Working paper

Optimization-based decision-making models for disaster recovery and reconstruction planning of transportation networks

Milad Zamanifar[1] and Timo Hartmann

Department of Civil Systems, Technical University of Berlin, Berlin, Germany,

Abstract:

The purpose of this study is to analyse 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 the 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 areas as 1] developing conceptual or systematic decision support in the selection of decision attributes, 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.

Keywords: *disaster, recovery, reconstruction, transportation network, optimization*

1. Introduction

We define decision-making model for Disaster Recovery Planning of Transportation Networks (DRPTN) as:

A prescriptive model responding to an extreme destructive event 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 iii) and can be alleviated only by physical constructing interventions such as repair, recovery or reconstruction operations.

The decision model of DRPTN formulates a prescriptive choice or design decision problem to find optimized strategies, actions or plans to timely and efficiently respond to the possible post-disaster failures of a transportation network's elements. As a tool for such a decision models, optimization programming formulates and solves numerous engineering and social problems including DRPTN. Many well-grounded studies have been providing state-of-the-art methods and methodologies on the optimization problems for DRPTN. The extent of our knowledge on the practicality and reliability of the methods is however limited. This is due to the *non-observability* of the disaster recovery problem as there is sparse matching data after disasters that can be compared with the output of previously designed models (Sargent 1996 and 2011; Day et al., 2009; Kadri et al., 2014). Even if data is partly available, performing a retrospective test to validate the models is a cumbersome task, if not impossible, due to the degree of inconsistency between two datasets of previous and probable future disaster (Zeigler 1976). That means, for example, traffic data of a specific disaster in a specific environment cannot be easily generalized for future

[1] *Email: Milad.Zamanifar@gmail.com*

cases with different network properties, traffic behaviors and damage conditions (Ashley 1980; Leurent 1996; Iida et al. 2000; Celik and Corbacioglu 2010; Leskens and Brugnach 2014). The non-observability of a problem emphasizes the pressing need for particular care for defining, formulating and solving prescriptive models that represent critical and sensitive real-life problems. This criticality and sensitivity are due to the cascading impact of disasters in an urban area, which propagates in a wide scale and emerges beyond the damage of physical assets since it adversely affects people, economy, environment, and social systems (Kadri et al., 2004). Therefore, it is logical to recognize the need for clear identification of possible uncertainty sources and vulnerable parts of DRPTN models that may be detrimental to the validity and quality of the outcome (Buchanan et al., 1998).

To address the need we analyse DRPTN decision models by considering optimization-based decision-making modeling as a four-phase process consisting of problem definition, problem formulation, problem solving, and model validation (Nocedal and Wright 1999; Horst and Tuy 1996; Williams 2013). To this end, we began with a systematic search based on our explicit representation of the DRPTN definition to identify relevant publications. We then used a systematic literature review approach for analyzing the existing literature. Based on the content analysis, we detected and discussed four research improvement areas as 1] developing conceptual or systematic decision support in the selection of decision factors, 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 remainder of this paper is structured as follows. The next section summarizes previous reviews on transportation network disaster management and optimization modeling. The third section explains how we approach and analyze the DRPTN literature with respect to the phases of optimization modeling. Doing so, this section discusses the concept of an optimization-based decision-making model for disaster recovery planning. Section four describes the framework of systematic search and content analysis of this paper. Section five and six irrespectively elaborate on the findings and provide related discussions. In the discussion section, we identify the challenges and opportunities within the DRPTN literature based on our interpretation of the findings. Suggestions for future directions of DRPTN research and bridging the detected gaps are also incorporated in section six. Finally, the paper provides a summary of results and conclusions in section seven.

2. Literature review and contributions

Within the last decade, a number of review papers addressed several disaster management fields in pre-event and post-event phases such as vulnerability, resiliency, emergency response and reconstruction planning. Among those a few were exclusively devoted to the transportation network and its functionality after disruptive events (Faturechi and Miller-Hooks 2015; Konstantinidou et al., 2014; Abdelgawad and Abdulhai 2009; Dehghani et al., 2013). However, despite outstanding findings, to the best of our knowledge, addressing the recovery and reconstruction phase of the transportation network was not the main focus of the mentioned existing. Instead, the pre-event phase and emergency response have been often emphasized. On the other hand, literature review on optimization is relatively common in different applications. Existing reviews analyze the optimization methods based on their formulation approach, solving technique, the application of methods and the comparison among them. Some research report solving techniques used in specific applications as either non-deterministic methods or deterministic methods such as Genetic algorithm, Tabu search, Simulated Annealing, or Branch and Cut (e.g., Marler and Arora 2004; Blum and Roli 2003). A number of studies focus on formulation approaches, variable properties and relaxation characteristics of methods (e.g., Vecchietti et al., 2003; Arora and wang 2015; Ríos-Mercado and Borraz-Sánchez 2015) or detailed applications of optimization programming in major fields (e.g., Baños et al., 2011; Evins 2013; Gamarra and Guerrero 2015). Some studies also provide comparative reports of different optimization solving methods for specific application (e.g., Maes et al., 1999; Moles et al., 2003; Udy et al., 2017) or present a combination of those approaches in one study (e.g., Mendez et al., 2006; Fernandes et al., 2018; Wu et al., 2018). While a review of used techniques in solving or formulating optimization problems is seen as a common trend within the state-of-the-art of optimization surveys, the phases of validation and problem identification have not been the main focus. Additionally, we could not identify a review that investigates the conceptual underpinnings and rationale of the structure of optimization methods within a specific application. Nevertheless, such an effort is of great importance since dealing with a context-sensitive and critical problem, there is a need to identify parts of DRPTN methodologies on which the quality of model's outcome depends and at the same time are not sufficiently addressed.

