27.942	25.878
Type	Natural	Constructive	Natural	Natural	Proxy	Natural
Objective	Accessibility	Effectivity	Efficiency	Efficiency	Accessibility	Mobility

3.7.2 Synthesis of the Framework's Outcome and Feedback of Participating DMs

Table 3.7 shows that the literature of DRPTN contributes to 59.64% of the initial alternative pool while the survey with experts formed 17.54% of attributes. Additionally, 13 attributes (22.8%) were added to the alternative pool during the evaluation process as by-products of the framework. Similar to the initial population of the alternative pool, in the first 10 and 20 ranked attributes, literature-based attributes have the largest share. In the selected set, half of the attributes belong to the literature review's output while the rest were introduced during the workshop. Results show that while collected attributes from 23 disaster managers DMs occupy 22.8% of the population of the initial alternative pool, they contribute the least in all ranked attribute classes and have no representative within the selected set.

Table 3.7: Distribution of attribute based on their source in the initial pool, first 5, 10, and 20 ranked attributes

	Selected set		*The first 5 ranked attributes*		*The first 10 ranked attributes*		*The first 20 ranked attributes*		*33 attributes of the choice region*		*The initial alternative pool*	
Redefined	3	50%	3	60%	3	30%	6	30%	10	30.3%	13	22.8%
Experts Survey	0	0%	0	0%	3	30%	4	20%	7	21.2%	10	17.5%
Literature	3	50%	2	40%	4	40%	10	50%	16	48.5%	34	59.6%

Table 3.8 shows the retrospective attributes which had been selected by participating DMs, for the same problem and the same geographical context as the working attributes of Tehran DRPTN. Model-driven attributes refer to the attributes selected by DMs following the proposed framework of the current paper. Two sets share two identical attributes based on equal serving objectives. The size of the model-driven attribute set is six members while the working attribute set contains nine attributes.

Table 3.8: An overview of the selected attributes by the framework and previously selected attributes by the DMs in an unaided process

Objectives	Accessibility	Effectivity	Efficiency	Mobility	Size
Model-driven Attribute	*Access level to critical nodes, Link centrality index*	*Travel delay of link * link flow*	*TTI/resources, TTI/recovery duration*	*Link capacity*	*6*
Working attributes	*Access level to critical nodes, access to main highways, west-east-north-south connectivity*	*Proximity population, Peak hour traffic flow*	*Traffic flow improvement/resource, Recovery duration*	*Link capacity, Density*	*9*

Table 3.9 shows the result of the information entropy analysis of the compensatory evaluation factors in the choice region. As described in subsection 3.6.4, the entropy values represent an index suggesting the amount of the information stored in each evaluation factor based on the DMs' input values during the evaluation process. Accordingly, E_j indicates to what extent information is preserved in an evaluation factor. Diversification value (D_j) suggests the extent of the domain of input values that DMs assigned to the alternatives. Based on the entropy analysis, the contribution of information in the final ranking is determined according to the sensitivity of DMs to the performance score of alternatives on evaluation factors. Therefore, the calculated E_j and D_j are directly influenced by relative comparison on the scores assigned by DMs. Following steps described in 3.6.4, related computation and values of E_j and D_j are depicted in Table 3.9. Consequently, "certainty" and "understandability" factors have less entropy value while diversification value is the least for "directness" and "representative". It means the value assigned by DMs varied more when scores for the alternatives were based on "understandability" and "certainty", therefore, more information concerning these two factors is added in the decision process. Conversely, the performance scores assigned by DMs were less different (more even) evaluating attributes based on "directness" and "representative" factors.

Table 3.9: Results of the information entropy analysis of evaluation factors of the choice region

	Understandability	**Directness**	**Representative**	**Certainty**
$-\sum_{i=1}^{m} p_{ij} \ln p_{ij}$	-3.40946	-3.46100	-3.43188	-3.40333
Entropy (E_j)	0.97510	0.98984	0.98151	0.97335
Diversification (D_j)	0.02489	0.01015	0.01848	0.02664
Scaled to sum 1	0.31050	0.12662	0.230	0.3323

With respect to the users of the framework, the results of the survey communicate a “moderately to strongly satisfactory” application of the framework while the majority of DMs were “strongly agree” with the quality of the framework’s outcome as the selected attribute set of the DRPTN problem. Table 3.10 shows the response of the participants to the question addressing to what degree users were satisfied with the application of the framework and Table 3.11 is the response to the question that to what degree do they agree with the improved quality of the framework’s outcome compared to the previously selected attributes.

Table 3.10: Agreement degrees to the quality of the selected

	Strongly agree	Moderately agree	Neutral	Moderately disagree	Strongly disagree
DM1	X				
DM2	X				
DM3	X				
DM4		X			

Table 3.11: Satisfaction degree for using the framework set

	Strongly satisfied	Moderately satisfied	Neutral	Moderately dissatisfied	Strongly dissatisfied
DM1	X				
DM2		X			
DM3		X			
DM4	X				

During the open discussion after the workshop, DMs confirmed that it was not foreseen for them to select an attribute set that significantly differed from the one they had previously selected. All participants agreed that disciplined and structured evaluating of candidate attributes could lead them to revisit the current working set of attributes. Two DMs were not completely satisfied with the evaluation process in the choice region due to the number of alternatives. One DM expressed that the evaluation process in the choice region was not as easy as it was for the screening region with non-compensatory decision rules. Another DM took a similar stance and suggested a mechanism to reduce the size of the alternative set in the choice region, while two other participants found the evaluation process of the framework relatively easy to use. Finally, DMs responded positively to whether the resulting attribute set fairly reflects a complete range of their interests and values concerning the objectives of the planning.

3.8 Discussion

Based on the characteristics of the framework and analysis of its outcome, the following argument discusses the reasons why we believe the application of the framework was successful. First, since the screening region allows for pre-evaluation, the framework is inclusive and open to alternatives suggested by diverse sources such as experts' opinions and literature. The framework also accepts the redefined attributes during the evaluation process which not only increases the likelihood of reaching a complete set of attributes, but also provides a basis for brainstorming, critical thinking, and creative input into the model. Harnessing the benefit of integration of compensatory and non-compensatory techniques, alternatives are evaluated in a thorough yet manageable manner. Therefore, although the modeled process is flexible in accepting alternatives as inputs, it is rigorous in evaluating them since only 26% of attributes from the alternative pool proceeded into the optimal region and above 42% of attributes were filtered in the screening region. Additionally, 100% of alternatives were evaluated at least once, while at least two stages of evaluation took place for 52% of alternatives, and 26% of alternatives have been assessed three times. Filtering 42% of attributes in the screening region could suggest a rigorous screening process due to the number of attributes in the alternative pool. Pre-evaluation or size of the alternative pool could impact this process, while the trade-off between the completeness of the input attribute list and rigor of the process should be taken into account.

Secondly, the framework remains contextual and problem-dependent because the evaluation process relies on the primary objectives of the original problem as the benchmark for the selection of candidate attributes (steps 1 and 2), evaluation (steps 4 and 5), and identifying the generic class of attributes for the final selection (steps 7 and 8). Furthermore, the dependency of the framework on the decision context resulted in the presence of four natural attributes in the selected set, which suggests the directness of the attribute set and context-centric performance of the framework. Moreover, the model not only evaluates individual attributes but also appraises the properties of desirable sets of attributes of the targeted problem, ensuring the non-redundancy and completeness of the set based on the primary objectives. Thirdly, the framework does not impose a significant cognitive burden because the evaluation factors are divided into three independent regions with a maximum size of four factors in a flat hierarchy format. It allows that individual judgments, in both articulating preferences among four compensatory evaluation factors and value assessments, remain in a relatively reasonable state (Bond et al. 2008; Marttunen et al. 2017; Cowan 2010).

Furthermore, evident from the experiment and participants' feedback, the structured, step-by-step framework of the model promotes an amount of supervision over the inevitable subjectivity associated with the attribute selection by allowing to track and locate where subjectivity might influence the evaluation process. Hence, the selected attributes are less likely to be prone to bias and error than attributes selected without a systematic, tractable, and transparent procedure. Based on the post-workshop survey, the model-driven attributes meaningfully integrated the concerns, values, and interests of the DMs into the decision analysis with a reduced size of the set compared to the previously selected attributes. However, we cannot dismiss the possibility that the positive feedback of the DMs could have originated from availability heuristic, courtesy, etc., and future research must re-implement this methodology in different settings.

The share of the redefined attributes during the workshop in the selected set, first 10, and 20 list of attributes suggests that the framework is likely to promote creative and critical thinking. Additionally, we observed that the evaluation factors and the evaluation process framed the discussion and provided a ground for brainstorming and collaborative decision-making. Moreover, according to Table 3.7, while the academic literature provided 50% of attributes of the selected set, DMs' local knowledge contributes to the other half of the attribute set which indicates the performance of the framework with regard to balance incorporation of available knowledge sources.

Results of the information entropy analysis suggest that DMs were more sensitive to the performance of attributes based on "certainty" and "understandability" factors, since the assigned values were more diverse for those factors and uniform for "directness" and "representatives" factors. This arrangement of information entropy is because first, attributes of the alterative pool originated from relevant literature and experts that are likely to be sufficiently representative and direct. Second, the non-representative attributes were already excluded thanks to the screening region and the condition of "coherency with primary objectives." Assuming that DMs fully understand the definition of evaluation factors, the result of entropy analysis could suggest that "certainty" and "understandability" of an attribute have higher relative importance for the DMs who used this framework in the workshop. Therefore, for the DMs of the case study, a certain and non-ambiguous disaster recovery planning, although not necessarily optimal, is preferred.

The developed framework can offer a practical application in the disaster resilient infrastructure context as it can support the problem structuring of these problems by facilitating the identification of problem-relevant decision attributes. The same process can (supposedly) be applied to other similar contexts, since selecting decision attributes is the primary and critical step of decision analysis and modeling in general, particularly when the popularity of MCDA in environmental, engineering, and management studies is growing (Keisler and Linkov 2014; Bruen 2021). Employing a systematically selected set of attributes for decision models could reduce the uncertainty related to decision factors in multi-objective or multi-criteria decision-making models. This study suggests that in the problem structuring phase of decision modeling, analysts employ the suggested framework or any other systematic attribute selection process to increase the likelihood of achieving a viable attribute set.

3.9 Limitations

Different preference elicitation techniques deliver different weights and the same holds for different experts. While weighting vectors mainly depend on the method and experts that generate them, uncertainty regarding the used preference elicitation method in this study still stands. Using any preference elicitation method due to the absence of a known solution or "true weight" cannot claim superiority. More evidence from the application of the employed method in section 3.6.1 is needed to provide a level of confidence in the trustworthiness of the generated weights. The preference elicitation process could be subjected to re-implementation, uncertainty analysis, or a wider domain of analysis to increase confidence in the robustness of weights. Having said that, future users of the framework could use other approaches to supply the relative importance coefficients of compensatory evaluation factors.

In this study, two major types of uncertainty are identifiable within the process. First is the uncertainty related to the application of the attributes in terms of measuring DRPTN objectives, and second is the uncertainty of the selection process. Uncertainty within the selection process can be related to the individual subjective value assignment, group dynamics, and preference determination. Uncertainty of attributes application is due to the lack of experimental investigation on the quality of attributes. Further evidence is required from 1) the application of this framework in different settings and 2) the application of the produced attributes in real-life problem or modeled disaster scenarios. For the former, we invite studies to employ the proposed framework, while the latter, we aim to address it in future research.

3.10 Conclusion

While social and infrastructure systems encounter an unprecedented risk of climate change and natural hazards, it is of paramount significance to develop DSSs that pave the way for well-informed collaborative decision-making. To develop such a DSS, modelers should feed the decision models with equitable and plausible attributes that are the result of a tenable systematic selection framework. This study sought to bridge the identified knowledge gap in the problem structuring of multi-criteria decision problems by proposing a choice-screening model to assist in the evaluation of decision attributes and prescribe a set. We illustrated the developed framework with a case study to select decision attributes of a disaster recovery planning problem. The innovative integration of compensatory and non-compensatory aggregation methods within a newly designed sequential, 3-stage evaluation process constituted the developed framework. The formalized attribute selection process facilitated harnessing DMs' knowledge and consequently led to a set of attributes of the case problem, although further evidence from field experiments or simulated implementation is required to support the quality of the produced attributes. DMs were able to systematically evaluate attributes and collaboratively produce a ranked list of attributes as well as the final selected set. We investigated the performance of the framework based on the typology of the produced results, the discussed characteristics of the framework, and the feedback from users. Observing the development of the discussion in the workshop and position of the redefined attributes in the final rank, it is not implausible to conclude that the evaluation mechanism within the framework facilitates critical and creative brainstorming, thus fostering the incorporation of the available knowledge sources. Using the proposed framework, one must take into account the size and completeness of the alternative set. A so-called diverse complete set of alternatives is required since the result will be as complete as the alternative pool. Nevertheless, analysts and further users of the framework must establish a balance between the desired completeness and the complexity of the model. One should also note that the effectiveness of the selected set remains dependent on recognition of the right problem and consequently defining the right objectives, since the framework remains true to the defined primary objectives of the decision problem.

This question of the extent to which decision aid interventions are successful in controlling the subjectivity and guiding the intuitive feelings to rational judgments has been discussed widely in other disciplines. However, data-driven, systematic, or evidence-based approaches do not always make a decision-making process immune to epistemological errors (Power et al. 2019). Therefore, we cannot rule out a possible implication of common cognitive biases prevalent in many decision processes. Nevertheless, it is reasonable to assume that the systematic attribute selection process could allow analysts to track and locate where subjectivity might influence the evaluation process. For further use of this framework, we suggest that a moderator oversees the evaluation session and acts as an opposite voice, if necessary, to facilitate the extraction of DMs' knowledge. Research and practice can both use the proposed framework for establishing an equitable set of attributes of decision problems, and even one who is not necessarily an expert in decision analysis. Future research must employ a systematic approach towards the identification and selection of decision attributes. Research must also dedicate more time and effort to a solid problem-structuring phase before formulating a decision problem, specifically with regard to complex and critical problems, such as those which address environmental challenges and disaster resilient infrastructure planning.

