Center for Accessibility and Safety for an Aging Population

Florida State University
In Partnership with Florida A&M University and University of North Florida

RESEARCH FINAL REPORT

Development of Efficient Algorithms to Facilitate Emergency Evacuation in Areas with Vulnerable Population Groups

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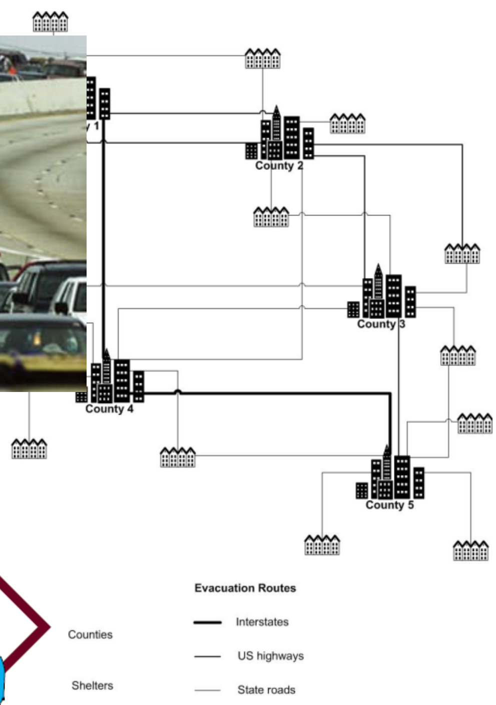

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Final Report Submitted to the University Transportation Center for Accessibility and Safety for an Aging Population (ASAP)

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16. Abstract

Many coastal areas across the United States (U.S.), including the East Coast, West Coast, and Gulf of Mexico, are characterized by a frequent occurrence of natural hazards. At the natural hazard preparedness stage, State authorities advise the population to evacuate the areas expecting potential impacts. In many cases evacuees are trying to use the same evacuation route, which may further cause congestion and significantly delay the evacuation process. Moreover, many coastal areas have a high percentage of vulnerable population groups (e.g., aging adults), who may require additional time to travel from the hazard location to a given emergency shelter. This project proposed a mathematical model for assigning evacuees to evacuation routes and emergency shelters, considering major driver characteristics (e.g., age, gender, racial group, driving experience, marital status, health condition, etc.), evacuation route characteristics (number of travel lanes), driving conditions (time of the day, day of the week), and traffic characteristics (space headway, time headway), with the overall objective to minimize the travel time of evacuees. A set of heuristic algorithms (including the Most Urgent Evacuee First heuristic, the Most Urgent Evacuee Last heuristic, the Most Urgent Evacuee Group First heuristic, and the Most Urgent Evacuee Group Last heuristic) and exact optimization algorithm (CPLEX) were proposed to solve the emergency evacuation optimization problem. The developed mathematical model and solution algorithms were applied to evacuate the population inhabiting Broward County (Florida), which is often impacted by tropical storms. The developed decision support tools are expected to improve the overall effectiveness of emergency evacuation process, and ensure safety of evacuees, including vulnerable population groups.

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EXECUTIVE SUMMARY

Many coastal areas across the United States (U.S.), including the East Coast, West Coast, and Gulf of Mexico, are characterized by a frequent occurrence of natural hazards. According to the Federal Emergency Management Agency, natural hazards, such as hurricanes, severe storms, tropical storms, straight-line winds, severe thunderstorms, and others, have occurred in Florida over recent decades and have resulted in damage to infrastructure and a significant loss of life. At the natural hazard preparedness stage, State authorities advise the population to evacuate areas expecting potential impacts, or announce a mandatory evacuation in the case of a devastating natural hazard. The evacuation process generally occurs in an unorganized manner, as evacuating populations are not instructed to use any specific evacuation route or travel to any specific emergency shelter. In many cases evacuees are trying to use the same evacuation route, which may further cause congestion and significantly delay the evacuation process. Furthermore, emergency shelters are not adequately utilized due to evacuees not being properly assigned to emergency shelters. Moreover, many coastal areas have a high percentage of vulnerable population groups (e.g., aging adults), who may require additional time to travel from the hazard location to a given emergency shelter. The latter deficiencies underline the need for efficient hazard preparedness to facilitate the emergency evacuation process and prevent untimely human deaths.

This study aims to develop a mathematical model and a set of solution algorithms for assigning evacuees to evacuation routes and emergency shelters, considering major driver characteristics (e.g., age, gender, racial group, driving experience, marital status, health condition, etc.), evacuation route characteristics (number of travel lanes), driving conditions (time of the day, day of the week), and traffic characteristics (space headway, time headway), with the overall objective to minimize the travel time of evacuees. The developed mathematical model and solution algorithms were applied to evacuate the population inhabiting Broward County (Florida), which is often impacted by tropical storms. The data (including potential evacuation routes and evacuation route capacity, emergency shelters and shelter capacity, demographic characteristics of the population, etc.), required to conduct the computational experiments were collected. A needs-based assignment of evacuees to emergency shelter was also considered in this study to account for individuals who require special needs (such as vulnerable population groups) during emergency evacuation.

A set of heuristic algorithms (including the Most Urgent Evacuee First heuristic, the Most Urgent Evacuee Last heuristic, the Most Urgent Evacuee Group First heuristic, and the Most Urgent Evacuee Group Last heuristic) and exact optimization algorithm (CPLEX) were applied to solve the emergency evacuation optimization problem. A number of computational experiments were performed, and managerial insights demonstrated the applicability of the proposed methodology for real-life emergency evacuation scenarios. The proposed mathematical model and optimization algorithm may be used as an efficient practical tool by State and local authorities in improving the utilization of emergency evacuation routes and emergency shelters, reducing or eliminating traffic congestion on roadways during emergency evacuation, and reducing the travel time of evacuees during emergency evacuation. Moreover, the developed decision support tools are expected to improve the overall effectiveness of emergency evacuation process, and ensure safety of evacuees, including vulnerable population groups.

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1. INTRODUCTION

This section of the report provides the background information for this project. Furthermore, the report structure will be outlined in this section as well.

1.1. Background

The coastal areas across the U.S. are subject to natural hazards, including severe storms, straight-line winds, severe thunderstorms, tornadoes, flooding, hurricanes, severe freezes, and others. Natural hazards can not only cause significant damages to the existing infrastructure, but also pose a major threat to human lives. Hurricanes Katrina and Sandy, which struck the U.S. coast in 2005 and 2012 respectively, are considered as the costliest disasters in U.S. history. Category 5 hurricane Katrina landed on the Southeastern Coast of the U.S. and affected the Bahamas, South Florida, Central Florida, Cuba, Louisiana, Mississippi, Alabama, and the Florida Panhandle (NOAA, 2005). Wind speed reached 175 mph (or 280 km/h) during hurricane Katrina. At least 1,245 people were killed by the hurricane, while the total property damage cost reached almost $108 billion (NOAA, 2005). Hurricane Sandy made a landfall in Cuba and was classified as a category 2 hurricane (NOAA, 2012). The hurricane affected Greater Antilles, Bahamas, most of the Eastern United States, Bermuda, and Eastern Canada. Throughout hurricane Sandy development, the wind speed increased up to 115 mph (or 185 km/h). The hurricane killed at least 233 people and caused approximately $75 billion in property damage (NOAA, 2012).

Efficient disaster relief operations are critical for preserving the existing infrastructure and, more importantly, ensuring the safety of humans. Generally, disaster relief operations can be classified into the following four categories (Altay & Green, 2006): 1) preparedness; 2) mitigation; 3) response; and 4) recovery. Preparedness activities are directed to prepare the community to respond in case of a disruptive event. Mitigation aims to prevent the disruptive event and alleviate negative effects in case the disruptive event occurs. Disaster response includes resources and emergency procedures that have to be performed in order to preserve life, environment, property, social, economic, and political assets (Altay & Green, 2006). Recovery activities are directed to stabilize the community and restore the infrastructure after the disaster strike. Preparedness activities are critical for efficient disaster relief operations. A lack of well-organized preparedness activities may impose risk to human lives and ultimately may even result in human deaths.