What we considered as the contribution of this study is, first, the focus on all four phases of the optimization modeling while approaching DRPTN models. Second, the specific application (DRPTN) that the review covers, and third, newly discussed challenges in applying optimization methods for DRPTN application. Authorities and administrations in disaster management, infrastructure asset management, and transportation planning can use the findings of this paper to evaluate the existing models or employ a reliable practical post-disaster decision-making model. The findings can also be useful for decision analysts and future studies that aim at developing optimization-based disaster recovery models. Accordingly, the next section briefly demonstrates the basic concepts of optimization-based disaster recovery planning models.

3. Optimization-based decision-making models and DRPTN

Optimization is designing or identifying the most favorable choice among a set of alternatives subjected to formalized bounds (Ceolho et al., 1981; 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 M 2005). Variables are alternatives that vary 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 other objectives. Accordingly, Pareto optimality expresses achieving a set of ideal solutions that indicates the optimum trade-off among those conflicting objectives (Jahn 2015).

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 as 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 computation 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 a fitting solving algorithm (Johannes 2013).

As Fig. 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.

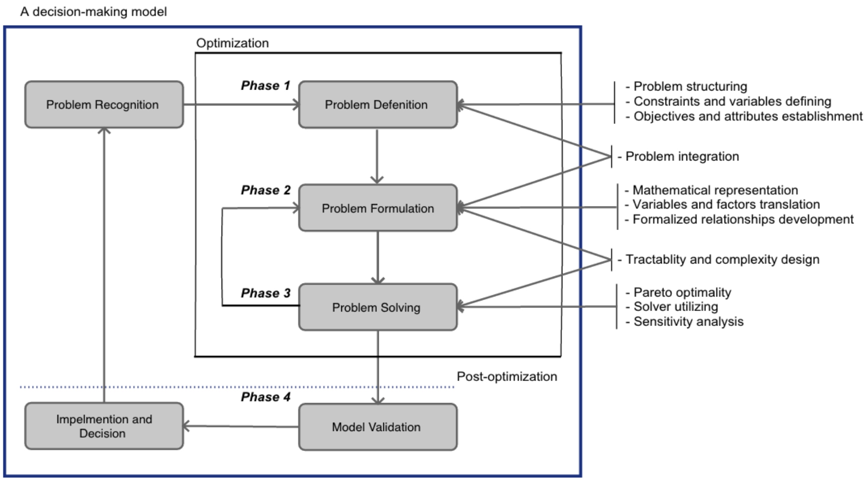

Fig. 1 *Phases of decision-making modeling and steps of optimization programming*

3.1. Problem definition

Modeling of a real-scale problem aims at abstracting the perceived system and the problem in one environment (Philips 1984). It initiates with identifying the problem and selecting its decision components (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 (Mitroff and Featheringham 1974; Keeney and Raiffa 1993; Belton and Stewart 2002; 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 (Guha-Sapir and Below 2002; Leskens and Brugnach 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.

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 their accredit 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 common 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 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. Usually, 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-dimensional problem of DRPTN needs to address the goal of modeling by incorporating effective problems. This motivated us to investigate the problem formulation phase to understand variables and the problem integration within DRPTN models.

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 (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; Horst and Tuy, 1996). 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 non-deterministic methods is a logical choice that relatively easily handle such a problem with the effort that grows polynomialy as do the size of the problem.

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. An 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). Specifically, 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. On this ground, we study the rationale behind utilizing solving algorithms in DRPTN models.

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 whether the result can be trusted as bases for making decisions in a critical engineering socioeconomic situation (Babuška 2007). To provide a better understanding of the significance of this question we investigate the validation and verification efforts within DRPTN models.