3.11 References

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Chapter IV

DECISION ATTRIBUTES OF DRPTN

“Decision aiding is meant to assist in constructing, establishing, and arguing for convictions.”

Bernard Roy (1996)

4 Decision Attributes of DRPTN

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4.1 Summary

This paper implements a structured framework to suggest decision attributes of transportation network disaster recovery planning. For this purpose, we collected 57 decision attributes from the relevant literature and experts' opinions. Following a framework with three sequential evaluation stages, decision-makers systematically assessed the attributes based on each evaluation stage's specific criteria. Thereafter, we aggregated the decision-makers' input values using a combination of compensatory and non-compensatory Multi-Attribute Decision-Making techniques. Results offer a ranked list of attributes and a recommended set of attributes for Tehran's road network as our case study. The findings suggest six attributes to be included in road network disaster recovery planning as 1) access level to service-providing nodes, 2) integration of link travel delay and traffic flow, 3) travel time improvement per recovery duration, 4) travel time improvement per resources, 5)

[1] ***Contributions**: The idea was built upon the advice of the second author, and he also proofread and commented on the general structure and communication of the paper. Both authors collaborated in the revision of the paper. The first author performed the focus group workshop, post-workshop analysis, interviews, literature search and survey, data analysis, drafting the paper, and establishing the discussion.*

centrality measures, and 6) link capacity. However, the recommended attributes are valid only when they remain as a set. Results contribute to the existing knowledge about concerns and values in the reconstruction and recovery of transportation networks after disasters. Transportation network planners and disaster managers can use the recommended attributes as key factors for post-disaster decision support systems or for evaluating available disaster resilience plans. Additionally, future research can adopt this research outcome as an input for the problem structuring phase of disaster recovery models.

4.2 Introduction

In the aftermath of a disaster, every decision's reliability is vital due to its potential impact on human life and socio-economic loss or gain. To support such decisions, studies developed decision models for Disaster Recovery Planning of Transportation Networks (DRPTN) that prioritize reconstruction operations on the network's components. Decision Support Systems (DSS) have been broadly used in the field of DRPTN to recommend decisions for an optimized reconstruction sequence of transportation links (for a review, see, e.g., Goujon and Labreuche 2015). Multi-objective and multi-attribute decision-making models have been serving DSSs that commonly yield optimum or compromise solutions (see, e.g., Galindo and Batta 2013; Colorni *et al.* 2019). While the extent of our knowledge on the validity of such models is limited, it is more or less accepted that the quality of outcomes depends on the model's decision parameters (Keeney 1992). One strand of decision parameters is attributes that measure the achievement of objectives of a decision problem. Even for decision models that are formulated with novel techniques and solved with sophisticated, intelligent algorithms; the merit of the decision remains dependent on *"the completeness of the model in representing the real system"* (Taha 2007), which is conditioned to the presence of well-thought-out decision attributes (Kenney and Gregory 2005). Notably, in the complex problem of DRPTN, the representativeness and completeness of a model are challenging yet critical and depend on the adopted attributes (Winter *et al*. 2018; Comes 2016). Therefore, the degree to which the uncertainty associated with identifying attributes is controlled contributes to the certainty and reliability of recommendations the model prescribes (Gregory and Failing 2002; Beven *et al.* 2015). This demonstrates the importance of defining tenable attribute sets for a DRPTN problem.

DRPTN studies have introduced a broad range of attributes to optimize or rank post-disaster recovery operations of transportation networks. However, insufficient work has been done to establish a sound argument as to how the problem of DRPTN is structured or key attributes are identified (Zamanifar and Hartmann 2020). Defining attributes for the problem of disaster recovery can be inherently error and bias-prone due to the non-observability of the post-event prescriptive model of the DRPTN problem and inevitable subjectivity associated with problem structuring in general (Cochran *et al.* 2011). Challenges arise during the selection of attributes since epistemic and aleatoric errors can propagate into the decision model's output even if the model is mathematically solvable and verifiable (Phillips-Wren *et al.* 2019; Wesley and Dau 2017; Beven *et al.* 2015). Furthermore, some reviews highlighted the absence of systematically produced attribute sets for disaster management models and pointed out the shortcomings (e.g., Zamanifar and Hartmann 2020; Gutjahr and Nolz 2016), which indicate the emerging necessity of a model-driven set of DRPTN attributes with supervised subjectivity. On this ground, the present paper suggests a set of attributes of a DRPTN problem that is the product of a systematic multi-stage evaluation and selection process. We developed a prescriptive decision model based on three decision regions with compensatory, non-compensatory, and optimal decision rules. First, we extracted data from the DRPTN literature as well as disaster management experts' input to identify the alternative pool containing candidate attributes of DRPTN problems. Second, we adopted ten evaluation factors as the criteria based on what the MCDM literature has suggested that represent desired properties of a good attribute and a good set of attributes. Consequently, we identified the trade-off among the factors that function under the compensatory rule. After that, a group of transportation network disaster recovery planning experts, who previously developed the DRPTN plan of the case study, systematically and critically evaluated attributes against those evaluation factors through three decision regions (for research data see Zamanifar 2020). Results suggest a ranked list and the selected set of attributes tailored for the DRPTN problem case of Tehran (Iran) in the mid to long-term recovery phase that satisfies evaluation factors and addresses the problem's defined objectives.

4.3 Disaster, Transportation Network, and Recovery Process

Disaster in a transportation network is a set of disruptive conditions that hinder connectivity, accessibility, and mobility, which leads to an extreme loss of network functionality. The transportation network is the sole post-disaster lifeline that in parallel grants mass mobility and provides access to essential origin and destinations (ODs) within the affected area. Transportation networks are not only structurally vulnerable to hazards but are also prone to cause failure for most of the infrastructure systems and disruptions in society's daily activities (Liu *et al.* 2019). In the aftermath of a major hazard, socio-economic restoration advances linearly with the transportation recovery rate. Therefore, successful recovery planning contributes to society's resilience by enhancing the recovery rate that can accelerate the system's serviceability during the recovery process (Zhang and Alipour 2020; Renne *et al.* 2020).

Planners and decision-makers intend to respond to disasters by employing optimal reconstruction plans to effectively and efficiently repair the damaged network and restore it to an acceptable level of service (Renne *et al.* 2020; Karlaftis 2007). Reconstruction planning of transportation networks is the outcome of a decision-making model that prioritizes a network's components for recovery such that it optimizes predefined objectives. Based on their properties, objectives can be *fundamental*, *means*, *process,* or *strategic* (see Keeney 1992). *Fundamental* and *means* objectives are the primary objectives of a decision model (Gregory and Falling 2002). Objectives of transportation recovery planning can be classified based on the characteristic of the i) performance of the network and ii) performance of the recovery process (Rozenberg *et al*. 2019; Benavidez *et al.* 2018; Zhang *et al*. 2017; Quarantelli 1999). Performance of the network includes measures that maximize links or the network's capacity in sustaining the traffic flow, quality of the level of service, connectivity of the network, and providing access. Performance of the recovery process contains variables that impact the network's functionality while minimizing recourses such as duration, budget, workforce, and equipment, leading to an improved recovery rate.

Attributes of a DRPTN problem measure the achievements of the planning objectives mainly to maximize mobility and accessibility in a network or the efficiency and effectiveness of the recovery process. While mobility is attached to the traffic characteristics of a network, accessibility considers characteristics of links in a network. Measuring mobility, attributes such as link capacity, link flow, travel time, and Average Annual Daily Traffic aim at facilitating the movement of users within the network considering the quality of traffic after disasters (Zhang *et al.* 2017; Bin *et al*. 2009; Vugrin 2014; Zhang *et al.* 2019). Accessibility is driven by the adjusted travel demand on the network under post-disaster circumstances and aims to provide access to nodes or other links and maintain the network's connectivity. As such attributes, access to service-providing nodes, centrality measures, and network topology have been used in DRPTN literature (Zhu *et al*. 2020; Helderop and Grubesic 2019; Aydin *et al.* 2018; Shiraki *et al.* 2017; Chang 2003).

Efficiency and effectivity of a recovery operation irrespectively represent the impact of recovery on users and resources. Effectivity is the property of recovery operation concerning the impacted users of the network, which includes attributes such as integration of network travel time improvement and traffic flow, affected population and travel delay, or social vulnerability and travel delay cost (Konstantinidou *et al*. 2019; Ho and Sumalee 2014; Unal and Warn 2015). The aim is to maximize the resulting improvement of network performance to serve a higher number of users, or a specific class of users, that are beneficiaries of the recovery operation. Efficiency considers resources such as time, equipment, work crew, and budget to provide the planning with low-cost, high-impact solutions and enhances the recovery rate. Some instances of the representing attributes for recovery efficiency are unrestored ratio, integration of travel cost and recovery duration, improved network performance in recovery duration, or improved network travel time per available recovery work units (Zhang 2017; Bocchini and Frangopol 2012; Zamanifar and Seyedhosseini 2017; Sato and Ichii 1995; El Anwar *et al.* 2016).

4.4 Knowledge Gap and Motivation

In general, research points out that part of the decision analysis literature neglects the role of problem structuring, including establishing a tenable set of attributes as a prelude to developing a decision-making model (Cochran *et al.* 2011; Belton and Stewart 2010; Corner *et al.* 2001). In particular, the focus of the DRPTN literature is mainly on the problem-solving step of the decision modeling, while an insufficient attempt has been made to establish attribute sets of DRPTN models (Zamanifar and Hartmann 2020). In this study, we intend to flip the focus and recognize the significance of problem structuring in terms of establishing tenable attributes for the sensitive and critical problem of DRPTN.

A few studies in the infrastructure disaster recovery field suggest attributes and decision factors (e.g., Martins *et al*. 2019; Carreño *et al*. 2007; Ghavami 2019; Contreras *et al*. 2018). While several studies discuss that some of the existing attributes of decision problems are likely subjective, intuitive, or adopted without contextual justification (e.g., Tiesmeier 2016; Xiaofei *et al.* 2018), it is critical for the model's quality that attributes are the result of a reliable structured approach. This criticality increases in disaster recovery planning research due to 1) extreme socio-economic stakes, 2) the challenge in the model validation due to the non-observability of the problem, and 3) the existing gap in DRPTN literature to formalize the attribute selection process. On the ground of supervising subjectivity in this sensitive and critical context, a formal approach for establishing effective and comprehensive decision factors for DRPTN problems is an imperative need. Bridging this gap, we formulate and solve a choice problem of selecting among a finite number of attributes inputted by the literature and experts of the field. Finally, the selected case study also justifies the necessity of this research. The existing hazard exposure and vulnerability in the study area, as well as available empirical knowledge among local decision-makers due to experience of confronting multiple hazards in transportation networks, motivated us to perform the analysis in the Tehran context.

Iran is a hazard and disaster-prone country. Tehran, in particular, is a metropolitan area developed over an asymmetric complex lifeline network and intricately interwoven infrastructure system (Monajem and Nosratian 2015). The city consists of structurally and socially vulnerable urban environments. On the one hand, fragile resilience capacities, ripple effect-prone civil systems, and fragmented coordination in crisis management that is associated with stiff decision-making flow raise the likelihood of exposure of the urban area to transforming hazards to disasters. On the other hand, given the experience of confronting multiple disasters, there are valuable insights and empirical knowledge among the local disaster managers and city planners, making it a reasonable case for our study.

4.5 Methods and the Research Design

To follow a systematic attribute selection methodology, we adopted the framework introduced in the previous chapter. Figure 4.1 provides a summary of the research approach. We followed a disciplined framework to extract, evaluate, and select DRPTN attributes. To build a screening-utility choice model, we integrated three main components of prescriptive decision modeling, including problem structuring, preference elicitation, and evaluation /aggregation. This section demonstrates how we followed the steps to accomplish the tasks of Figure 4.1.

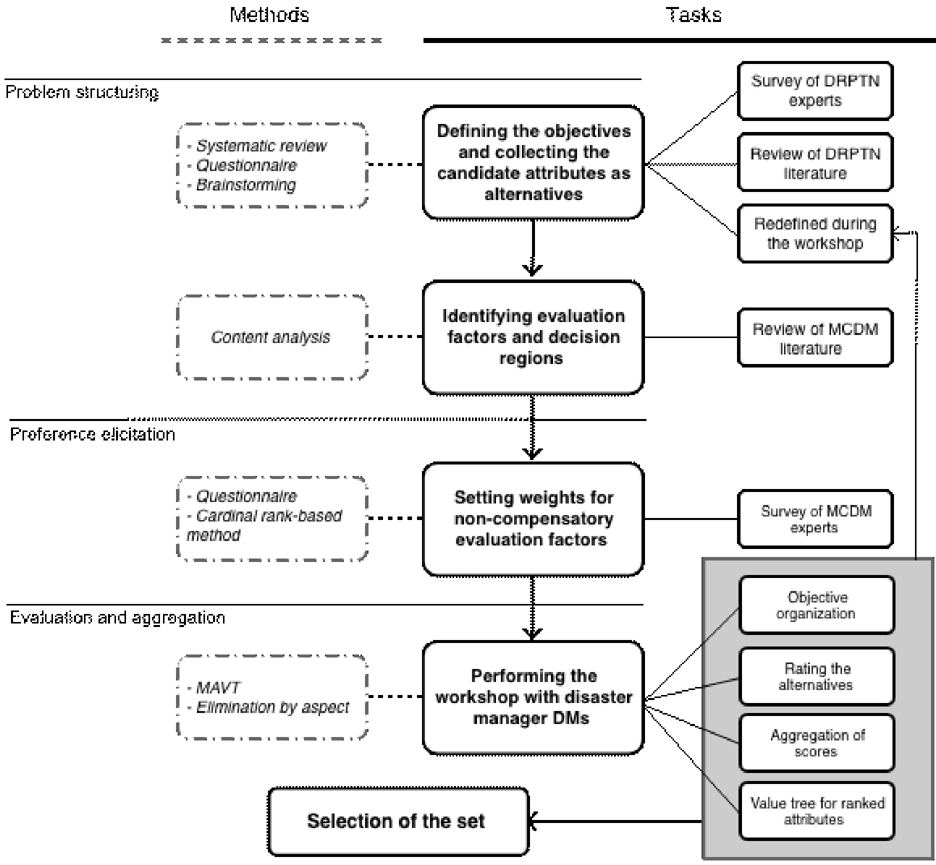

Figure 4.1: Schematic consecutive of the research framework.