In case of approaching natural hazards, the population inhabiting areas that would be affected is advised to evacuate. When the potential impact is expected to be devastating, State authorities announce a mandatory evacuation. Throughout the evacuation processes, the major Interstate highways are designated as evacuation routes (CBS News, 2016). Using the dedicated evacuation routes, evacuees are able to travel to one of the emergency shelters, where they can temporarily stay until the natural hazard passes a given metropolitan area. Generally, the evacuation process happens in a chaotic manner, as the evacuating populations are not instructed to use any specific evacuation route and travel to any specific emergency shelter. The latter negatively affects the overall evacuation process. Specifically, in many cases evacuees are trying to use the same evacuation route, which may further cause route congestion (as the evacuation routes have a limited capacity) and significantly delay the evacuation. Furthermore, without a proper assignment of evacuees to emergency shelters, the emergency shelters typically are not being utilized effectively (i.e., some of them may operate under capacity, while the others may not have a sufficient capacity to accommodate arriving evacuees).

Emergency evacuation is quite a challenging task, especially for individuals who have never experienced the evacuation process before, and vulnerable population groups (such as aging adults). Safe driving under both normal conditions and emergency evacuation critically depends on a number perceptual and cognitive processes. With advancing age, a number of these abilities change, potentially resulting in a mismatch between the abilities of the aging driver and the demands of the driving task that can reduce driver comfort and increase crash risk. These changes include declines in vision, hearing, attention, speed of processing and responsiveness, as well as an increased presence of chronic diseases which can negatively impact driving performance (Boot et al., 2014).

For example, driving requires an individual to process the visual environment quickly and in detail, and any declines in vision can not only reduce driver comfort but can also significantly increase crash risk (Owsley & McGwin, 1999). Moreover, the eyes of aging adults are able to admit much less light compared to younger adults under low light conditions, which can make driving at night especially challenging (Boot et al., 2014). As age increases, so does the prevalence of a number eye diseases (e.g., glaucoma, cataracts, diabetic retinopathy), which significantly impair vision. Despite the fact that driving is mostly a visual task, hearing is also important when making roadway decisions. Hearing a warning horn from another motorist may allow for a collision to be avoided. Furthermore, emergency vehicles typically rely on sirens in order to rapidly pass through the traffic. Li-Korotky (2012) underlines that the hearing of individuals 60 years of age or older can start to rapidly decline, which further causes difficulties in processing important driving-related sounds. Green et al. (2013) observed that older adults with vision problems who also have hearing problems are especially at risk for experiencing a crash.

To ensure safe driving each individual should be able to efficiently scan the visual field, identify the relevant objects, and take an appropriate maneuver. Bédard et al. (2006) highlight that visual search ability and attention decline with age, and older adults tend to return attention to already searched visual locations. Furthermore, speed of processing and responsiveness are significantly lower for older adults as compared to their younger counterparts. It takes approximately 1.7-2.0 times longer for an older adult to process elementary information (Jastrzembski & Charness, 2007). In the meantime, the aging population is likely to have different chronic diseases (e.g., cancer, heart disease, dementia, diabetes). To cope with chronic diseases, older adults are required to take the prescribed medications, which may further affect their driving ability. For example, diabetic drivers are generally 1.5 times more involved in crashes as compared to drivers that do not have diabetes (Boot et al., 2014). Furthermore, as a result of a crash more serious injuries and higher fatality occurrence are generally observed for aging adults due to increased fragility with age.

Natural hazards frequently occur in the coastal areas with a high percentage of aging population. For example, the State of Florida has the largest proportion of 65+ years old population in the nation (U.S. Census Bureau, 2017) and experiences a relatively frequent occurrence of devastating natural hazards (FEMA, 2017). A total of 19.1% of the Florida's population are 65+

years old. Sumter County (Florida) is the only U.S. County, where more than a half of the population are 65+ years old residents, and the median age comprises 65.9 (Kent, 2015). Taking into account the aforementioned factors, this project aims to facilitate the natural hazard preparedness operations and develop an optimization model and solution algorithms for assigning evacuees to evacuation routes and emergency shelters, considering major driver characteristics (e.g., age, gender, driving experience under both normal driving and emergency evacuation conditions, health conditions, and others) and evacuation route characteristics (e.g., number of lanes, route capacity). A number of computational experiments will be conducted to demonstrate applicability of the proposed methodology for real-life emergency evacuation scenarios. The proposed methodology is expected to assist State authorities with improving efficiency of the disaster relief operations and ensuring safety of all population groups (including aging population).

1.2. Report Structure

This technical report is structured in the following manner. The next section provides a detailed description of the literature search and analysis of the collected studies. Section 3 provides a detailed description of the emergency evacuation optimization problem addressed in this study, while section 4 presents a mixed integer programming model for the problem. Section 5 focuses on the solution algorithms (heuristics and exact optimization algorithms) applied to solve the problem. Section 6 provides a detailed description of the methodology that was adopted (including the data collection process, major assumptions for the optimization problem and the evacuation scenarios considered) to solve the problem. Section 7 provides a detailed description of numerical experiments performed to evaluate the developed solution algorithms, while section 8 presents important managerial insights drawn from conducting the numerical experiments. The last section summarizes findings of this research and provides future research extensions.

2. LITERATURE REVIEW

2.1. Literature Review Methodology

For the review of the scientific literature, the Content Analysis research method was adopted. The Content Analysis is a methodology, which is used to make inferences from the text to the context of its use (Krippendorff, 2004). The Content Analysis method has three features that distinguish it from the other research methods, including the following (Krippendorff, 2004): (a) the Content Analysis method is an empirically grounded method, which is exploratory in process and predictive or inferential in intent; (b) the Content Analysis method transcends traditional notions of symbols, contents, and intents; and (c) the Content Analysis method allows the researchers execution, critical planning, detailed communication of findings, reproduction of methodology, planning and assessment of the results analysis. The major steps of the Content Analysis method, used throughout the literature review in this study, are presented in Figure 1 and include the following: 1) Identify research questions; 2) Perform a literature search; 3) Detailed review of literature; 4) Interpret findings from literature and make deductions; and 5) Answer research questions.

In the first step, the research questions of interest will be clearly identified. In the second step, a literature survey will be performed to collect the published peer-reviewed articles, which contain the information related to the research questions posed. In the third step, a detailed review of the collected studies will be performed, while findings from the literature will be interpreted to draw inferences in the fourth step. In the fifth and final step, based on the inferences drawn, comprehensive answers to the research questions listed will be provided. The next section of this study elaborates on the research questions considered and the literature survey process.

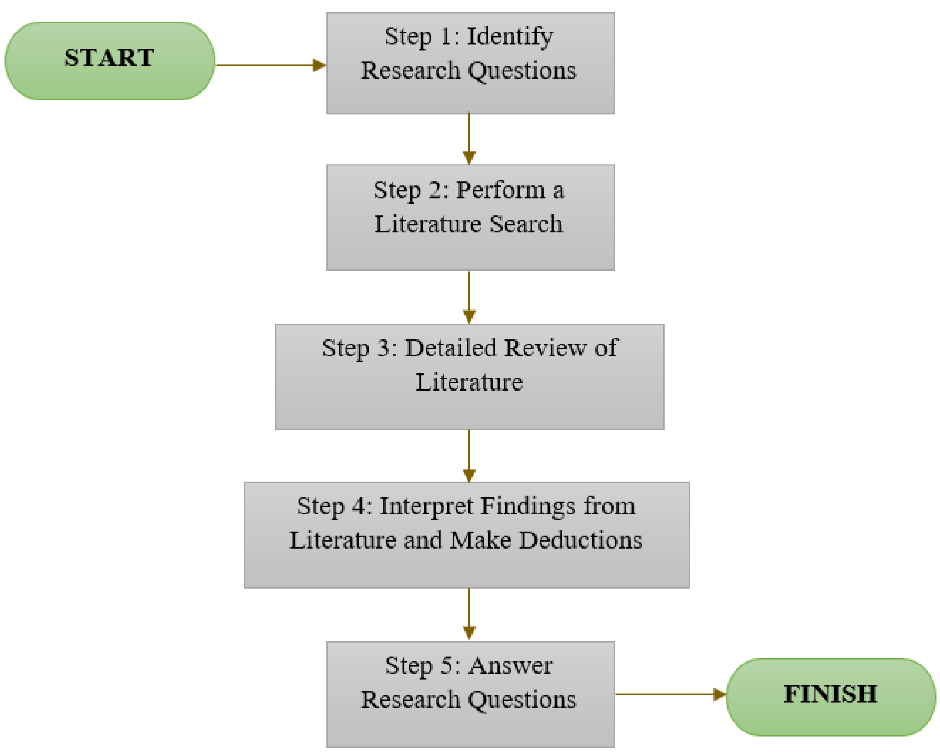

Figure 1 Literature review methodology.