4. Review and analysis framework

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 abstract, title and keywords of the publications. We repeated the search task with different terms representing the same concept. For example, addressing disaster, we performed the search with terms such as "disaster", "hazard", "extreme event", "earthquake", "landslide", "emergency" "flood", and "tsunami". Likely for the transportation network, we checked for ''transportation'', "traffic", "bridge", "link", "road", "highway", and "network". Thereafter, we discarded duplicate publications as the outcome of multi-source searching and sifted the searching process by limiting disciplines as well as the 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 to not 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.

4.2. Content analysis

The content analysis is based on analyzing the methodology of DRPTN studies following the phases presented in sections 3.1. to 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. We framed two review questions to approach the publications as 1) what are the possible challenges and opportunities for the validity of results in the methodological structure of disaster recovery models? 2) How the rationales for structuring the four phases of optimization modeling are conceptually supported? Figure 2 shows the detailed steps of the content analysis framework that we describe in the rest of this subsection.

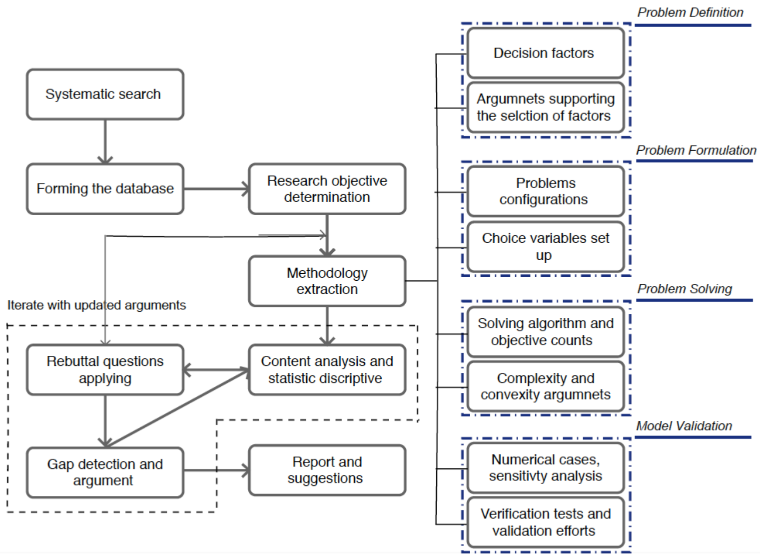

Fig. 2 *The systematic review and gap analysis flowchart for the literature of DRPTN*

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 3. Doing so, we analyzed various components of methodologies such as decision attributes, formulation approaches, solving methods, convexity and computational complexity arguments, 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.

5. Findings

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

5.1. Problem definition

Figure 3 shows the attributes that DRPTN models employ. Additionally, table 1 demonstrates the types of attributes and their combinations that are categorized according to whether they focused on emergency, traffic or economic goals.

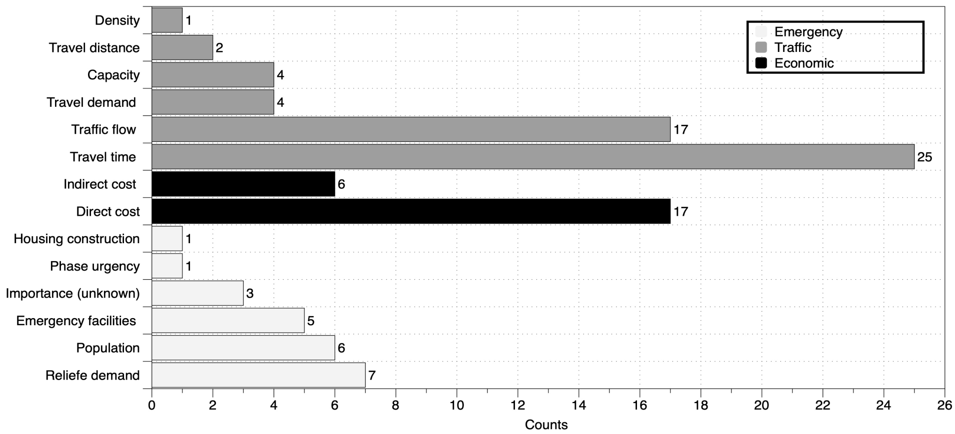

Fig. 3 *Attributes employed in DRPTN as well as their categories.*

Table 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 3 and Table 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 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 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.

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 shows the choice variable sets of optimization DRPTN models.

Table 2 *The condition of variables as the alternatives 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. 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.

As the second part of the findings, table 3 shows the integration of objectives and consequently sub-problems within DRPTN.

Table 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

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 problem 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.

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 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.