4.5.1 Problem Structuring

In the first step, we identified four objectives of a DRPTN model, as discussed in section 4.3. Objectives are organized into means and fundamental objectives representing the primary objectives of the at-hand DRPTN problem shown in Figure 4.2. Fundamental objectives seek to achieve targeted properties of the network, while means objectives aim at targeted properties of the recovery operation.

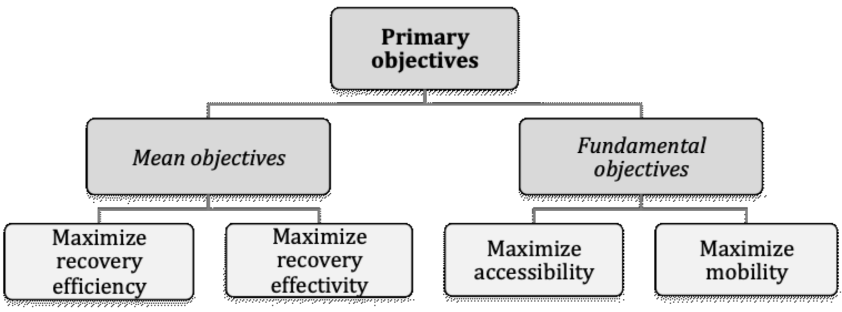

Figure 4.2: The structure of objectives of DRPTN problems.

In the second step, we identified a list of DRPTN-related attributes as the alternative pool of the model. To do so, we used attributes suggested by both literature and disaster management experts to obtain an expanded list of candidate attributes. Extracting literature-based attributes is based upon our previous work (Zamanifar and Hartmann 2020), where we performed a content analysis within DRPTN literature that led to 34 unique decision attributes. Besides, we conducted a survey of 23 experts working in Tehran's crisis management organizations, which resulted in ten additional attributes after excluding duplicated items (total: 27 unique attributes). We provided experts three questions with a beforehand description of the survey and presentation of a disaster scenario. The first question was to list three main important links with the highest priority of recovery operation in the local traffic zone for which they are responsible. Second, we asked them that based on what attributes those links have been selected. Accordingly, the third question was: for a new network with which they are unfamiliar, what information do they need to plot a possible recovery plan to prioritize links? The first question was to establish a degree of familiarity with the problem and promote case-based deep thinking. Finally, we extracted attributes that experts mentioned in the questionnaire responding to the second and third questions. Moreover, 13 attributes have been added to the alternative pool as the product of redefining attributes during the evaluation process. Table 4.1 shows the distribution of the population of the alternative pool based on the source of inclusion.

Table 4.1: Sources of attributes as the input of the decision model.

	Share in the alternative pool	
Redefined during the evaluation	13	22.8%
Survey of DRPTN experts	10	17.54%
Literature of DRPTN	34	59.64%

In the third step, we adopted existing evaluation factors for attributes as "properties of a good attribute" (Keeney 1992) according to what literature on MCDA problem structuring has been suggesting. Besides, we distinguished between properties of a desired single attribute in isolation and attributes in a set. On this ground, while seven factors evaluate attributes (members), three factors evaluate the set of attributes.

Thereafter, we divided ten evaluation factors into three decision regions with their associated known decision rules as compensatory, non-compensatory, and optimal. The first region is the screening region with a non-compensatory decision rule that acts as a filtering step of the evaluation process. The screening region is responsible for excluding attributes that i) are irrelevant to the decision context (coherency with objective), ii) are not commensurable in a consistent manner and with a reasonable amount of effort (operational), and iii) do not clearly compare and distinguish among all alternatives (discriminative).

Attributes that satisfy all factors of the screening region enter the choice region. The choice region accepts a compensatory decision rule, that is to say, a compromise among attributes is a valid consideration. This region ensures that an attribute receives a higher utility when first, it has a clear and unambiguous definition (understandable). Second, it yields a reasonably certain measured value for the respective objective (certainty). Third, it directly measures the primary objectives of the decision problem (directness), and fourth, it represents essential characteristics of the modeled problem (representative). Unlike the first two regions that evaluate "individual attributes", the third group of factors evaluates "sets of attributes" based on an optimal decision rule. An optimal decision rule can be formulated as a presumably ideal outcome for a set of attributes that captures the key aspects of all objectives (completeness) while keeping the size of the attribute set to a minimum (concise). Besides, the set should not contain a double-counting attribute (non-redundancy), which can be expressed as the constraint of the optimal region.

4.5.2 Relative Importance of Compensatory Factors

Step four is to assign a trade-off among compensatory evaluation factors. To do so, we used the inputs of six MCDM experts for the preference elicitation task. Experts provide an ordinal rank for evaluation factors from the most important to least important and adjust the distance among those sorted attributes on a visualized slider to input their cardinal preference between each pair of evaluation factors.

Table 4.2 shows the weights of compensatory evaluation factors.

Table 4.2: The trade-off among compensatory evaluation factors.

Compensatory evaluation factors	Understandable	Representative	Direct	Certainty
Ordinal value	3	2	1	4
Relative importance	20.68	27.44	36.56	15.32

4.5.3 Evaluation and Value Aggregation

To measure the performance of alternatives on each evaluation factor, as the fifth step, we held a workshop with a focus group consisting of four members of a group of experts that previously developed the disaster recovery planning of the Tehran transportation network. At the time of the research, three of the experts held a Master's degree in urban planning, civil engineering, and transportation planning disciplines and one a Ph.D. in disaster management. The working experience of four experts was eight, 11, 13, and 16 years with ongoing involvement in the field. As the official decision-makers of crisis management organizations, they had direct responsibility for and experience of the problem in question. Therefore, the DMs met the inclusion criteria of authority, stake, knowledge, and experience that qualify them to be considered subject-matter experts. Before the evaluation session, we elaborated on the structure and function of the model and discussed the problem at hand by presenting a brief disaster scenario as well as detailed descriptions and definitions of the evaluation factors. At first, experts evaluated alternatives based on three non-compensatory evaluation factors and assigned a binary value of 1 or 0. Obviously, alternatives that did not pass the screening step have zero probability of being chosen unless experts define a revised version. We then used a direct rating on a local scale of 0 to 10, where 10 represents the best performance of the alternative and 0 represents the worst. Accordingly, experts evaluated each alternative's performance based on the four evaluation factors of the choice region. In this step, the group was also allowed to redefine the attributes that did not satisfy the evaluation factors of the screening region. Experts collaboratively came to a consensus on the score of each alternative and reported it afterward. Consequently, we calculated the utility of 33 alternatives of the choice region based on the input of the focus group, the weight vector of the previous step, and the aggregation methods introduced in the next step.

In the sixth step, we used a combination of compensatory and non-compensatory MADM methods. We employed a version of Elimination by Aspect method (Tversky 1972) for the screening region and Multi-Attribute Value Theory (MAVT) (Keeney and Raiffa 1976) for the choice region to aggregate DMs' input values on the performance of each alternative against evaluation factors as the criteria of the decision model. MAVT is a well-axiomatized method, easy to understand, apply, and track, which is widely discussed in compensatory MCDM literature (see, e.g., Munda 2005). Elimination by aspect is a robust yet straightforward non-compensatory approach that follows the axioms presented with the lexicographical choice concept (see, e.g., Fishburn 1975). It is a useful approach for managing the problem's size and remains true to the non-compensatory rules where the preference transitivity is not desirable. In the seventh step, conceptual mapping of attributes based on their generic representative value took place. Here, DMs assigned the ranked attributes of the previous step to each representing objective to understand if attributes reflect the expected achievements designed as goals of the decision analysis. Finally, the last step inherits the ranked list of attributes from screening and choice regions classified with the objective-based value tree of the previous step. In this step, the task is to evaluate sets of attributes based on completeness, size, and non-redundancy. Non-redundancy ensures that in the selected set, an identical value is not dually counted. In the optimal region, the minimum size of a non-redundant attribute set that satisfies the set's completeness is the selected set of attributes.

4.6 Main results

4.6.1 Evaluation and Value Tree

The utility value and rank of the first 16 attributes are shown in Table 4.3. Initially, 24 attributes were excluded in the screening region based on the non-compensatory evaluation factors. The full list of attributes of the alternative pool, the evaluation inputs, and the attributes' aggregated utilities are available online as the supplementary material (Zamanifar 2020) and appendix (B) of this dissertation.

Table 4.3: The first 16 ranked attributes as the outcome of the choice region and their utility scores.

Attribute	Utility/Rank	Attribute	Utility/Rank
Access level of link to SP nodes	29.675 (1)	Connectivity to other traffic zones	25.524 (9)
Travel time improvement/resource	29.375 (2)	Social vulnerability*link flow	23.548 (10)
Travel delay of link *flow of the link	28.912 (3)	Annual Average Weekly Traffic (AAWT)	23.257 (11)
Travel time improvement/recovery duration	28.448 (4)	Social vulnerability* zone travel demand	22.948 (12)
Centrality measures	27.942 (5)	Network topology	22.787 (13)
Impact on total network travel time	27.193 (6)	Annual Average Daily Traffic (AADT)	22.151 (14)
East-west and north-south connectivity	26.63 (7)	Traffic density	22.024 (15)
Link capacity	25.878 (8)	Recovery efficiency	21.969 (16)

By transmitting the ranked output of the choice region into the optimal region, the first 16 ranked attributes are distributed through the objective-based value tree, as shown in Figure 4.3. The assignment of attributes is based on identifying the objectives that are measured by attributes. In our workshop, the task of assigning attributes to their representative objective was terminated once each objective received at least three attributes.

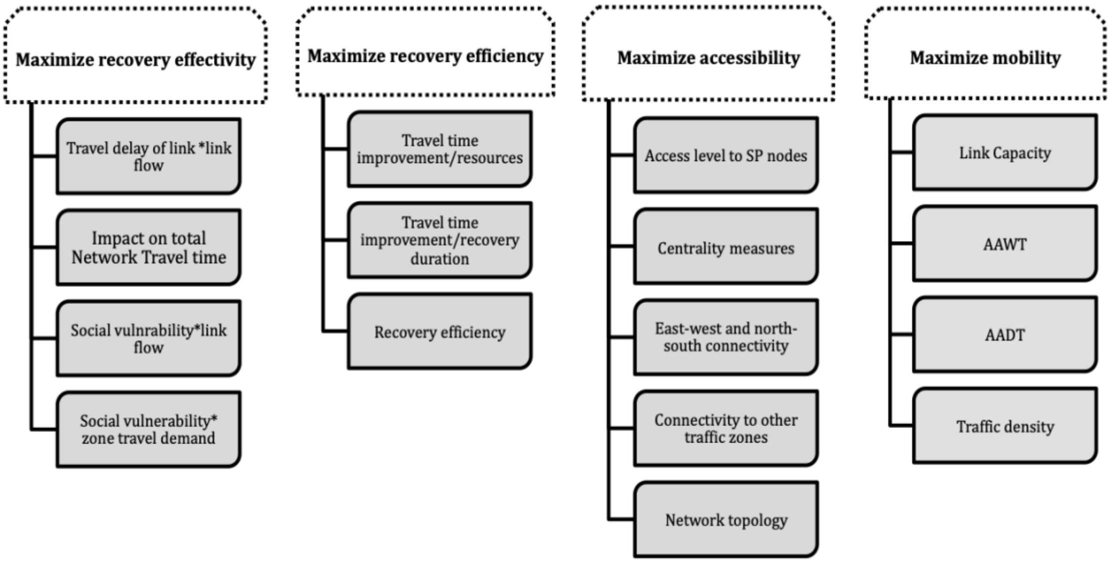

Figure 4.3: The generic distribution of the first 16 attributes to the respective primary objectives.

4.6.2 Recommended Set

Based on the generic distribution of attributes to their respective objectives mapped in Figure 4.3, the focus group agreed on six attributes as the recommended attribute set for the DRPTN model that includes: *Access level to Service-Providing nodes* (rank 1), *Travel delay of link *flow of the link* (rank 2), *Travel time improvement (TTI) per resources* (rank 3), *Travel time improvement per recovery duration* (rank 4), *Centrality measure* (rank 5), and *Link capacity* (rank 8). The first five ranked attributes of Table 4.3, plus *capacity* ranked as the 8th attribute, constitute the recommended set. Table 4.4 offers an overview of the rank, related objectives, and utility of the attributes of the recommended set, followed by brief descriptions of the final set of attributes.

Table 4.4: Attributes of the recommended set, utility score, and their associated objectives.

Attribute	*Access level to SP nodes*	*Travel delay of link *flow of the link*	*TTI/resources*	*TTI/recovery duration*	*Centrality measure*	*Link capacity*
Rank	(1)	(2)	(3)	(4)	(5)	(8)
Score	29.675	29.375	28.912	28.448	27.942	25.878
Objective	Accessibility	Effectivity	Efficiency	Efficiency	Accessibility	Mobility

(1) ***Access level to Service-Providing*** **nodes**- Service-Providing (SP) nodes are critical sources and sinks that produce emergency travel demand to which safe and fast access is necessary for the social system after a disaster. Service-providing nodes deliver critical services and commodities such that delays in their functionality or administrative operations execute adverse impacts on the economy, daily life, civil protection, and social wellbeing. All those origins and destinations fall in the category of nodes to/from which travel demand is generated due to the post-disaster emergent condition. This attribute measures the capability of links in providing access to the location of SP nodes on the network (Ulusan and Ergun 2018; Miller *et al.* 2003).

(2) Travel time improvement per resources- This attribute refers to the impact of a link reconstruction on network travel time given the resources required to implement such a recovery. Network travel time is a time-based metric for the network performance, which can account for the impact of the network's physical deterioration, as well as for the possible variations of travel patterns in a post-disaster setting (Kostanisou *et al.* 2019). The attribute represents the amount of machinery, work units, or monetary resources that have to be assigned to achieve a certain improvement of network travel time.