2.1.1. Research Questions

This study will primarily focus on answering the following research questions:

RQ1. What types of hazards have been mostly considered in the literature?

RQ2. What are the effects of roadway capacity and travel demand on emergency evacuation?

RQ3. What are the effects of roadway geometry (e.g., number of lanes, road class, road curve, shoulder width) on emergency evacuation time?

RQ4. What are the effects of shelter capacity on emergency evacuation?

RQ5. What are the effects of shelter location on emergency evacuation?

RQ6. What are the effects of driver characteristics on emergency evacuation?

RQ7. What are the other effects (e.g., adverse weather, visibility, type of the vehicle used) that may influence emergency evacuation?

RQ8. What are the mathematical models (e.g., linear programming models – LP, integer programming models – IP, mixed integer programming models – MIP, nonlinear programming models – NLP, mixed integer nonlinear programming models – MINLP) that have been used for the emergency evacuation optimization problems?

RQ9. What are the common objective functions of the presented mathematical models?

RQ10. What are the solution algorithms that have been used for emergency evacuation planning?

RQ11. What are the research methods commonly applied for the emergency evacuation optimization problems?

RQ12. What are the major challenges associated with emergency evacuation planning?

Based on findings from a detailed review of the literature regarding each of the research questions posed, this study will present a detailed description of the state-of-the-art solution algorithms that have been used for emergency evacuation planning, the effects of driver characteristics, roadway geometry, travel demand, and other factors on emergency evacuation, and assignments considered in the emergency evacuation optimization problems. Also, this study will identify the gaps that should be explored in the future.

2.1.2. Literature Survey

The litearuture survey was performed using a structured keyword search to find studies relevant to the research questions posed. This study relied on the Scopus scientific database throughout the literature search (www.scopus.com) and focused primarily on the major scientific publishers (i.e., Elsevier - www.elsevier.com, Springer - www.springerlink.com, Wiley - www.wiley.com, and American Society of Civil Engineers - www.ascelibrary.org). The keywords used in the structured search include: 1) Natural hazards; 2) Aging adults; 3) Natural hazard preparedness; 4) Emergency evacuation; 5) Emergency shelters; 6) Emergency evacuation planning; 7) Emergency evacuation optimization; 8) Emergency evacuation modeling; 9) Emergency evacuation algorithms; and 10) Traffic assignment algorithms.

The following delimitations were posed throughout the literature search process:

i. The studies considered were selected from the peer-reviewed scientific journals majorly in social and behavioral sciences, psychology, transportation, and engineering only.
ii. Only journal papers written in English were considered. Conference papers and manuscripts, written in the other languages, were excluded.
iii. Studies that applied the solution algorithms in solving problems not related to emergency evacuation were not considered. This study specifically focuses on the solution algorithms, developed for the emergency evacuation optimization problems.
iv. Articles/newspapers published in the on-line journals were excluded from the analysis.

The main solution algorithms used in traffic assignment throughout emergency evacuation will be discussed in detail throughout this report as well (see section 2.3 of this report).

2.2. Descriptive Analysis

More than one thousand scientific articles were identified as a result of the literature survey. However, a total of 117 studies that were closely related to the research questions posed were selected for a detailed review. Prior to the review of each study, a statistical analysis was conducted. Figure 2 shows the distribution of studies collected by year, while the distribution of studies by journal is presented in Figure 3 and Table 1.

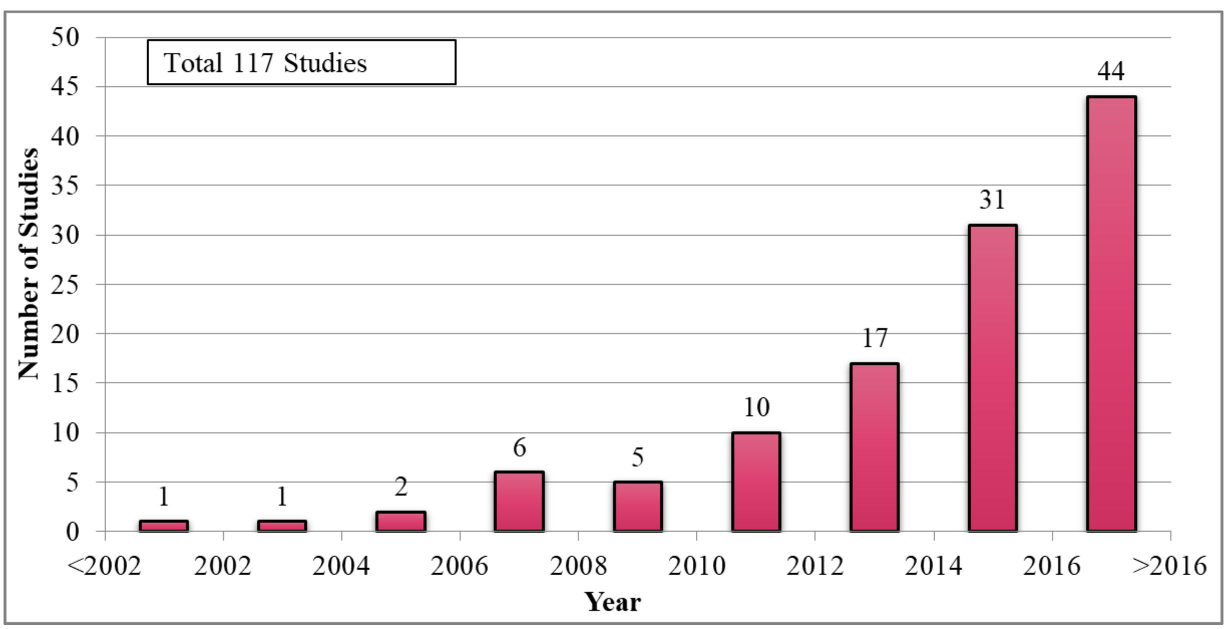

Figure 2 Distribution of studies by year.