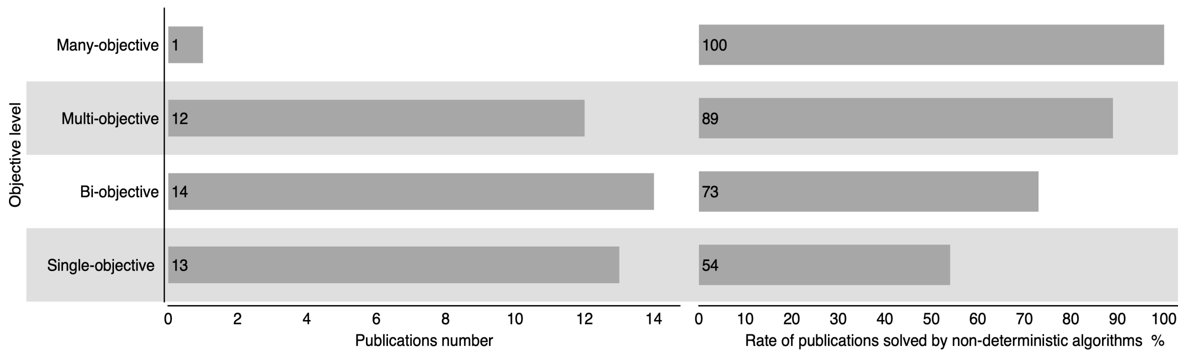

Fig. 4 *The use of single, bi, multi and many objectives formulation in DRPTN research (left) and percentage of used non-deterministic methods in each objective number level.*

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 5 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 4 provides an overview of the rationale that DRPTN studies reported for choosing non-deterministic optimization methods.

Table 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.

5.4. Model validation

In the validation phase of the optimization decision-making models, DRPTN studies provide several approaches and arguments to assess the quality of algorithms and models. Table 5 and 6 demonstrate how reviewed DRPTN studies evaluate the performance of algorithms and validate the solution of models.

Table 5 *Efforts and arguments toward verifying and validating DRPTN models.*

Argument on validation		
Case	*Count*	*%*
Numerical case for validation	8	20
Validation is left for future studies	4	10
No argument provided	28	70

Table 6 *Efforts toward verifying solving algorithms of DRPTN models*

Efforts on evaluating the performance of the algorithm		
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 state 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%) analyse the sensitivity of variables and weight vectors aiming at assessing the performance of models.

6. Discussions 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.

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, while the expected outcome of a disaster recovery model in practice is to alleviate the calamitous impact of disasters on societies given its sociotechnical aspects yet, 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; Menoni 2001; Cavalieri et al., 2012; Brown et al., 2004; 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 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 access restoration to service providing places 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 detected gap by other 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, infrastructures interdependencies and social vulnerability 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. 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 theoretical 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.

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 post-disaster situations. However, all 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 improving the quality of the post-disaster traffic in surviving networks with the recovery schemes. This interpretation is apparent based on Tables 2 and 3 as we failed to find 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 personal 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 treating 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 (eg., 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.

6.3. Problem solving

The incorporation of non-deterministic algorithms within the problem of DRPTN in many cases overcomes the challenge of solvability of 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 5 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 models incorporate, the less certain the final solution is. On the contrary, the more solving algorithms try to yield an accurate mathematical outcome, the less objectives models can cover. 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 use of non-deterministic algorithms due to complexity of the 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 (Figure 5) 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 2014). 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 and in 50% of studies we failed to spot any 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 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 in this regard we can mention the work of el-Anwar et al., (2016a and b) that formulate a mix-integer optimization problem with a convex cone in DRPTN, which could efficiently improve the near-optimal solution to the optimal solution.

6.4. Model validation

In spite of 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 27.5% of total DRPTN studies. 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 the algorithm 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, 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 (Wang and Shan 2007; Oberkampf et al., 2003; Babuˇska and Oden 2004; Sandizzo 2016). Because sensitivity analysis neither evaluates the validity of the information fed into a model nor assesses the validly 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 mean 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 to initiate efforts toward simulating a comprehensive visualized multi-dimensional, multi-disciplinary, post-disaster environment that can capture the complexity of the system and allow users to directly evaluate the consequences of different optimized recovery strategies.

7. Summary and conclusions

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. Second, despite successful divers formulations of the recovery problem we could not identify an integration of traffic management and the disaster recovery problem and treating 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. Moreover, taking into account the information regarding the complexity and convexity of the problem, utilizing deterministic methods is a recommended approach toward achieving a global solution in DRPTN optimization models. 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 infrastructure 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 models and systematic frameworks that stand as a solid foundation for models' construction (Landry et al., 1983) in problem definition, solving and validation phases to avoid a method-rich-but-methodology-poor phenomenon in the optimisation-based DRPTN context.

Supplementary document:

The full-detailed report of the content analysis results within 40 publications based on attributes, types of problems, formulation approaches and solving algorithms is available on TU Berlin server, Depositonce, accessible on http://dx.doi.org/10.14279/depositonce-9077 as the supplementary document of this paper.

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