(3) Travel delay of link * link flow- This attribute calculates the travel delay that a link causes to network travel time during closure or reduced functionality, integrating to the amount of the traffic volume that the link sustains. Similar to the previous attribute, this composed attribute indicates the importance of a link for network travel time, but it also includes the magnitude of users impacted by the link's dysfunction. However, unlike the travel time improvement, it computes the disutility that closure or reduced capacity of a link dictates to the travel time on the serving network.

(4) Travel time improvement/recovery duration- As a metric of impact per consumed time, this attribute is a simple form of representing the temporal rate of recovery that implies the impact of links' reconstruction in a "recovery duration–travel time improvement graph". The attribute directly measures the extent to which the recovery of a link has an influence on achieving travel time improvement in a specific unit of time to represent the recovery operation's efficiency.

(5) Centrality measures- Centrality measures indicate the topological merit of a link in a network regardless of the traffic flow. In the context of graph theory and traffic engineering, centrality importance refers to attributes that measure the degree of connectivity or topological importance of a link within the embedding network.

(6) Link capacity- A definition of capacity is: "the maximum sustainable hourly flow rate at which vehicles reasonably can traverse a point or a uniform section of a lane or roadway during a given period under a prevailing roadway, environmental, traffic, and control conditions" (TRB 2000). Link capacity determines each link's ability to carry the traffic as a measure of the mobility performance of a link.

4.6.3 The Selected Set and DRPTN Literature

The *link capacity* attribute has been used in 17.5 % of the reviewed DRPTN studies (Zamanifar and Hartmann 2020) as a flow-independent parameter of a transportation network (e.g., Zhang and Miller-Hooks 2015; Bin et al. 2009; Vugrin et al. 2014). However, several other studies suggest flow-dependent attributes such as free-flow speed, density, Average Daily Traffic, or Annual Average Daily Traffic as a representative metric of network mobility and ability of links to maintain the traffic load or to provide access (e.g., Ho and Sumalee 2014; Hackl *et al.* 2018, Sato and Ichii 1995; Zhao *et al.* 2020, Sohn 2006). Similarly, the attribute *Travel delay of link *flow of the link* integrates "traffic flow," which is argued favorably by Chang (2003), while Chang and Nojima (2001) suggest a limited application of flow-based measures after a disaster. Two attributes of the recommended set incorporate "travel time" as a recognized factor in estimating the performance of perturbed transportation networks (e.g., Orabi *et al,* 2009; Kepaptsoglou *et al.* 2014; Liberatore *et al*. 2014). Furthermore, the attribute *Travel time improvement per recovery duration* represents the recovery rate that is aligned with many DRPTN studies and perhaps is the most commonly agreed attribute in the DRPTN model (e.g., Zhang 2017; Bocchini and Frangopol 2012; Sato and Ichii 1995; El Anwar *et al.* 2016).

Unlike the attributes mentioned above, *centrality measure* has not been broadly used in DRPTN literature. Among 46 reviewed DRPPT studies, we could identify two studies (Ulusan and Ergun 2018; Merschman *et al.* 2020) that adopt the centrality measure as a decision attribute in DRPTN optimization problems. Furthermore, although the attribute *access to SP nodes* is initially inputted to the evaluation process by DRPTN literature, only 12.5% of the DRPTN studies included the level of access to critical facilities.

4.7 Sensitivity Analysis

We performed a local preference sensitivity analysis to understand how the resulting ranks of attributes are sensitive to supervised parametric variations in the weighting vector (Bertsch *et al.* 2007). This analysis reveals the range of robustness of the rank of the prioritized attributes based on the change of each evaluation factor's relative importance coefficient at a time (Li *et al.* 2013). Therefore, ρ is defined as a unitary preference variation coefficient that indicates the domain of change for each weight of four compensatory evaluation factors of *certainty*, *directness*, *understandability*, and *representativeness*. The corresponding utility of respective ρ in both upper and lower bound for ten schemes from -50% to +50% was calculated and new rankings were analyzed. Table 4.5 reports the rank reversal of the first eight attributes to demonstrate the change in the rank of the six selected attributes of the final set. The rank reversal locations are highlighted, and the border of rank discrepancies is identified for each R_i denoting the original rank of attributes.

Table 4.5: (Next page) the rank reversal and thresholds of rank sensitivity to weights of evaluation factors for attributes of the selected set

Evaluation factors	Certainty								Directness							
Ranked attributes	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8
Ratio	**New rank under unitary preference variation**															
$\boldsymbol{\rho^{-}_{0.1}}$	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
$\boldsymbol{\rho^{+}_{0.1}}$	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
$\boldsymbol{\rho^{+}_{0.2}}$	1	2	3	4	5	6	8	7	1	2	3	4	5	6	7	8
$\boldsymbol{\rho^{-}_{0.2}}$	1	2	3	4	6	4	8	8	1	2	3	4	5	6	7	8
$\boldsymbol{\rho^{-}_{0.3}}$	1	2	3	4	7	5	6	8	1	2	3	4	5	8	6	7
$\boldsymbol{\rho^{+}_{0.3}}$	1	2	3	5	4	7	9	6	1	2	3	4	5	6	7	8
$\boldsymbol{\rho^{-}_{0.4}}$	2	1	3	4	7	5	6	8	1	2	3	4	5	8	7	8
$\boldsymbol{\rho^{+}_{0.4}}$	1	2	3	5	4	8	9	6	1	2	3	4	5	6	7	9
$\boldsymbol{\rho^{-}_{0.5}}$	2	1	3	5	7	4	6	8	1	2	3	5	4	8	7	8
$\boldsymbol{\rho^{+}_{0.5}}$	1	2	3	5	4	8	9	6	1	2	3	4	5	6	7	8

Evaluation factors	Understandability								Representativeness							
Ranked attributes	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8
Ratio	**New rank under unitary preference variation**															
$\boldsymbol{\rho^{-}_{0.1}}$	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
$\boldsymbol{\rho^{+}_{0.1}}$	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
$\boldsymbol{\rho^{+}_{0.2}}$	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
$\boldsymbol{\rho^{-}_{0.2}}$	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
$\boldsymbol{\rho^{-}_{0.3}}$	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
$\boldsymbol{\rho^{+}_{0.3}}$	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
$\boldsymbol{\rho^{-}_{0.4}}$	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
$\boldsymbol{\rho^{+}_{0.4}}$	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
$\boldsymbol{\rho^{-}_{0.5}}$	2	1	3	4	5	6	7	8	1	2	3	4	5	6	7	8
$\boldsymbol{\rho^{+}_{0.5}}$	2	1	3	4	5	6	7	8	1	2	3	4	5	6	7	8

For the evaluation factor of *certainty,* the final rank of eight attributes changes when the weight coefficient increases or decreases by ±10%, whereas, for the first three ranked attributes, this variation leads with the change of ±30% in the factor's initial weight. Under the preference change of the *understandability* factor, the overall rank of attributes exhibited a relatively insignificant alternation while the order of attributes remains utterly stable for the *representativeness* factor. Therefore, Table 4-5 shows that the sensitivity of attributes' ordinal rank to the weights of those factors is remarkably low, which is logically predictable, as the same holds for the diversification of assigned values for the performance of attributes within the evaluation process. Furthermore, no rank reversal is observable for the first three attributes when we applied a series of variations to the weight of the *directness* factor. The impact is, however, noticeable within the range of rank four to eight, should the weights increase or decrease by ±30%.

In general, a moderate rank reversal is noticeable only for the *certainty* factor corresponding directly to the diversification of DMs' assigned values in the evaluation process. Therefore, the analysis suggests that considerable information is preserved in the assigned values to the *certainty* factor; thus, the certainty of an attribute could have attained higher relative importance for the participating DMs. In total, a significant shift in the rank of attributes or extreme rank reversal was not detected. This can suggest that, concerning preference values, the outranked outcome is relatively robust. One should note that this analysis cannot be safely counted as hard evidence for the general robustness of the final results since this behavior is not unconventional for a prescriptive model with a flat hierarchy of evaluation factors and no inflection point in the linear weighting vector that allow an undeviating transition of preferences to the aggregation model. Nevertheless, findings of the performed analysis do provide an understanding of how non-deterministic inputs could impact the rank of attributes and what uncertainty thresholds could be drawn.

4.8 Discussion

4.8.1 Analysis of the Attribute Set

Access level to SP nodes obtained the first rank in the choice region. As a universal goal for every crisis, restoring society to a normal condition is a logical target for DRPTN problems. Therefore, the accessibility index to nodes such as critical facilities was expected to obtain the highest utility and establish itself as the main concern of DMs. The attribute *Travel time improvement/resources* aims at providing low-cost high-impact solutions after a disaster, which renders the attribute an attractive option for DMs. Decision-makers also emphasized the significance of certainty about available and dispensable resources after disasters and indicated that the efficient use of resources is of utmost importance in their planning approach toward prioritizing recovery operations. *Travel delay of link *flow of the link* measures the effectiveness of the recovery operation. The focus group was leaned toward solutions that impact a larger amount of the population and satisfy a broader range of users to ensure the effectiveness of recovery operations. Broadening the extent of public satisfaction was also a motive for DMs to be interested in this attribute. The attribute of *Travel time improvement per recovery duration* represents the progressive performance of recovery in units of time. Clearly, an incremental recovery rate, i.e., the slope of the duration–improvement graph, yields reaching an improved state of the network promptly. DMs stated that it is not only important to shorten the period that the crisis impacts the transportation network but also to generate psychological comfort when users observe short-time progressive shocks to the system which can project a timely elevation of network quality level.

Centrality measure is a contextually relevant and practical attribute after disasters since a known pre-event traffic stream will not remain the same under post-event circumstances, and overall connectivity of the network pertains to restoration of centrality-centric important links. The certainty of performance of *centrality* indicators was the key feature of this attribute's favorability since it is less likely that the topological position of a link varies after a disaster compared to the same probability for the traffic flow. Another justification for employing this attribute was the extent that centrality importance contributes to maintaining connectivity in a network since it is reasonable to assume that the degree of connectivity of a network with restored central links is meaningfully higher than a network that is rehabilitated without considering centrality features of links. *Link capacity* with the eighth highest utility represents the objective of mobility. In the post-disaster setting, prioritizing links based on the traffic capacity improves the network's performance in operating post-event travel demand. DMs' main motivation was to accommodate higher travel demand into the network in the early stages of a recovery process by accelerating the recovery of high-capacity links. It is a reasonable assumption in post-disaster conditions that users are more inclined to choose roads with higher capacity to avoid undesirable congestion in the small streets. Although *capacity* received a medium score for directness since it does not take into account any characteristic of disaster condition, perhaps for the same reason, it received the full score of the *certainty* factor. In fact, both *centrality* and *capacity* are important indices of links concerning mobility and accessibility regardless of the perturbed condition of a network. While they do not represent characteristics of a disrupted network, their resulting lower score for *directness* and *representativeness* is compensated with a higher score in *certainty* and *understandability* of attributes.

As a set, the selected attributes cover the concerns related to the problem and ensure that objectives are completely measured. Although each attribute deems to be individually an important factor, to address all defined objectives, the implication of the recommended attributes is meaningful only by remaining as a set. Within the case study domain, results suggest the feasibility of following a structured decision framework for selecting decision attributes of a DRPTN problem. The carefully collected, systematically analyzed, and critically evaluated attributes allow the harnessing of the knowledge of subject-matter experts in the context of DRPTN. Therefore, DRPTN research can use the outcome of this research as the input of the problem structuring phase of newly developed disaster recovery models.

4.8.2 Practical Implications

Determining decision attributes of disaster recovery planning is the hardest yet most important task in a decision modeling process of a DRPTN problem. This study harnessed DMs' knowledge as subject-matter experts for identifying attributes of DRPTN through a formalized systematic evaluation and selection process. On this ground, while making decisions on the priority of recovery operations, we suggest that disaster managers consider using the proposed key attributes to evaluate the consequence of choices on recovery options. Based on the description of the six selected attributes, should this set be utilized in a DRPTN model, a recovery strategy will receive a higher utility if it:

1) Has a higher impact on reducing travel delay and affected users;
2) Requires fewer amounts of recovery recourses for improving travel time;
3) Provides a wider access level to the service-providing places;
4) Prioritizes the links with higher capacity;
5) Has a higher centrality importance;
6) Leads to an earlier recovery impact on network travel time.

According to Table 4.4, the six key attributes represent the four defined objectives. Hence, a formulated plan based on the recommended set potentially maximizes the impact of recovery while covering a wide range of users to expand the threshold of resilience. Additionally, it allows the prioritizing of links that facilitate access to critical nodes and a maximizing of the capacity of network mobility. However, it might be cumbersome to formulate an optimization problem that can incorporate all four objectives and provide a feasible solution space with reasonable computational complexity. Therefore, attributes of the set can also be used individually if the goal of the planning is to address one or more of those objectives. For example, as Figure 4.4 demonstrates, to focus on maximizing the efficacy of post-disaster recovery operations, the attribute *Travel delay of link *flow of the link* is recommended. For maximizing the efficiency of recovery planning, two attributes *Travel time improvement per resources* and *Travel time improvement per recovery duration,* form a representative and complete set. At the same time, DMs need to incorporate the attribute *Access level to SP nodes* if maximizing network accessibility is intended as well.

As a remark for DRPTN modelers, the resulting attribute set suggests that the integrating of parameters to develop as Keeney (1992) defined *constructed attributes* is required to address the DRPTN primary objectives. For instance, the attribute *Travel time improvement/recovery duration* underscores that "recovery duration" would be a practical parameter only if it portrayed the network performance progression per consumed time and indicated a ratio of recovery progress in terms of its impact on technical characteristics of the network. Similarly, regarding the attribute *Travel time improvement /resources,* single traffic properties such as travel time will be more effective when integrated with contextual characteristics of recovery operations. With respect to the attribute *Travel delay of link *flow of the link*, disaster managers should note that a road with higher traffic volume is not necessarily more important, but attention should be paid to the extent to which this traffic volume is vulnerable to travel delay due to the damage at a network level. Finally, it is reasonable to believe that post-disaster travel demand patterns will not remain as the pre-disaster condition. Hence, centrality measures, as a flow-independent attribute, would perhaps be a robust representative of links' merit. The proposed attribute set would be useful for disaster managers to employ as key factors for developing recovery planning decision support systems or as key performance indicators for evaluating successful recovery and resilience plans.