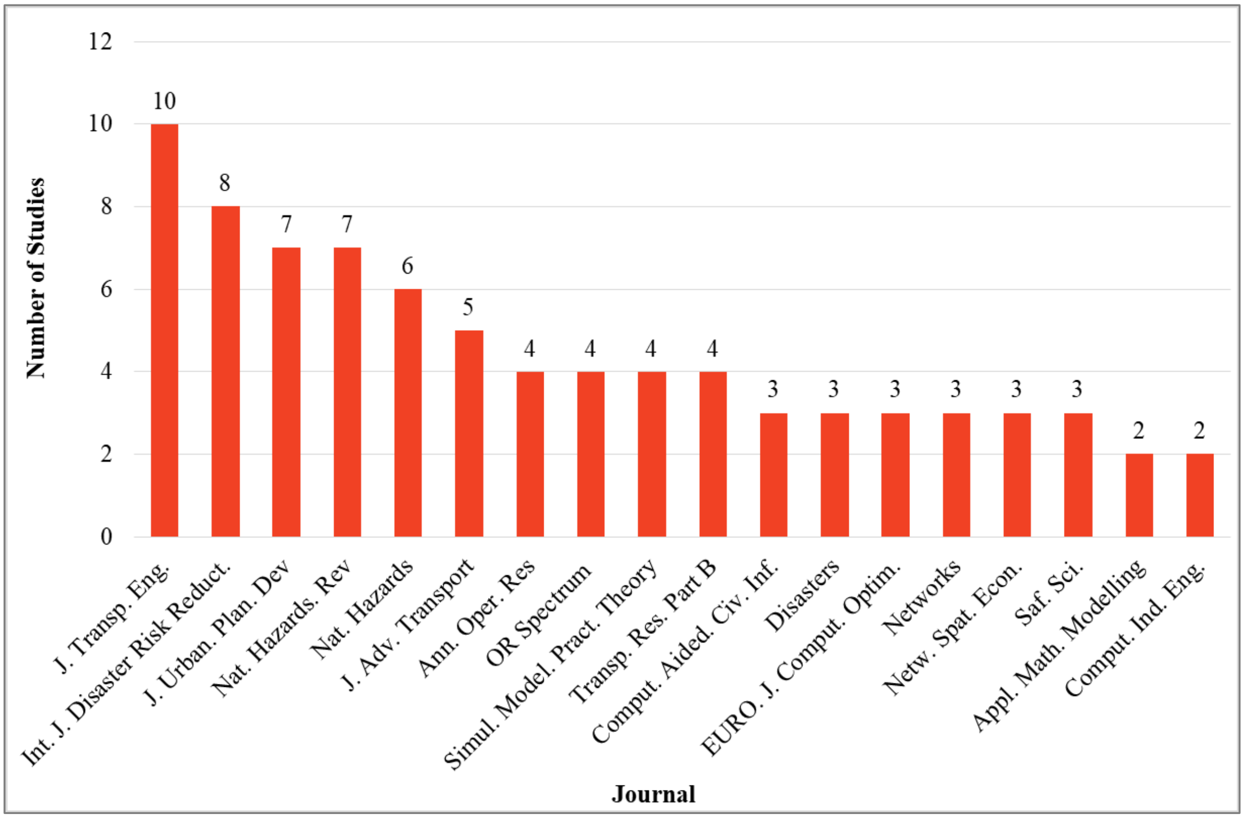

Figure 3 Distribution of studies by journal.

Results from the conducted literature survey show that the development of efficient algorithms to facilitate the evacuation process given certain operational features and constraints (such as travel demand, capacity of evacuation routes, shelter location, driver characteristics, etc.) has received an increasing attention from the research community over the last decade. In addition, about 32.5% of the reviewed studies are published in Journal of Transportation Engineering, International Journal of Disasters Risk Reduction, Journal of Urban Planning and Development, Natural Hazards Review, and Natural Hazards.

The Journal of Transportation Engineering publishes peer-reviewed studies that focus on planning, design, construction, maintenance, and operation of air, highway, and urban transportation. The International Journal of Disasters Risk Reduction focuses on various emerging risks from multifaceted and cascade disasters, development of disaster risk reduction strategies, implications of climate change on sudden disasters, vulnerability trends, and vulnerability analysis. The Journal of Urban Planning and Development presents the studies, which apply civil engineering principles to different areas of urban planning, such as transportation planning, land use planning, development and redevelopment of urban areas, and infrastructure management. The Natural Hazards Review Journal presents the studies, which offer cutting edge approaches for natural hazard preparedness, damage reducion, and cost reduction. The interdisciplinary studies, which are published in Natural Hazards Review, focus on the loss reduction, hazard mitigation, land use, and human response. The Natural Hazards Journal is decicated to publishing novel research work related to forecasting hazards, categories of hazard, disaster and risk management, as well as precursors of natural and technological hazards. The average impact factor of all considered scientific journals was found to be higher than 2.1.

Table 1 Distribution of studies by journal and publisher

a/a	Journal	#Studies	Publisher	Impact Factor
1	Journal of Transportation Engineering	10	ASCE	1.100
2	International Journal of Disasters Risk Reduction	8	Elsevier	1.603
3	Journal of Urban Planning and Development	7	ASCE	1.090
4	Natural Hazards Review	7	ASCE	1.650
5	Natural Hazards	6	Springer	1.833
6	Journal of Advanced Transportation	5	Wiley	1.813
7	Annals of Operations Research	4	Springer	1.709
8	OR Spectrum	4	Springer	1.557
9	Simulation Modelling Practice and Theory	4	Elsevier	1.954
10	Transportation Research Part B	4	Elsevier	3.769
11	Computer-Aided Civil and Infrastructure Engineering	3	Wiley	5.786
12	Disasters	3	Wiley	1.255
13	EURO Journal on Computational Optimization	3	Springer	1.330
14	Networks	3	Wiley	1.213
15	Networks and Spatial Economics	3	Springer	2.662
16	Safety Science	3	Elsevier	2.246
17	Applied Mathematical Modelling	2	Elsevier	2.350
18	Computers & Industrial Engineering	2	Elsevier	2.623
19	European Journal of Operational Research	2	Elsevier	3.297
20	Others	34	N/A	N/A
	Total Number of Studies:	117		

Note: ASCE – American Society of Civil Engineers.

Next, each one of the collected scientific studies was reviewed in detail, following the Content Analysis method. The review of the literature was targeted towards the following aspects: 1) distribution of studies by the hazard type considered; 2) distribution of studies by the driving conditions modeled; 3) distribution of studies by the roadway characteristics considered; 4) distribution of studies by the driver characteristics considered; 5) distribution of studies by the other effects considered; 6) distribution of studies by the mathematical model type (if applicable); 7) distribution of studies by the mathematical model objective(s) considered (if applicable); 8) distribution of studies by the assignments considered; 9) distribution of studies by the solution algorithm adopted; 10) distribution of studies by the research method applied; and 11) distribution of studies by future research directions. Results of the performed literature analysis are presented in sections 2.2.1 – 2.2.11 of this report.

2.2.1. Hazard Type

The distribution of studies by the type of hazard considered is presented Figure 4. The analysis of the reviewed studies revealed a total of 13 types of hazards considered in the literature. The major types of reported hazards include the following: (i) general chaotic condition (38 studies or 32.5%); (ii) natural and man-made hazards (22 studies or 18.8%); (iii) hurricane (17 studies or 14.5%); (iv) wildfire (11 studies or 9.4%); and (5) earthquake (7 studies or 6.0%). Some studies considered several other types of hazards, including flood, natural hazards (without specifying a certain type of a natural hazard), aircraft emergency, tsunami, nuclear plant radiation, radioactive propagation, terrorist attack, and toxic cloud releases. Some of the models, reported in the literature, could be applied for different types of hazards, while the others were developed for specific hazards only. Also, a number of studies (4 studies or 3.4%) did not model natural and/or man-made hazards, but the proposed algorithms can be applied to facilitate emergency evacuation planning.