4.9 Limitations and Future Research

Finally, to point out possible limitations of the research approach, one should note that the evaluation task within the model is one of the subjective parts of the decision process as an inherent feature of all decision models. Consequently, the selection of the attribute, in the end, always depends on experts' opinions and their collaboration structure, which is, to a great extent, influenced by various factors such as their area of expertise, the socio-geographical factors, degree of availability cascade effect, availability heuristic bias, herd behavior, working memory capacity, their stake and knowledge. Therefore, the concern over the generalizability of the result is valid. However, the systematic framework generates tractable outcomes that make it possible to locate where exactly the subjectivity might influence the evaluation process. The model also promotes creative and critical thinking and provides ground for collaborative decision-making, as we evidentially observed during the workshop. Therefore, it is not absolutely irrelevant if we assume that the suggested decision recommendations offer meaningful insights and inference for possible attributes of a universal DRPTN problem. In the meantime, future research is needed in various geographical contexts to re-implement this research in different urban settings.

In this research, we incorporated the input of the focus group, the survey of experts, and DRPTN literature as three sources to fill the alternative pool. However, it still falls short in covering the contributions of a broader range of stakeholders. Since the outcome is as complete as the alternative pool, it is important to provide a so-called expanded complete list of attributes, including experts, literature, decision-makers, actors, and all stakeholders. Obviously, the completeness of the alternative pool significantly escalates the size of the problem and the likelihood of exposure to bias and error accordingly. Moreover, a further enhancement could be the possibility to reduce the number of attributes in the initial alternative pool. During our research, we did not look into such possibilities to logically analyze attributes to understand whether several attributes can be effectively subsumed into a single one.

4.10 Conclusion

While urban systems are encountering an unprecedented risk of climate-induced and natural hazards, it is of paramount significance to develop decision support systems that pave the way for well-informed collaborative decision-making. In order to develop such a DSS, modelers should feed the decision models with tenable and plausible decision attributes resulting from a reliable formal selection process. Based on this premise, we used a new modeling paradigm to aid decision-makers in selecting attributes of a DRPTN model of Tehran. The aim was to formally extract the knowledge of subject-matter experts as DMs about concerns and values in the reconstruction and recovery of transportation networks after disasters. DMs proceeded to evaluate 57 attributes through multi-stage yet non-hierarchy three sequential decision regions. Six key attributes were identified as the recommended set to cover the main concerns of the decision problem based on the primary objectives. The recommended set is supposed to be complete and non-redundant with compromise in conciseness. Additionally, all attributes individually obtained a relatively high utility, satisfying representativeness, directness, unambiguity, and certainty of measure. The model-driven attribute recommendation allows decision-makers to choose a more contextually related set to the decision environment's specific conditions, such as available local data, computational power, objective preference, and certainty threshold. Given the circumstances under which other attributes with the trajectory utility fit DRPTN model requirements, the set can adapt accordingly. The implementation of the framework was successful in harnessing collaborative experts' input in a structured manner. However, it by no means presents an assertive uniform prescription, but indeed offers the ability to track the decision process, organized and critical thinking, and an enhanced quality of choice. While the attribute set is defined, an emergent challenge is to formulate a problem that can be solved with a reasonable computational cost. As we pointed out in the discussion section, using the recommended set of attributes in a disaster recovery planning decision model is expected to provide effective and efficient solutions that maximize mobility and accessibility in the network. Therefore, we call for studies that formulate and solve a decision problem by integrating the decision attributes introduced in this research.

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Chapter V

CONCLUSION

"We are in great haste to construct a magnetic telegraph from Maine to Texas; but Maine and Texas, it may be, have nothing important to communicate... We are eager to tunnel under the Atlantic and bring the old world some weeks nearer to the new; but perchance the first news that will leak through into the broad flapping American ear will be that Princess Adelaide has the whooping cough."

Henry David Thoreau, Civil disobedience, (1849)

5 Conclusion

5.1 Summary and Main Findings

This research began with a comprehensive and systematic literature review that sought to identify knowledge gaps in the DRPTN decision modeling process. Optimization-based DRPTN modeling was considered as a process comprised of four primary phases: problem definition, problem formulation, problem solving, and model validation. For each phase, certain challenges and opportunities were articulated, as were suggestions concerning how the identified gaps could be overcome. In order to address the knowledge gaps related to the lack of problem structuring in DRPTN models, I then developed a prescriptive decision aid mechanism that can harness experts' knowledge base on the value of DRPTN decision attributes and prescribe an attribute set. Accordingly, the process of attribute evaluation and selection was formulated as a screening-choice utility decision model. To implement the framework in a real-world DRPTN problem, I collected expert and literature-based potential attributes to develop an alternative pool by using a survey that contained results from 23 senior experts and content analysis of 46 DRPTN studies.

In the next step, I extracted evaluation factors from literature related to decision analysis and problem structuring that were subsequently utilized in a workshop to appraise the attributes of the alternative pool. Next, the challenge was to determine the relative importance of compensatory evaluation factors based upon six MCDM experts' opinions. Once the set of alternatives, evaluation factors, and their relative weights had been established, I held a focus group workshop featuring four disaster managers, which included several tasks to implement the framework, and observe its performance. The newly developed framework consists of innovative integration of compensatory and non-compensatory aggregation methods within a sequential discrete three-stage evaluation process, employing ten evaluation factors. During the workshop, maximizing mobility, accessibility, recovery efficiency, and recovery efficacy were considered the primary objectives. The experts were then asked to evaluate and rate individual attributes within two stepwise decision regions based upon region-specific evaluation factors. Each decision region had its own decision rules. The first decision region submitted to a non-compensatory decision rule, wherein Elimination by Aspect was used to screen the candidate attributes. The second decision region operated under a compensatory decision rule for the task of direct point allocation. When the evaluation process of single alternatives had been completed, I then calculated the utility of attributes using MAVT, and presented the focus group with the resulting ranked list of attributes. After that, the evaluation within the third decision region was conducted with an optimal decision rule by developing a value tree as a concept map of objectives and their respective representative attributes. The focus group then selected a set of attributes based upon the sorted attributes and the value tree to satisfy the three optimal region's evaluation factors. The after-workshop analysis included a feedback session using a survey with two direct questions, an analysis of observations during the evaluation process, an open discussion with users, sensitivity analysis, and entropy information analysis of the factors, as well as a typological and descriptive analysis of the final attribute set. The chosen attributes were also compared to the working attributes that the decision-makers selected for the same context in an unaided procedure. The findings of the research have been reported in three sections, which are outlined in detail below.

The findings of my gap analysis suggest that existing DRPTN models face critical challenges in adopted decision attributes and introduced a lack of theoretical argument for inclusion of attributes and the absence of a formal process that justifies and supports the selection of decision factors. Furthermore, the inclination towards using meta-heuristic solving algorithms where linear programming could provide a globally optimal solution, as well as the general absence of explicit or implicit justification of solving methods (e.g., convexity, linearity, or complexity analysis of mathematical programming), characterized the problem-solving phase of DRPTN modeling. However, the existing user-friendly tools supporting meta-heuristic solving algorithms, the perceived novelty associated with their applications, and the ability of these methods to perform an exhaustive search within a reasonable computational cost make it an interesting approach, especially where non-experts are engaged with optimization models. In the problem formulation phase, limitations in integrating traffic management measures and post-event travel demand models into the formulation process of network recovery were highlighted. Finally, challenges in validating DRPTN models in terms of presenting a benchmark or level of confidence to support the reliability of outcomes rounded out the reported gap analysis. The first section's conclusion argues that DRPTN research needs to raise awareness of method-rich but methodology-poor syndrome as a persistent challenge for disaster recovery models.

The second section reported on findings related to the developed attribute selection methodology and the framework. Accordingly, the framework was designed as a toolkit for processing experts' input as relates to selecting decision attributes and framing a disciplined decision process. The multi-stage yet non-hierarchical structure of the framework allowed for a critical and thorough evaluation of candidate attributes to be undertaken in a relatively user-friendly manner. Users were able to systematically evaluate attributes and collaboratively produce a ranked list of attributes, as well as the final selected set. During the implementation of the proposed methodology, it was possible to observe that the framework could act as a tool to extract DMs' knowledge and help in the isolation of the elements of the decision context that are most relevant to the problem. Based upon observations of the discussion developments in the workshop and the position of the certain attributes in the final ranking, the embedded evaluation mechanism facilitated critical and creative brainstorming, thereby fostering the incorporation of available knowledge sources. Therefore, as the framework's output, the recommended set is the result of a systematic process and collaborative decision-making, and consequently offers a set of attributes for both practice and research. Further, the model-driven attribute selection process can also be adapted to the specific conditions of the decision environment, such as locally available data, computational power, objective preferences, and certainty thresholds. Given the circumstances under which other attributes with trajectory utility fit DRPTN model requirements, the set can be adapted accordingly. Therefore, the approach employed in this research paper enables informed and flexible decision-making for the selection of tenable attribute sets. It is reported in chapter three that more attributes are obtained from the literature. However, this does not suggest any meaningful insight concerning the framework's performance since it can be a random event or only because the process initially started with extracting attributes from the literature, and attribute sources did not have identical numbers in the alternative pool. Nevertheless, I have not drawn any conclusion based on this observation. The idea is to maximize the total number of relevant attributes in the alternative pool. Although extracting attributes initially started with literature, in the evaluation process, all attributes have been presented together as a single alternative pool, including attributes extracted from experts and literature. The argument developed in chapters three and four concluded the framework's satisfactory performance based upon the evaluation of the outcome, the discussed characteristics of the framework, and users' feedback.

Finally, decision-makers were able to select six attributes to be included in Tehran road network disaster recovery planning. These attributes included 1) access level to service-providing nodes; 2) integration of link travel delay and traffic flow; 3) travel time improvement per recovery duration; 4) travel time improvement per resource; 5) centrality measures, and 6) link capacity. The recommended set is intended to be concise, non-redundant, and complete. Additionally, all six attributes obtained a relatively high utility value, satisfying the criteria of representativeness, directness, unambiguity, and certainty of measure. The analysis of the results discussed in chapter three suggests that the framework leads to improved quality of the attributes compared to the selected set in an unassisted manner. This claim may need further evidence to be thoroughly validated. Nevertheless, if it is not possible to compare the quality of outcome attributes from two different processes, the comparison of the two processes that yield the attributes is still a viable option. In the light of sufficient insights that could indicate the quality of one process over another, it is unwise to deny the improved quality of output only because the two sets of outcomes are too qualitative to be compared.

The sensitivity analysis confirms that the outranked outcome is relatively robust with regard to the assigned preferences, although given the number of evaluation factors and their single hierarchy level, it was an expected outcome from such an analysis. This argument was also supported by information entropy analysis. Sensitivity and information entropy analyses were both aligned in suggesting sensitivity and information preservation in the "*certainty*" evaluation factor. This result supports the hypothesis that participating DMs prioritized concerns about the uncertainty associated with attribute values for each alternative.

As was concluded in chapter four, using the recommended set of attributes in a disaster recovery planning decision model is expected to provide effective and efficient recovery solutions that maximize mobility and accessibility in the affected network. One should note that the completeness of the attribute set is defined based on the determined objectives for this specific case study and not all aspects and dimensions of a general disaster recovery process. Based upon the description of the six attributes, a recovery strategy will have a higher utility when it meets the following criteria: 1) Has a higher impact on reducing travel delay and affected users; 2) Requires fewer recovery recourses for improving travel time; 3) Provides a wider access level to the service providing places; 4) Prioritizes the links with higher capacity; 5) Has higher centrality importance, and 6) Leads to earlier recovery impact on travel time.

Finally, the recommended set does not claim universal validity, nor does it constitute a uniform prescription for DRPTN models, as it is utter context-dependent. Instead, the framework offers the ability to track the decision process, organizes and facilitates critical and collaborative thinking, and presents an enhanced quality of choice. The possibility of involving cognitive biases related to preference elicitation, value assignment, and group decision-making cannot be dismissed. To better understand the quality of the developed attributes, future research is needed.

Nevertheless, it is reasonable to assume that the systematic attribute selection process allows analysts to track and locate where subjectivity might influence the evaluation process.

Finally, there is no “correct” attribute, but some sets of attributes could be more indicative of the objectives they are supposed to represent and more operational for the intended application of the decision model at hand. If we take the association of a model’s outcome with the quality of its attributes as a given, investing in selecting reliable attributes is a rational choice. As Ralph L. Keeney once wrote, "the selection of an attribute is a decision" (Keeney 2007). Therefore, a decision aid mechanism, such as the framework proposed in chapter three, can increase the odds of arriving at useful or better attributes. Essentially, the path toward a better attribute can be paved by following a systematic, transparent approach with the added value of allowing for collaborative decision-making, creative thinking, and structured experts' tacit knowledge elicitation.

5.2 Contributions

Assuming that “improved decision structuring will improve the quality of the decision outcome” (Corner et al. 2001), the findings contribute to the construction of more reliable DRPTN models and informed decisions for recovery of transportation networks in the aftermath of disasters. The contributions can be grouped as follows: 1) gap analysis; 2) developed framework; and 3) suggested attributes. First, the gap analysis discussed in chapter two is an original investigation of problem structuring and methodology of optimized DRPTN models that offers perspectives and suggestions regarding how to supplement approaches that mainly focus on optimizer algorithms. Second, the framework presented in chapter three is designed to bridge the knowledge gap in DRPTN decision analysis problem structuring and serve as a means for 1) structuring knowledge; 2) communicating key information; 3) analyzing the extracted knowledge; and, finally, 4) facilitating the selection and evaluation process of attributes. The innovative design of the framework reduces the complexity and cognitive burden of a model, while still including ten evaluation factors for thorough and critical evaluation that also serve to expand the capacity for inclusiveness in accepting input alternatives. Third, the selected attributes introduced in chapter four are the result of having provided a systematic strategy for channeling experts' knowledge toward selecting a reliable and calibrated attribute set. The following subsections summarize the contributions and originality of this research with regard to each of its stated objectives.

5.2.1 Contributions toward Meeting Objective 1

The findings related to the first objective open up a new discussion on the application of optimization methods in low-validity decision environments, as well as the application of non-deterministic optimizers in exploring the solution space of DRPTN models. These findings challenge the existing approaches to selecting attributes and validation of models within the reviewed papers from the existing literature. This research also offers suggestions for all four phases of DRPTN optimization programming. Notably, this research answers pressing questions regarding necessary improvements in developing optimized DRPTN decision models. The identified gaps feature important areas of optimization modeling in the context of disaster recovery that could contribute to the improvement of future DRPTN models' performance. The efforts add to our collective knowledge of the application of optimization programming and decision modeling in the disaster management context, and advance the understanding on decision modeling for recovery planning of critical infrastructures. At the same time, this work poses the following question: to what extent the lack of formalized problem structuring can refute the validity of existing optimization models, and what would be the uncertainty threshold for decisions in the context of DRPTN? The following overview outlines this research's contributions and originality related to meeting Objective 1.

The presented findings, research design, and arguments in chapter two:

- Provide a holistic, systematic literature review of DRPTN studies with respect to the methodological application of optimized decision models in the DRPTN context and its problem structuring;

- Approach the DRPTN optimization programming as a process constituted by four phases of problem definition, problem formulation, problem-solving, and model validation;
- Identify the decision factors of DRPTN suggested by related studies;
- Investigate complexity and convexity analysis within the DRPTN models;
- Review the verification and validation process of the selected DRPTN models;
- Analyze the correlation of non-deterministic optimizers and objective levels in the DRPTN models;
- Identify auxiliary problems integrated into the DRPTN models as well as the alternative set of DRPTN models; and,
- Suggest improvements for DRPTN models related to overcoming the detected challenges within the decision modeling process of DRPTN problems, paving the way for future DRPTN research.

5.2.2 Contributions toward Meeting Objective 2

The developed methodology contributes to existing decision analysis literature by proposing the integration of compensatory and non-compensatory decision rules, as well as by introducing a framework for selecting decision attributes. Portraying a systematic attribute-selection procedure as a tool, this research extracts knowledge from the relevant literature, and systematically harnesses experts' opinions to produce knowledge and contribute to the construction of a better model. This research also demonstrates how using a systematic framework influences the quality of selected attributes in the setting of disaster recovery models. The findings further challenge existing approaches employed for the selection of decision attributes and argues that, to develop decision models, a formal process capable of generating suitable decision attributes is necessary. The following list indicates contributions and originality toward meeting Objective 2.

The presented findings, research design, and arguments in chapter three:

- Present the attribute selection task as a formalized discrete screening- utility choice decision model with three sequential evaluation stages;

- Introduce a prescriptive decision analysis framework integrating three decision rules in a single decision environment for selecting attributes; and,
- Propose a set of evaluation criteria to evaluate both an attribute in isolation and attributes in a set, as well as the preferential model of trade-off among compensatory factors;
- Develop an integrated non-compensatory screening and compensatory choice mathematical model as a customized value aggregation method; and,
- Assess the performance of the framework through surveys and interviews to collect feedback from users on the application of the framework, performance observation of the evaluation process, and typological analysis of the selected set with regard to the properties of attributes.

5.2.3 Contributions toward Meeting Objective 3

The results of this study contribute to existing knowledge about concerns and values in the reconstruction and recovery of transportation networks in the aftermath of disasters. The recommended attribute set is the primary contribution as a result of a delicate implementation of the framework conducted with subject-matter experts in a critical disaster-prone context. The findings point to key factors that constitute an set of decision attributes, and answer the question of how such an attribute set can be identified. The results provide a practical understanding of values for drafting post-disaster recovery plans for transportation networks. The suggested set covers several post-disaster recovery aspects, including traffic engineering challenges, recovery's social impact and post-disaster needs, as well as construction management in the recovery process. It also opens a new space for developing related measuring methods for the presented attributes in future works. The following list indicates contributions and originality toward meeting Objective 3.

The presented findings, research design, and arguments in chapter four:

- Collect the DRPTN decision attributes from literature and experts;
- Implement the developed methodology in a real-world case study; and,
- Propose an improved set of attributes for Tehran DRPTN model and discuss their applications.

5.2.4 Application of Findings

The practical contribution of this study is to help decision-makers and analysts make [more] informed choices and tenable decisions within the construction of DRPTN decision models and, eventually, to develop more contextual and useful models. The findings demonstrated in chapter two present a contextual understanding of the process of DRPTN model construction, which provides decision-makers with insight into what can be expected from the existing models' performance and the limits of these expectations. The gap analysis of DRPTN methodologies also explains what decision-makers cannot expect to learn from a DRPTN model, as well as outlines the uncertainties they must take into account while receiving decision recommendations based upon an optimization-based DRPTN model.

The proposed framework presented in chapter three supports the selection of attributes of complex decision problems or high-performance indicators of design, policy, and engineering problems in practice. Furthermore, researchers who develop multi-objective or multi-attribute decision models can use this framework as a guide for the problem structuring of their modeling process. Research and practice can apply the proposed framework for establishing a calibrated set of attributes of decision problems even for those who are not necessarily experts in decision analysis.

The DRPTN attribute set reported in chapter four offers DRPTN decision-makers and modelers with a set to be utilized as decision factors for future recovery planning. This set could also be used for evaluating existing disaster recovery plans, or as input for the construction of DRPTN decision support systems. Additionally, future research can use the findings of this study as a problem structuring phase when developing new disaster recovery models. Another application of the key attributes for disaster managers might be their use as criteria for identifying an optimized post-disaster emergency road network in the immediate response phase. More specifically, the integration of three attributes (link capacity, access to SP nodes, and centrality importance) can identify disaster response routes with optimized, involved link recovery operations, so that maximized level of service and access is more likely.

5.3 Future Research, Open Questions, and Remaining Gaps

Future research should recognize the significance and necessity of time and effort for problem structuring of DRPTN decision modeling, including problem conceptualization, executing formal processes to select decision parameters, examining well-supported assumptions and their impacts on a model's outcome, assessing the typology of the decision model, and conducting sufficient computational justification of selected methods. These tasks are particularly vital in the field of disaster management. Academic networks and practitioners should take the problem structuring of DRPTN as a starting point and tailor sets of attributes according to local, context-dependent characteristics of the problem with the aid of a systematic and transparent framework. Problem structuring should begin with problem recognition, focusing on the discrepancy between the status quo and the desired state of the modeled system while also accurately identifying the threshold of uncertainties. The following sections highlight some open research questions and knowledge gaps for future studies to approach.

5.3.1 Sensitivity to Local Minima and Converting Objectives to Constraints in DRPTN Optimization Models

Future research is encouraged to investigate the impact of choosing deterministic or non-deterministic optimizers on the DRPTN model's outcomes. This investigation provides insight into the extent to which the solution DRPTN decision model is sensitive to locally optimal solutions as compared to globally optimal ones. The findings of this investigation support the possibility of developing an optimization problem that is either solvable with a deterministic method or that is not completely reliant upon global optimization. Comparing the final rank of recovery operations or damage links in two cases where non-deterministic and exact methods are used provides valuable knowledge regarding how the outcomes might be different which would aid in selecting a more efficient optimizer.

Furthermore, the number of objectives, as a driving factor in choosing an optimizer, creates a barrier in adapting deterministic algorithms. Reducing objective numbers can decrease the computational overhead of the DRPTN optimization problem as long as it does not adversely impact the completeness of a model. One approach is to define a bound or deterministic desired value for an objective, as a threshold, which can limit the solution space and render exhaustive searches computationally more reasonable. Some examples of this approach have been previously discussed in the multi-objective optimization programming context. Therefore, further studies are needed to explore this possibility and identify/quantify the desired state of post-event network performance and answer the question of what the targeted performance of the network is in the aftermath of the disaster.

5.3.2 Future research on the Implementation of the Framework and the Recommended Attributes

Applying the attribute selection methodology in different contexts would provide useful knowledge regarding the impact of local factors in the final recommended attribute set and as auxiliary evidence for the framework's performance. Moreover, it is recommended that future research (not only that limited to the DRPTN field) adopt the framework in the formulation of the decision problems and implement this formal systematic process to select attributes for their focused problems.

While the attribute set is defined, it remains a challenge to formulate a problem with the recommended set so that it can be solved in a reasonable amount of time. The six attributes represent four defined objectives according to the expert's opinion and previous disaster recovery plans described in chapter four. Since the completeness of the attribute set is based on measuring this study-specific four objectives, it has been shown through the concept map value tree (Fig. 4.3) in chapter four that all four objectives have been assigned at least one indicative attribute. However, it might be cumbersome to formulate an optimization problem that can incorporate all four objectives and provide a feasible solution space with reasonable computational complexity. Therefore, the attributes of the set can also be used individually if the goal of the planning addresses one or more of the defined objectives. For example, to focus on maximizing the efficiency of recovery planning, two attributes (travel time improvement per unit of resources and travel time improvement per unit of recovery time) form a representative and complete set. Therefore, future studies with different objective sets can formulate and solve a decision problem by integrating decision attributes introduced in this study.

Finally, future research can investigate the possibility of reaching a complete attribute set in the sense of addressing various multifaceted dimensions involved with the concept of disaster risk governance. The author believes that it may be possible to address (force-include!) various dimensions of disaster resilience interventions, including social, economic, engineering, cultural, health, and well-being, simultaneously in one set of attributes. However, it remains tedious (if not impossible) to develop a decision model to operationalize this so-called "complete" set of attributes in a computationally or cognitively manageable form for which either a compromise or optimum solution would be feasible. Such a decision modeling with unconceivable uncertainty is a set up for misleading decision makers who could very likely perform better naturalistically without any decision aiding intervention. For this reason, perhaps "the mere the merroir" is ill-advised regarding the size of the attribute set. As a result, the third stage of the framework includes the "concise" evaluation factor to ensure the minimized number of attributes in the set for which its completeness— in an attainable scope of objectives— can be achieved."

5.3.3 Does Preference for a Certain Objective Impact the Selection of Attributes?

Although the set containing six recommended attributes is supposedly complete and non-redundant, it is not minimized in size, which indicates the compromise in the optimal region between size and completeness. This compromise may itself suggest the presence of a possible indirect indication for identifying the relative importance among the different objectives. Nevertheless, the question of understanding whether inclination toward selecting additional attributes for an objective is derived from the utility of the attribute or is instead derived from the preference of the objective that the attribute measures is an intriguing question that remains unanswered. However, one should note that it is possible that an objective demands more than one attribute to be collectively measured.

Future research could also consider applying sensitivity analysis to understand whether, under various point allocation scenarios, the change in preference of a specific evaluation factor or its assigned value could have a meaningful impact on the rank utilities such that an indication concerning the statistical significance of certain evaluation factor can be suggested. Additionally, sensitivity analysis is also useful for defining the thresholds for which the change in assigned weight or values of a particular attribute could impact the model's outcome. In the meantime, it is important to understand the application of sensitivity analysis, whether it can provide meaningful knowledge or, if it does, how this knowledge can be used to improve the decision model or reduce uncertainty.

5.3.4 Integrating Traffic Management of Surviving Networks with Recovery Planning

The current DRPTN studies provide analytical decision recommendations for the recovery process of a damaged network's components after a disaster; they offer very little in terms of how the surviving network (undamaged or slightly damaged functional components) should be operationalized and managed to meet travel demand in the traffic engineering context. Further research is needed to investigate traffic management in the post-disaster surviving network; the issue of integrating post-disaster traffic management and recovery planning remains almost untouched. This investigation can advance our knowledge of possibilities for including traffic management measures as choice set alternatives along with recovery projects to maximize mobility in the network and utilize both administrative and construction options toward satisfying the same objectives.

5.3.5 DRPTN modeling: Do Social Vulnerability Variables Matter?

Emergency and recovery planning of infrastructures against hazards in urban areas requires addressing social factors and socially vulnerable groups while seeking to efficiently maximize the technical objectives of the planning. It is well established that recovery planning of transportation network, although aims at solving engineering and construction management problem, serves the social process. The performed content analysis reveals that social vulnerability variables have been adopted in only 12.5% of the DRPTN studies reviewed. Moreover, during the implementation of the framework in the Tehran context, the attribute of "social vulnerability" did not occupy a place on the selected set, despite obtaining a relatively high utility score. Furthermore, the observation of experts' knowledge acquisition and review of DRPTN literature suggests a systemic exclusion of social vulnerability indicators from network disaster recovery planning. Future research is needed to probe the validity of this observation and to investigate the possible causes of this exclusion. The outcome could shed light on where social vulnerability variables lie in the DRPTN equation.

5.3.6 Lack of Validation Tools

In the DRPTN literature review, often, the implementation of a method with illustrative numerical examples has been interchangeably used as an alternative for validation of a method. The fact that the DRPTN model is a complex, non-existing decision environment explains the growing use of hypothetical, small size, and limited numerical examples as a validation approach. Perhaps this challenge of validation is the reason that, to date, available post-disaster recovery tools have not meaningfully found use among decision-makers. Nevertheless, it is important to note that a disaster recovery problem formulated for a certain scenario has limited applicability for other similar scenarios since the network zone, phase of reconstruction, time of disaster occurrence, damage state, vulnerability level, and decision-makers might not remain identical for two scenarios in a real-world instance of disasters. Therefore, scenario-based approaches should be very conservative in generalizing the performance of the proposed model that is solely numerically instantiated. As long as the problem under investigation is non-observable, conducting an experiment-driven validation is a tedious task. More importantly, this intransitivity in generalization is also valid for retrospective validation approaches as a natural feature of non-observable problems. For example, using historical data on traffic behavior after the 1995 earthquake in the city of Kobe (if there is any) to validate or predict the resulting traffic behavior of a hypothetical earthquake in the city of Tehran would not be suitable, nor could we use the observed traffic data following that event to validate a decision model for recovery planning in the aftermath of a hypothetical future earthquake in Kobe with a certain degree of confidence that the second event's characteristics would mimic the behavior of the previous disaster and subsequent network interactions.