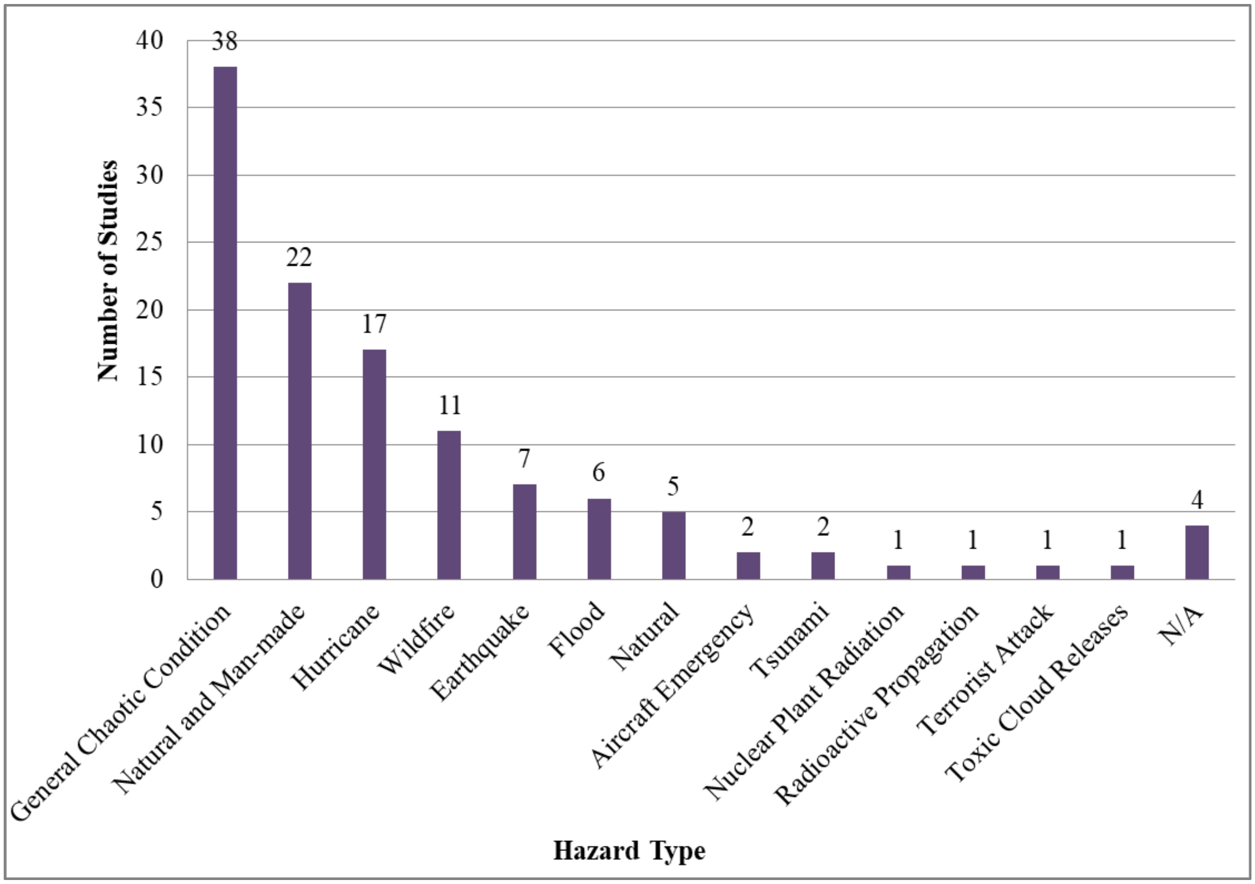

Figure 4 Distribution of studies by hazard type considered.

2.2.2. Driving Conditions

The driving conditions, considered by the collected studies, were categorized into: a) normal; and b) disruptive conditions (e.g., emergency evacuation). Figure 5 presents the distribution of reviewed studies by the driving condition modeled. The analysis showed that majority studies focused on modeling the disruptive driving condition (94.0% of studies). The latter finding can be explained by the fact that most of the studies considered the hazard preparedness and modeled one or several types of natural or man-made hazards. Some studies focused on the normal conditions (2.6% of studies), while certain studies (3.4% of studies) considered both normal and disruptive driving conditions. Some of the disruptive driving conditions considered by the studies include hurricane evacuation, wildfire evacuation, earthquake evacuation, and flood evacuation (as discussed in the previous section of the report).

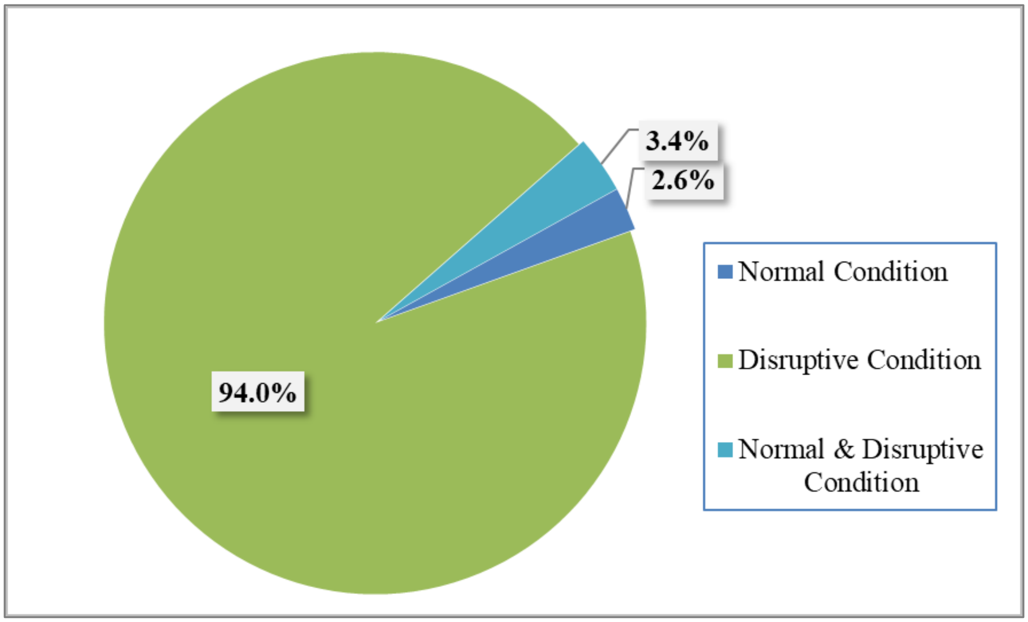

Figure 5 Distribution of studies by driving conditions modeled.

2.2.3. Roadway Characteristics

The analysis of studies revealed that the roadway geometry and other roadway characteristics could significantly affect the efficiency of the evacuation process. Figure 6 illustrates the distribution of studies by roadway characteristics. It was found that a total of eight geometric and other roadway characteristics were considered among the reviewed studies. The geometric and roadway characteristics highlighted by the collected studies include: 1) number of lanes (underlined in 18 studies or 15.4%); 2) road length (underlined in 11 studies or 9.4%); 3) road alignment (underlined in 5 studies or 4.3%); 4) shoulder width (underlined in 5 studies or 4.3%); 5) surface condition (underlined in 4 studies or 3.4%); 6) median width (underlined in 3 studies or 2.6%); 7) lane width (underlined in 2 studies or 1.7%); and 8) road class (underlined in 1 study or 0.9%).

2.2.4. Driver Characteristics

From the analysis of the reviewed studies, it was found that a large number of driver characteristics could affect the efficiency of emergency evacuation. Figure 7 illustrates the distribution of studies by driver characteristics considered. Some of the important driver characteristics underlined include: 1) age; 2) driving experience; 3) gender; 4) health condition; 5) reaction time; 6) residency; 7) education; 8) income; 9) marital status; 10) race; and 11) psychological condition. Findings from the state-of-the-art revealed that age (underlined in 9.4% of studies), driving experience (underlined in 6.8% of studies), as well as gender and health condition (underlined in 6.0% of studies), are the driver characteristics that might influence the driving performance of individuals throughout the emergency evacuation process the most. In addition, a few studies highlighted a number of other driver characteristics (e.g., reaction time, lifestyle, driver aggression, perception, occupation, attention, and others).

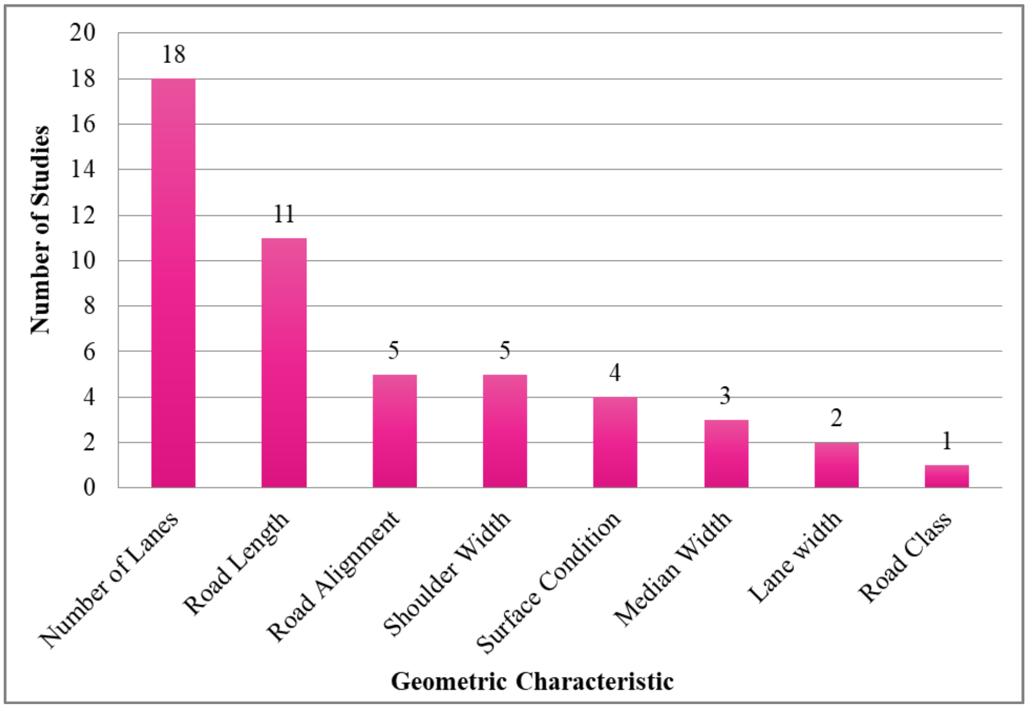

Figure 6 Distribution of studies by roadway characteristics.