Accordingly, decision models for disaster recovery of infrastructures require high-resolution comprehensive simulations of the urban system at a microscopic level that facilitates the modeling of the performance of influential critical infrastructures and their post-disaster interactions, as well as users' behavior and the socioeconomic responses of an urban system to various recovery strategies. In doing that, more study on the collection of perishing post-event real-time data, as well as the selection, navigation, and analysis behaviors of DMs and users, can help in developing a simulated environment that enables to test DRPTN models as well as the findings of this study. Developing a systematic approach to provide a degree of confidence in the quality of non-observable models' solutions remains a compelling direction of inquiry for future research.

5.4 Key Recommendations for Decision-Makers and Research

The following remarks are based on thematic analysis of the current trend of DRPTN models discussed in chapter two, the development process of decision-making model for problem structuring presented in chapter three, and the selected attributes suggested in chapter four. These recommendations are categorized into three groups that address a) the necessity of the application of formal problem structuring in the DRPTN modeling context; b) key remarks that should be considered while developing a DRPTN decision model; and c) considerations necessary with respect to attributes of a DRPTN model that include lessons learned from the implementation process of the framework. Research on DRPTN, in general, has direct demand and application in practice. While the increase in intensity and extent of disasters and their health and socioeconomic consequences in the last two decades suggests that the battle of risk reduction is perhaps lost for the time being, the attention of practice recently has bounced back to "recovery planning" rebranded as "resilience". Therefore, the following points may also be useful for both decision-makers and practitioners that seek to re-invest in disaster recovery planning.

5.4.1 Problem Structuring Necessity in the DRPTN Modeling Context

5.4.1.1 Proactive structured choice rather than intuitive, reactive judgment

Many empirical studies have suggested that in low validity decision environments where one encounters a non-observable predictive problem, even formulas constructed simply with partial information perform equally or better than experts' judgments based on intuition in the majority of cases (Kahneman and Klein 2009; Meehl 1954; Kahneman 2011). Predictive intuition might be valid in decision environments where an expert has the chance to learn and understand the stable regularities of the system or where the system exhibits the same behavior in each iteration of occurrence. In a random, high entropy decision environment (as is the case in a DRPTN context), influential factors, decision players, objectives, and decision attributes need to be identified proactively, as they are likely to be vague, multiple, and associated with unknown or difficult-to-know uncertainties. Planning for recovery after the occurrence of a disaster also involves factors such as insufficient time, high stress, panic and emotional influences, unverified data, public and media pressure, as well as a lack of tools, workforce, and the removal of the possibility of seamless, collaborative decision-making. These challenges underscore the necessity of problem structuring in advance for possible future DRPTN. Decision-makers must explore, understand, and articulate their values, interests, and concerns and accordingly establish a set of attributes through a formal process. Therefore, context-dependent descriptive and conceptual studies are very important for tackling non-observable problems to support problem structuring for DRPTN models and attribute selection before a disaster occurs.

5.4.1.2 Selecting attributes through disciplined problem structuring

Disaster recovery decision problems are difficult to model; they are made only more difficult by the fact that it is a demanding task to gain reliable insight into how accurate or effective the models really are. This causes the disaster recovery modeling to be more vulnerable in its problem definition and problem validation phases. Within the process of problem structuring, determining the decision attributes of disaster recovery planning is difficult, yet it is also the most important task. Selecting attributes through a structured problem framing provides opportunities to reduce the modeling procedure's error and bias. By adopting the proposed framework or any other formal method for problem structuring, this study strongly suggests that decision-makers and disaster risk management planners should employ a systematic approach toward identifying and selecting decision attributes, indicators, and objectives. Selecting attributes and other decision factors intuitively, arbitrarily, or without following a formalized process, in turn, increases the likelihood of solving a partial and/or unrepresentative problem, thus committing the error of the third kind.

5.4.1.3 Tackling the DRPTN validation challenge with problem structuring

The term "validated" might not accurately reflect on the performance and reliability of DRPTN models, which can lead to a false impression or overestimation of the model's capability for possible future users. I believe that validation claims should be made with great caution in modeling non-observable problems in which predictive accuracy is very limited. A single numerical example may neither verify nor validate the developed model but is able to serve as a refutation cycle in testing the performance of the model within a validation process. Nevertheless, one should note the limitation of applying scenario-based numerical illustrative examples as the validation phase. Earlier, this issue was illustrated more soundly by Konikow and Bredehoeft (1992) in the ground-water modeling context. The fact that this dissertation replicates such a recommendation from almost three decades ago is itself alarming. Further, a comprehensive and well-stated description of validation challenges in disaster management research is also offered by Galindo and Batta's work (2013), in which they addressed the concept of assumption validity in the Operations Research methods utilized in disaster operation management studies. Therefore, it might be reasonable to assume the priority of developing error-minimized models rather than validated ones by relying on a robust problem structuring, including tasks such as testing the logical relationship of variables, methodological support for identifying decision factors, justification of the selection of solving methods, and robust verification of the preliminary assumptions and phased outcomes, among others.

5.4.2 Modeling a DRPTN Problem

5.4.2.1 "After disaster": when exactly? "Disaster": what exactly?

As a possible result of the absence of problem structuring from the DRPTN decision modeling process, the temporal phase of planning is often neglected in the reviewed DRPTN studies, which challenges the coherency and relevance of the planning. Although the disaster risk management community is in the era of "biblical confusion" (Thywissen 2006) with newly coined/adopted terms emerging in the field such as "multi-stage", the post-disaster planning needs to be phase specific. In both practice and science, the "Multi-" approach is highly encouraged: multi-hazard, multi-modal, multi-sector, multi-actor, multi-everything. However, a successful disaster recovery plan needs to be hazard specific, sector specific, component specific, and temporal phase specific, while taking the integrated risk assessment approach and other sector synergies into account. The term "post-disaster" carries very little specificity in terms of a temporal period in the aftermath of a disaster. In chapter one (1.5.3), the distinction among different temporal phases after disasters is discussed. DRPTN models should be tailored for a specific planning phase, such as immediate response, mid-term recovery, or long-term. At the same time, a good DRPTN model needs to be dynamic to expedite emergency activities in an urban area at the early stage of the recovery phase, to establish safe and prioritized access and mobility in the mid-term, and, later, to accelerate the recovery of the economy and social affairs.

Similarly, a DRPTN model requires a hazard-specific approach since the nature of disruption and travel demand in the aftermath of different hazards (e.g., earthquake, flood, or landslide) are considerably different. Therefore, local characteristics of "disaster" should be specified as a comprehensive disaster scenario, including hazard type, hazard intensity, hazard duration, hazard occurrence time, structural and social vulnerabilities, and the component under study, among others.

Furthermore, during the review of DRPTN studies, I observed that the majority of DRPTN models tended to satisfy the technical (traffic) objectives of the network, which is mainly expressed through the performance of the transportation system (e.g., travel time, travel cost, delay cost, network traffic flow). This means that the impact of recovery strategies is measured based upon their success in improving transportation networks' technical performance, while hardly considering other aspects of the urban system and recovery process. However, taken as a whole, civil society, which includes entities functioning in sociocultural, health, economic, and technical contexts, requires planning that satisfies the objective of the collective rather than merely meeting a need of an entity.

5.4.2.2 Computational justification for the use of optimizers based on complexity and convexity of problems

DRPTN problems require a computational justification for the selection and application of the solving methods. Therefore, greater effort should be devoted to identifying the mathematical problem's local characteristics with respect to both complexity and convexity as a rationalization for choosing deterministic or non-deterministic methods. Due to the critical context of disaster recovery, it is reasonable to assume that DRPTN cannot afford a good-enough solution. Therefore, when formulating an optimization-based DRPTN model, the use of a non-deterministic method – when the problem is solvable with deterministic optimizers that yield exact solutions – is not justifiable. Aharon Ben-tal[1] describes the challenge of formulating and solving an optimization problem in the following way: "For an optimization problem under uncertainty, the real problem is to offer models for which *the user can provide the data*, and the optimizer can solve efficiently the resulting mathematical programming problem." An operational optimization model recognizes the balance between complexity and convexity (i.e., aims to add features as long as the problem results in a convex solution space). Convexity or non-convexity can be regarded as a major criterion toward understanding the complexity of a problem and selecting an efficient optimizer. Determining the convexity status of a problem provides useful insight that can be used to assimilate the complexity of the problem. The convexity analysis of a problem is superior to linearity analysis, as proofs of convex solution space ensure the existence of a globally optimum solution, which might not necessarily contain linear objectives or constraint functions. The

[1] https://pubsonline.informs.org/page/moor/bental

knowledge of complexity and convexity can be used as reliable justification for selecting the solving algorithm.

5.4.2.3 Properties of a useful DRPTN model and a robust decision-modeling process for DRPTN models

Several possible sets of criteria can be developed to assess the performance of post-disaster recovery planning of transportation networks. Disaster managers can expect that a DRPTN decision model (after the phase of emergency response) addresses the following demands:

1) Assists the swift restoration of lifelines;
2) Provides safe mobility and an acceptable level of service in the network;
3) Ensures an adequate level of accessibility in the network;
4) Contributes to the alleviation of the calamitous social effects of disaster;
5) Functions inclusively and recognizes the socially vulnerable share of the affected population;
6) Functions exclusively in the sense that it recognizes critical users and critical facilities of the urban system;
7) Easy to update upon the arrival of new data; and,
8) Remains adaptable to parallel and related decisions.

Furthermore, among the many properties of a good model, a possible suggestion for developing a DRPTN model is the following criteria:

1) Essential characteristics of the transportation system, the disaster impact, and the recovery operation are clearly identified;
2) The decision values and objectives are collectively and clearly defined;
3) Their structure, interrelation, and hierarchy are organized;
4) Viable attributes are accurately articulated and prioritized;
5) The model is tractable, comprehensible, and optimal in size; and,
6) Data is available for its defined parameters.

It is self-evident that meeting these criteria requires structured problem framing as a promise of a formal problem-structuring approach.

5.4.2.4 Integrating compensatory and non-compensatory decision rules

Chapter three discusses that in some decision contexts when a number of criteria are indefinitely more important; employing either of the compensatory or non-compensatory decision rules alone cannot meet the characteristics of the modeled problem. In many disaster recovery models, several aspects involved in decision analysis are often not meaningfully compensable, judgmentally dependent, or strongly conflicting. Hence, a compromise between values of criteria based on compensation would not lead to a desirable choice. Integrating different decision rules, tailored to meet the limitations of preference transition, could be a possible solution. Incorporating both compensatory and non-compensatory decision rules in a single decision context increases the amount of incorporated information, therefore reducing information loss during the evaluation process. Further, when the size of an alternative set allows, multi-stage decision environments and distributing attributes to separated stages of the evaluation process can also increase the likelihood of assigning more reliable weights because it is a cognitively demanding task for experts to process information chunks related to more than five attributes (see, e.g., Timersman 1993; Cowan 2010). Additionally, separated decision regions based on different decision rules, particularly in the screening decision region, would also be an option for managing the complexity of a problem as the implementation of such a strategy showed satisfactory performance in chapter three.

5.4.3 Attributes for a DRPTN Model

5.4.3.1 Good attributes do not necessarily form a good *set* of attributes

I highlighted the necessity of not only observing the properties of attributes, but simultaneously the properties of sets of attributes, as well. This is also generalizable to other disciplines and models that seek to represent a multi-criteria decision model. The attribute-selection process needs to recognize the quality of a set independent from the quality of members. Therefore, using evaluation factors for attributes in a set is just as necessary as it is for attributes in isolation. This approach increases the chance of achieving a complete, non-redundant, and concise attribute set.

5.4.3.2 Accelerated temporal recovery rates contribute to network resilience

Considering the impact of the recovery process per unit of time aims to accelerate the resiliency of the transportation network before the network's lack of service exhausts social tolerance. This was the argument that the experts leveled for justifying two decision attributes of the recommended set. Therefore, adopting the attribute of "Travel time improvement/recovery duration" facilitates capacity building for increasing the resilience of urban areas by representing the recovery process as a ratio of progress in restoring the technical performance of the transportation network. Particularly, as discussed in chapter four, experts emphasized that initial progress in the improvement of travel time (i.e., early-stage recovery) is of utmost importance, which is also aligned with the findings of studies that quantitatively analyze this impact and point out the necessity of attention to skew of the trajectory of travel time progression (e.g., Zhang et al., 2017). The network recovery duration, if used alone, is a misleading indicator for representing the success of a recovery operation; rather, one should focus on the amount of improvement in the performance of the system (travel time, access, etc.) or on resources consumed within the recovery duration to represent a ratio of the recovery impact.

Additionally, "emergency routes' downtime" should also be taken as an important factor in the emergency phase; however, this may not be the case in a network-scale for recovery operations that occur after the emergency response phase. Once the maximum recovery rate has been achieved, minimizing the recovery duration is of secondary importance. Minimizing the post-disaster total recovery duration, as a primary objective, could be arguable because the initial improvement of network performance is crucial, which might not be entirely aligned with the rapidity of the whole recovery process. Therefore, as two attributes of the selected set, hybrid attributes that take into account the integration of recovery progression and recourses/time can contribute to the network resilience.

5.4.3.3 Centrality is a fair representative of a link's importance in terms of accessibility

In the aftermath of a disaster, maximizing accessibility and restoring network connectivity is of the utmost importance. However, only two studies among the 46 reviewed publications include attributes that measure the ability of a link to maintain accessibility at a network level with regard to the geometric centrality of links. Disregarding the topographic properties of a network to measure the accessibility index of each link may challenge the application of models, should an alternative attribute not be substituted. Given the uncertainty that accompanies post-disaster traffic assignment in a perturbed network as well as a significant dearth of information, pre-event known traffic flows might not be a reliable performance metric for links. Therefore, it may be more reliable to determine the functional importance of links with less reliance on traffic demand and employ flow-independent, and connectivity-based attributes such as link capacity, lane-based properties of links, and centrality measures.