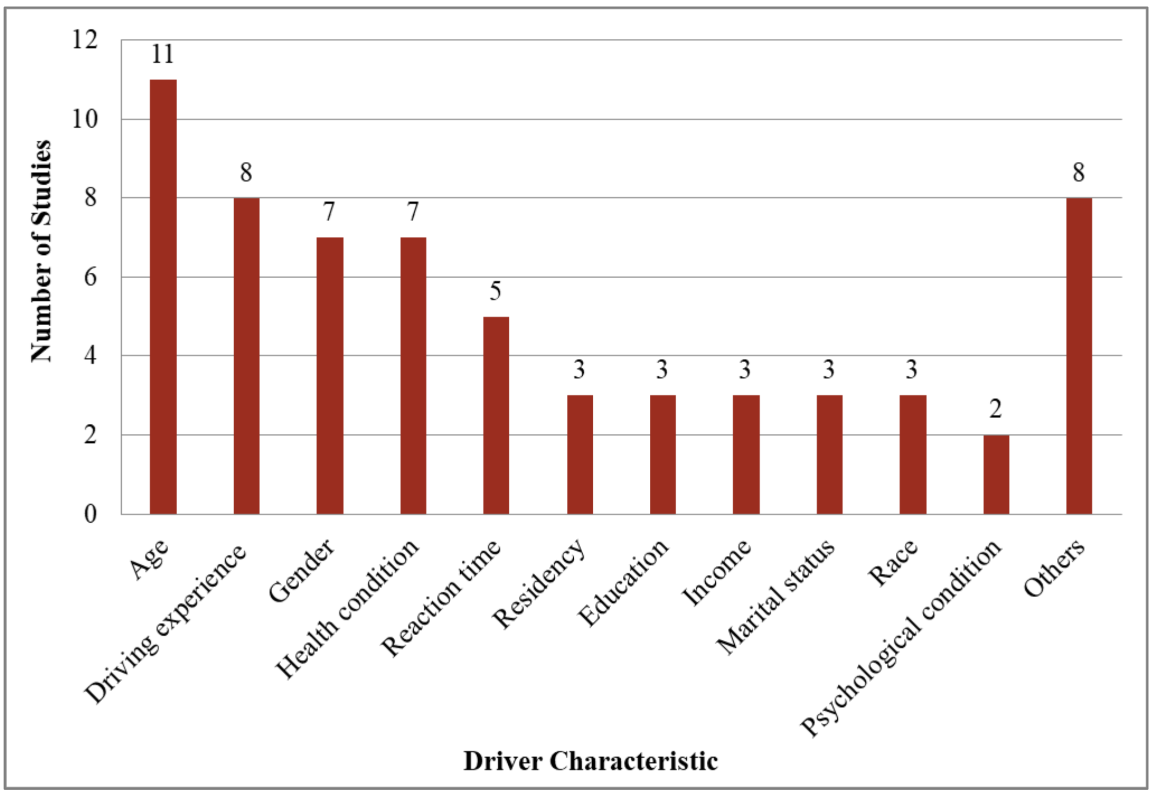

Figure 7 Distribution of studies by driver characteristics.

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2.2.5. Other Effects Considered

Table 2 presents the distribution of studies by other effects considered. The review of literature revealed that the effects of some other factors (aside from the driver and roadway characteristics) on the efficiency of the evacuation process and the decision to evacuate had been reported. From the analysis of the collected studies, a total of 20 attributes were found to be significant as they could directly affect the efficiency of the emergency evacuation process. The majority of studies considered the effect of the following factors: (i) evacuation time (46 studies or 39.3%), (ii) number of vehicles available for passenger pick-up (20 studies or 17.1%), (iii) evacuation demand (18 studies or 15.4%), (iv) traffic flow (17 studies or 14.5%); (v) cost of evacuation (12 studies or 10.3%); and (vi) route disruption (10 studies or 8.5%).

Table 2 Distribution of studies by other effects considered

a/a	Other Effects Considered	#Studies	%Studies
1	Evacuation time	46	39.3%
2	Number of vehicles for passenger pick-up	20	17.1%
3	Evacuation demand	18	15.4%
4	Traffic flow	17	14.5%
5	Evacuation cost	12	10.3%
6	Route disruption	10	8.5%
7	Population density	7	6.0%
8	Congestion	7	6.0%
9	Evacuation risk	6	5.1%
10	Travel speed	6	5.1%
11	Vehicle type	4	3.4%
12	Hazard type	3	2.6%
13	Storm category	3	2.6%
14	Household size	3	2.6%
15	Hazard awareness	3	2.6%
16	Shelter type	3	2.6%
17	Weather	2	1.7%
18	Emission	2	1.7%
19	Route density	2	1.7%
20	Presence of children	2	1.7%

Some studies have also highlighted the effect of other attributes, including the following: 1) population density (7 studies or 6.0%); 2) congestion (7 studies or 6.0%); 3) evacuation risk (6 studies or 5.1%); 4) travel speed (6 studies or 5.1%); 5) type of vehicle (4 studies or 3.4%); 6) hazard type (3 studies or 2.6%); 7) storm category (3 studies or 2.6%); 8) household size (3 studies or 2.6%); 9) hazard awareness (3 studies or 2.6%); 10) shelter type (3 studies or 2.6%); 11) weather (2 studies or 1.7%); 12) emission (2 studies or 1.7%); 13) route density (2 studies or 1.7%); and 14) presence of children (2 studies or 1.7%).

2.2.6. Mathematical Models

Figure 8 presents the distribution of reviewed studies by the mathematical model used. It was found that majority of the studies (55 studies or 47.0%) used mixed integer programming models, where some of the decision variables are constrained to have integer values, as well as linear programming models (18 studies or 15.4%), in which the relationship between variables and objective function(s) are linear. Also, certain studies (13 studies or 11.1%) adopted the mixed integer nonlinear programming models, in which the relationships between certain variables and/or objective function(s) are nonlinear, and some of the variables are constrained to be integers. A few studies (5 studies or 4.3%) used nonlinear programming models (some of the constraints are nonlinear and/or the objective function(s) are nonlinear), while 2 studies (or 1.7%) used integer programming models (in which all the variables are restricted to be integers). Certain studies presented the non-linear programming models with discontinuous derivatives (derivatives of the objective functions or the constraints are not available) and mixed integer quadratic programming models (the problems have linear constraints and linear or quadratic objective functions). Some studies (23.9% of studies) did not propose any mathematical models and adopted either other modeling approaches (e.g., simulation model) or alternative research method (e.g., analytical method, theoretical method, literature review method, etc.).

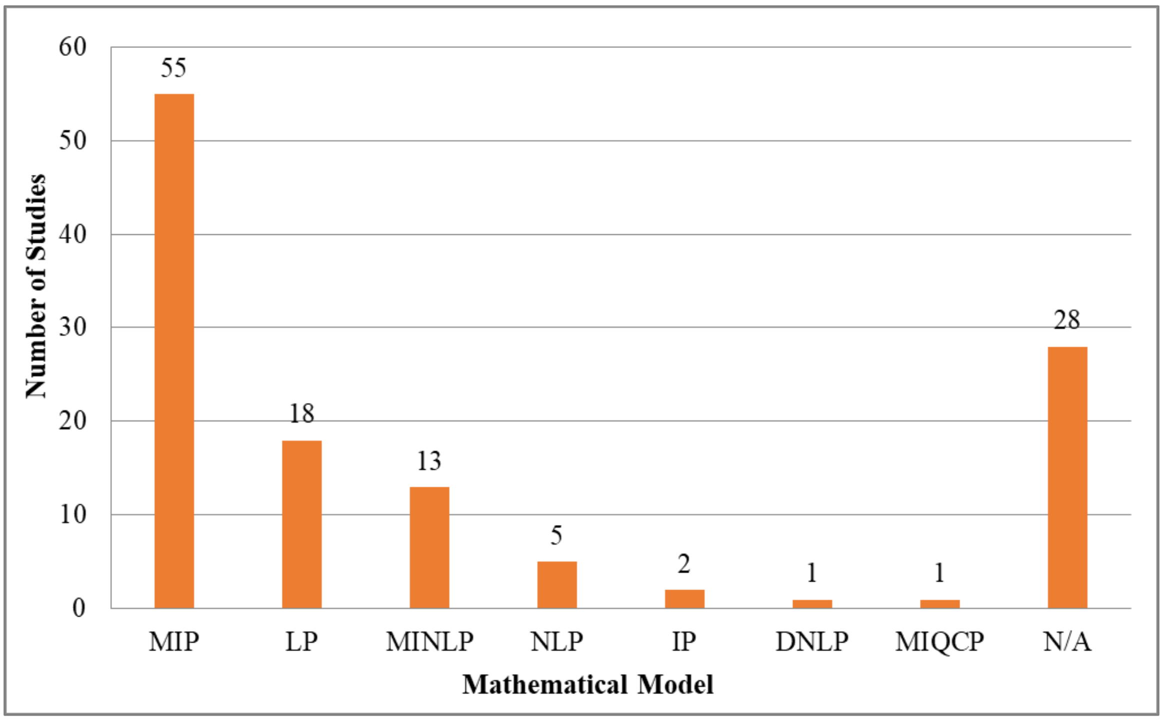

Figure 8 Distribution of studies by mathematical model used.

2.2.7. Model Objective(s) Considered

Table 3 presents the distribution of collected studies by the model objectives. Findings from the literature review revealed that the majority of studies focused on minimization of the total evacuation time (45 studies or 38.5%) and maximizing the number of evacuees transported to shelters (12 studies or 10.3%). The latter two facts underline that the overall efficiency of an evacuation process is measured in terms of the number of evacuees transported and how fast evacuees are moved out of the hazard zone to a safe destination. A significant number of studies (10 studies or 8.5%) focused on minimization of the evacuation cost (i.e., the cost, which is associated with the hazard preparedness activities). A total of 9 studies (or 7.7%) presented the mathematical models, where the evacuation distance was minimized, aiming to assign evacuees to the nearest shelter. Some studies (7 studies or 6.0%) proposed the mathematical models, minimizing the network clearance time, while a number of studies (6 studies or 5.1%) focused on minimization of the risk along the evacuation path. Other objectives considered by the collected studies include: (1) maximization of traffic flow; (2) maximization of network coverage; (3) maximization of shelter coverage; (4) minimization of congestion on the evacuation route; (5) maximization of travel demand; (6) minimization of waiting time of evacuees at pick-up locations; (7) maximization of number of vehicles; (8) minimization of overload capacity of shelters; and (9) minimization of transfer time from shelter to hospital. Furthermore, some studies (18.8% of studies) captured multiple objectives in decision making.

Table 3 Distribution of studies by model objectives

a/a	Model Objectives Considered	#Studies	%Studies
1	Minimize total evacuation time	45	38.5%
2	Maximize number of evacuees	12	10.3%
3	Minimize cost	10	8.5%
4	Minimize evacuation distance	9	7.7%
5	Minimize network clearance time	7	6.0%
6	Minimize path risk	6	5.1%
7	Maximize traffic flow	4	3.4%
8	Maximize network coverage	4	3.4%
9	Maximize shelter coverage	3	2.6%
10	Minimize traffic congestion	3	2.6%
11	Maximize traffic demand	3	2.6%
12	Minimize waiting time of evacuees	2	1.7%
13	Maximize the number of vehicles	2	1.7%
14	Minimize overload capacity of shelters	1	0.9%
15	Minimize transfer time from shelter to hospital	1	0.9%

2.2.8. Assignments Considered

Figure 9 illustrates the distribution of studies by the assignments considered. From the analysis of reviewed studies it was found that the assignments, which were commonly modeled in the emergency evacuation optimization problems, include the following: (1) evacuation route assignment (75 studies or 64.1%); (2) destination assignment (70 studies or 59.8%); (3) shelter assignment (58 studies or 49.6%); (4) pick-up location assignment (52 studies or 44.4%); and (5) vehicle assignment (34 studies or 29.1%). Furthermore, some studies (12 studies or 10.3%) specifically focused on the assignment of evacuees to evacuation routes and/or emergency shelters. In the event of a hazard, some studies (3 studies or 2.6%) considered allocating response resources (such as ambulances, police vehicles, fire trucks, relief materials, etc.) to improve the efficiency of the evacuation process and preserve safety of human lives. Moreover, 2 studies (or 1.7%) considered assignment of evacuees to medical centers.

2.2.9. Solution Algorithms

The conducted literature review revealed that studies adopted the heuristic, metaheuristics and exact optimization methods for solving the emergency evacuation optimization problems. Distribution of studies by the solution algorithms adopted is presented Figure 10. It was found that a total of 32 studies (or 27.4% of studies) proposed heuristic algorithms, where 6 studies (or 5.1% of studies) proposed local search heuristics and 2 studies (or 1.7% of studies) used the User Equilibrium Traffic Assignment Algorithms. Moreover, 31 studies (or 26.5% of studies) adopted metaheuristics, where 13 studies (or 11.1% of studies) proposed Evolutionary Algorithms, 6 studies (or 5.1% of studies) relied on Ant Colony Optimization, while 5 studies (or 4.3% of studies) used Simulated Annealing. Approximately 17.9% of studies applied the exact optimization methods, some of which include: 1) CPLEX (6.8% of studies); 2) Dijkstra Algorithm (4.3% of studies); and 3) Frank Wolfe Algorithm (1.7% of studies).

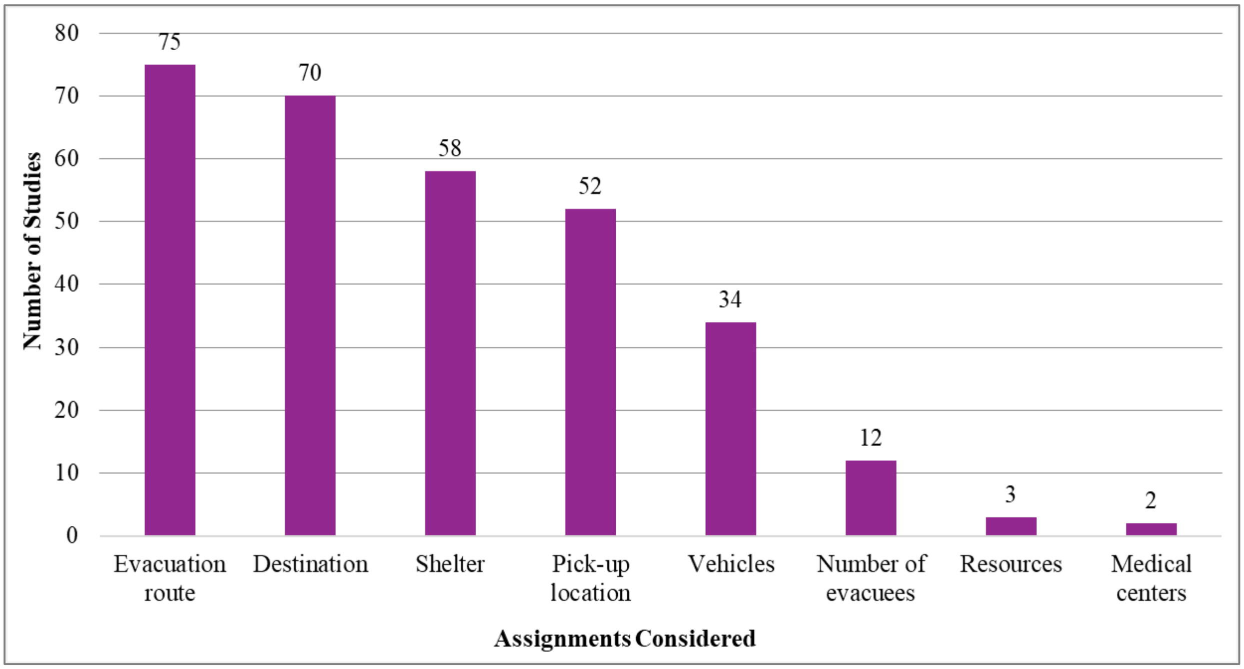

Figure 9 Distribution of studies by assignments considered.