5.4.3.4 Lifeline interaction must be considered in DRPTN, although not necessarily as an attribute

Considering the interaction of transport network components with other critical infrastructures is a relevant factor for prioritizing the recovery of links for early-stage assessment and damage control in other linear interconnected infrastructures such as electrical grids and gas-delivery systems. Timely attendance to other damaged lifelines is essential to avoid secondary, technical, and cascading hazards. However, this attribute was not included within the selected set in this study, as it fails to meet the condition of discriminability. The reason for this exclusion was that DMs argued that almost all major links in Tehran’s road network have overlap with at least one lifeline, such as a natural gas network or water-delivery system, that prevents a meaningful comparison among links based on such an overlap. However, DMs advised that this attribute should be treated as a decision constraint, included in protocols at the operational and tactical levels in which cascading or technological hazards are predicted or considered in critical nodes clusters under the category of accessibility.

5.4.3.5 Understandability and certainty are incentive factors for the favorability of attributes

Based on the values that experts assigned to the attributes of the alternative pool in the choice region, the evaluation factors of "certainty" and "understandability" supplied more information than "directness" and "representativeness." The entropy value of certainty and understandability suggests that experts were more sensitive to these factors while evaluating the attributes since the assigned values were more diverse for "certainty" and "understandability" and more uniform for "directness" and "representativeness" factors. This can also suggest that for the DMs who used this framework, "certainty" and "understandability" of an attribute have higher relative importance than two other evaluation factors. Therefore, in that context, a certain and non-ambiguous disaster recovery planning, although not necessarily optimal, was preferred; i.e., a more understandable and certain DRPTN attribute could compensate for its lower representativeness and directness. Similarly, sensitivity analysis presented in chapter four also points out the relatively higher sensitivity of the outranked attributes to the weight of the "certainty" evaluation factor, while this sensitivity was significantly less for "representativeness," for instance. The inherent uncertainty in the DRPTN context leaves less room for adding uncertainty to the DRPTN model by including attributes that introduce uncertain values, either due to limitations of measurement, data, or ambiguous definitions.

5.4.3.6 For future use of the framework

For the further use of this framework, it would be advantageous for a moderator to oversee the evaluation session and act as an opposing voice, if necessary, to facilitate the extraction of DMs' knowledge. However, there is an indirect association between the degree of control and subjectivity within moderating this framework. The principal task is to find a fair trade-off and keep this compromise balanced and understand where this control leads to creativity and/or hinders it. Furthermore, when using the proposed framework, one must take into account the size and completeness of the alternative set. A so-called diverse complete set of alternatives is required since the result will be as complete as the alternative pool. Nevertheless, analysts and future users of the framework must establish a desired trade-off between the desired completeness and the complexity of the model. Users of the proposed framework can also consider reducing the initial alternative pool's size by allowing homogenous attributes to merge into a single one and proceed with the resulting attributes in a smaller alternative pool. Finally, when choosing a method of aggregation, I suggest noting the tractability of calculations, as well as minimized processing of the experts' numerical input.

5.5 The Art of Modeling in Disaster resilience planning Contexts

There are infinite ways to model a problem. Determining “how good the model is” appears to be as difficult as indicating otherwise. At the same time, the urge to present “innovative research” and “novel contributions” may drive researchers to include sets of attributes distinct from those that have already been introduced in the literature. This impulse encourages the intuitive selection of attributes on the sole merit of “having not been previously addressed.” Perhaps for the same reason, some journals and communities express concerns about research designs with artificial, unsupported variables and arbitrarily selected attributes (e.g., “4OR; A Quarterly Journal of Operations Research”). The reason for this concern is that the same process can indefinitely be repeated with different decision parameters (typically formulated into a complex NP problem and solved with a randomly chosen optimizer) without providing meaningful insight into the problem under investigation.

The demand is rising for numerically analytical automated studies that are conducted with so-called sophisticated and novel combinatorial meta-heuristic algorithms and visualized with cutting-edge tools and codes. However, the method-rich but methodology-poor syndrome in chapter two, indicates that for sensitive, critical, and low-validity decision environment problems such as those in disaster management, the level of effort should also be proportionally channeled to initially build up descriptive, conceptual, and contextual foundations of the problem to support and justify the methods used and methodologies employed. This could open up opportunities to develop simple, representative, robust, and understandable models. Non-conformist critical, independent research is needed to question commonly held assumptions and to select tools and methods that are context-appropriate and serve the decision problem. The field of DRPTN needs a dedicated, strong problem-structuring phase to avoid tailoring the problem to the method at hand, rather than to either find or develop a tool that submits to the property of the problem under consideration.

The goal for decision modeling in disaster recovery planning should focus on the exclusive and tractable format of the model. The author is aware that, in decision analysis, exclusivity and tractability often conflict. Nevertheless, harnessing the advantages of problem structuring allows for greater attention to the contextual and local situation/information of each problem and avoids one-method-fits-all formulations. This approach supports the necessity of context-dependent features of disaster recovery models and helps modelers prioritize and include what is most relevant and important for each specific problem.

Many experienced researchers refer to problem structuring, in general, as an art. In the DRPTN context, regularity is rare, data is often absent, and DMs' experience is low because they do not have many chances to familiarize themselves with regularities of the problem and decision environment. These properties are attributes of the stochastic nature of disasters, the infrequent and sudden-onset occurrence of major hazards, various unknowns and hardly predictable variables, and chaotic post-disaster conditions. Therefore, to compensate for these inherent challenges of DRPTN modeling, problem structuring in this context might require more than just art to measure up to the task at hand. One approach is to minimize bias and error in the modeling and solving process by ensuring that the decision model's components are generated through a formal, systematic process that can be, to a large extent, obtained by following a methodological problem-structuring approach.

Furthermore, in the era of real-time big data and computational power, the art of modeling turns out to be a “complexity manipulation,” that is to say, to find a balance between the amount of complexity we are willing to transmit into our model against the amount of uncertainty we add to the model in return. In the problem structuring of optimized DRPTN decision models, modelers should decide whether they prefer a less accurate solution to a loosely perceived problem that fairly reflects the complexity of the system or a more accurate solution to a well-perceived problem that does not completely represent the complexity of the modeled problem. According to the argument leveled in chapter two, for DRPTN models, the complexity of the problem in terms of comprehensiveness of decision parameters is directly associated with the uncertainty of results. Therefore, I argue that one feature of a well-perceived modeled problem is that the modeler considers the limitation and uncertainties of the modeling procedure and identifies the minimum essential characteristics of the system with which the directness and completeness of the decision model can be maximized. In other words, it is important that the possible sources of errors and uncertainty be minimized by confining decision parameters to those that cover the most important concerns about the defined objectives and that possess the desired properties of a good attribute. Well-perceived problems result in a tractable model, in which the major relevant decision parameters and information are isolated, prioritized, and organized to allow for accurate and efficient answers or a close approximation to the mathematically programmed model.

To address these concerns, methodological problem structuring can assist modelers in an accurate perception of the problem and its modeling process. A successful disaster resilience decision model calls for formal problem structuring to support the design of a model with a well-adjusted relationship between the perception of a system and the complexity of its model. The model should be capable of being solved at a reasonable computational cost and return deterministic solutions or proof as to how the returned solution relates to the ideal solution. Even though DRPTN decision models are complete, novel, and original in automation, visualization, and mathematical programming, without strong problem structuring, they remain incomplete and constitute partial, poor reflections of the system's collectivity, failing to grasp adequate, logical relationships among the components of the modeled systems.[1] Developing a useful model (if there is such a thing) requires dedicating significant and serious efforts to creative, disciplined problem structuring while accepting as little compromise as possible with regard to the completeness and representatives of a model. The art of modeling in disaster recovery contexts relies upon the extent of effort dedicated to the model's problem structuring.

[1] “As they can never reflect the whole, they fail in that they are partial” (Bos and Tarnai, 1999).

5.6 References

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Appendix A

(Examples of information for disaster scenario familiarization)

Table A.1: Example of information presented to experts for familiarity with the context and disaster scenario

City	Tehran
Region code	2
Zone numbers	9
Area	4690 Hectare
Population	Approx. 1.000.000
Households	256992
Population density	144 p/h
Perimeter	40584
Hazard(s)	Earthquake, secondary hazards
Season	Spring
Network status	Damaged links approximately 60% of network in slight, medium and sever damages levels, 50% of the network nonoperational
Operational status	Main phase of search and rescue and emergency response is accomplished
Available data	Demographic, damage level, geometric, service providing sites, topology, traffic counts, available resource, travel times, critical nodes, …
Temporal phase	Mid-term recovery after emergency response (72 hours)

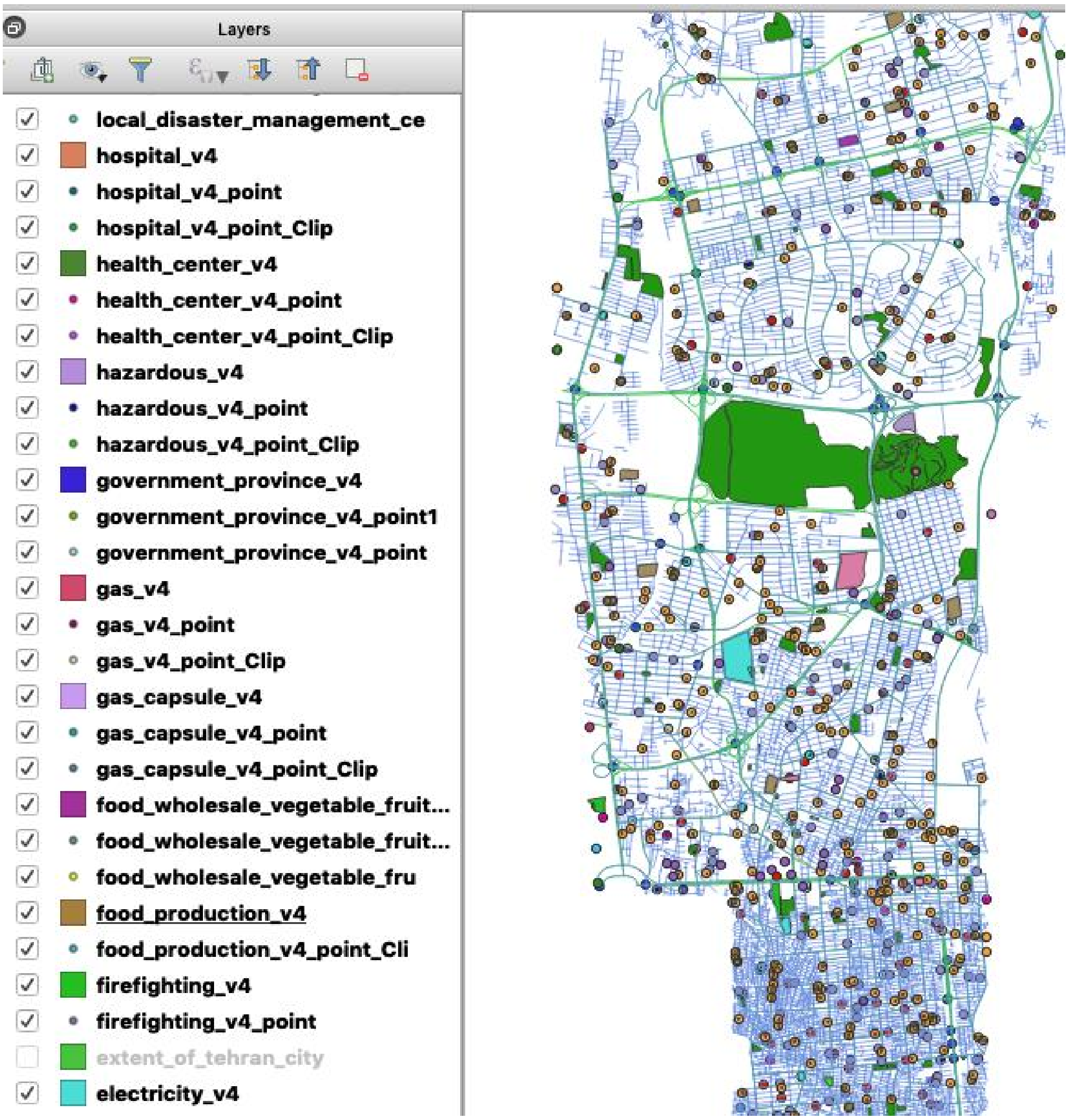

Figure A.1: *A screenshot of a material example used to familiarize experts with the case study concerning data available for post-disaster recovery planning*

Appendix B

Table B-1: *Rank and utility of 33 attributes of choice region*

Rank	Attribute	Utility
1	Access level of link to SP nodes	29.67575758
2	Travel time improvement/resources	29.37575758
3	Travel delay of link *flow of the link	28.91212121
4	Duration* travel time improvement	28.44848485
5	Centrality importance	27.94242424
6	East-west and north-south connectivity	26.63030303
7	Impact on total network travel time	26.3030303
8	Link Capacity	25.87878788
9	Connectivity to other traffic zone	25.52424242
10	Topography	24.17878788
11	Social vulnerability*link delay	23.548
12	AAWT	23.25757576
13	Social vulnerability* zone travel demand	22.948
14	AADT	22.15151515
15	Link Density	22.02424242

16	Recovery efficiency	21.96969
17	Total network Traffic flow	21.2
18	Impact on Total network flow	20.77272727
19	Total Network Travel time	20.54848485
20	Level of service	20.24242424
21	Population*link delay	20.14848
22	Travel delay imposed by link failure	20.05151515
23	Links to airport and exit ways	19.2969697
24	Population density based on age, gender and number of households	18.71818182
25	Traffic redundancy	18.67575758
26	Access to socially important sites	18.25151515
27	Social importance	18.06060606
28	Travel demand	17.29393939
29	Recovery duration of link	17.01818182
30	Link volume	16.06666667
31	Relief demand nodes	15.3969697
32	Population accessed by the link	15.33636364
33	Depot and need nodes	14.22424242