2.2.10. Research Method

The reviewed studies were classified based on the research methodology adopted in the following categories:

1) ***Theoretical or conceptual method*** - this approach may suggest a new concept related to the topic by using a conceptual framework. The conclusions made by studies that use this approach are not supported with any mathematical calculations or models.
2) ***Analytical method*** - this approach uses mathematical calculations, statistical analysis, and other analytical methods to evaluate a new approach to a topic. Inferences drawn are based on the results obtained from the method of analysis used.
3) ***Survey based method*** - questionnaire surveys or interviews, administered to a specific or random sample, are used to obtain information about the subject, which can be an existing topic, a proposed topic, an invention, policy, among others. Inferences drawn from the survey are used in making conclusions about the subject topic.
4) ***Literature review method*** - involves the collection and detailed analysis of scientific studies to examine the extent of existing work on a particular subject, review of various approaches that have been established and determine potential future research works in the same area.
5) ***Modeling method*** - this approach relies on development of different models in order to solve a specific problem (e.g., optimization models, simulation models, agent-based

models). Findings are based on mathematical and computational experiments, which may involve the development of an algorithm, simulation and/or optimization models.

The distribution of reviewed studies by research method is presented in Figure 11. It was found that majority of studies (92.3%) were based on the modeling method. The latter finding can be justified by the increasing number of algorithm-based solution approaches, used in solving the emergency evacuation optimization problems within an acceptable computational time. It was also found that most of the modeling studies used a mathematical model in their research (92 studies or 78.6%). Furthermore, some studies (3.4% of studies) used the theoretical method, while the other studies used the analytical method (1.7% of studies) and the literature review method (1.7% of studies). Only one study out of the reviewed studies used the survey method.

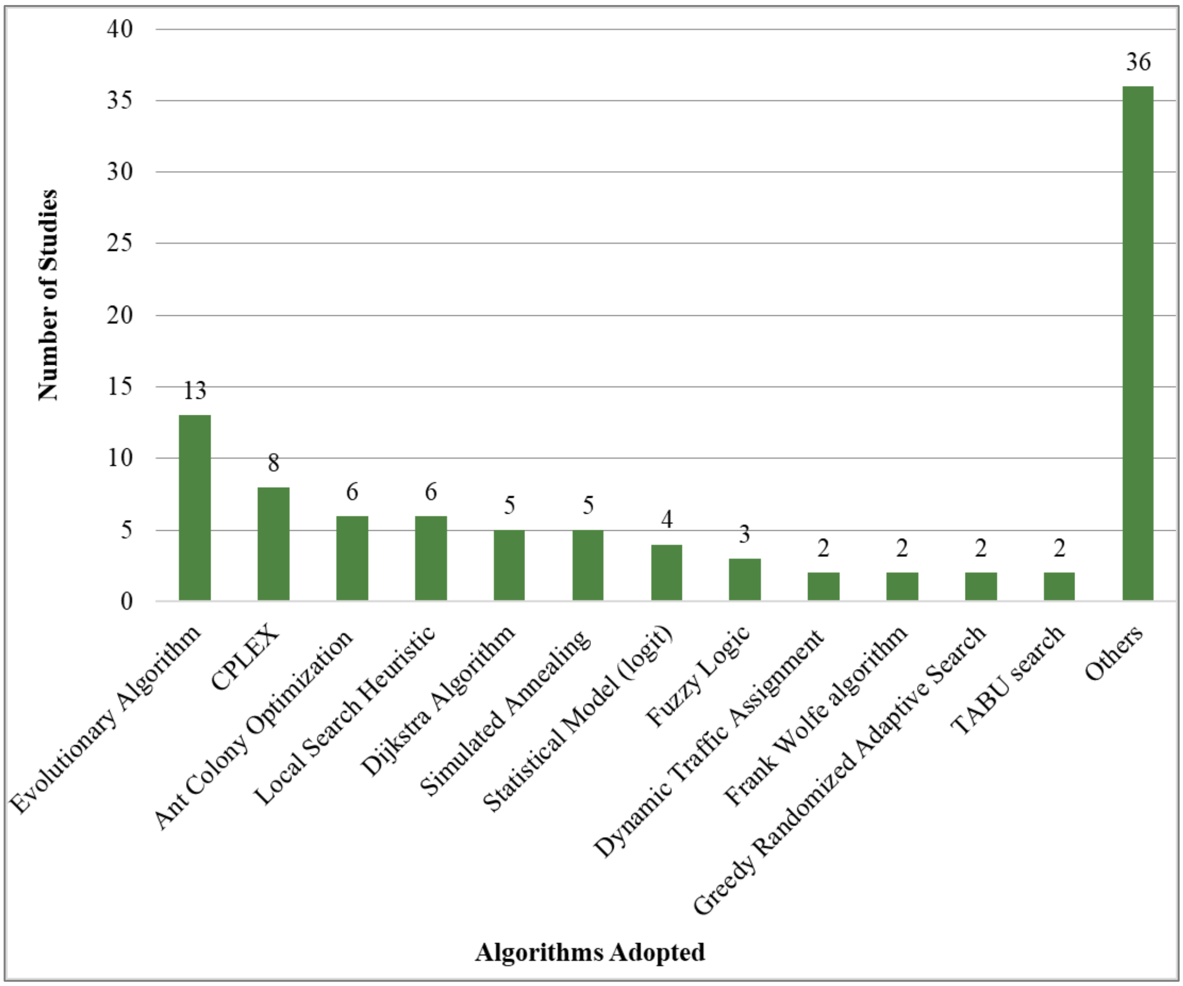

Figure 10 Distribution of studies by solution algorithms.

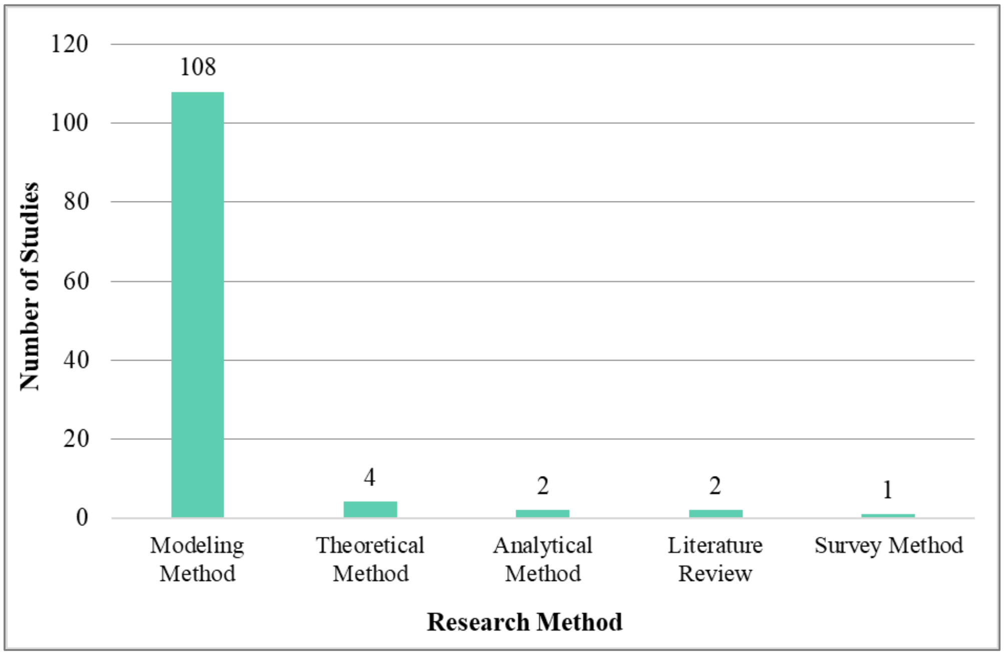

Figure 11 Distribution of studies by research method.

2.2.11. Limitations of Studies and Future Research

Table 4 presents the distribution of studies by the future research directions. It was found that many studies (29.9% of the reviewed studies) emphasized that it was necessary to consider other important factors (such as traffic attributes, hazard awareness, weather, shelter type, household size, and others) to improve accuracy of the proposed models and make them more realistic. A total of 10 studies (or 8.5% of the reviewed studies) recommended that there was a need to account for evacuees' behavior in the models, while 10 other studies suggested incorporating uncertainty in the models, as well as implementing the models on a large-scale network.

Table 4 Distribution of studies by future research direction

a/a	Future Research Direction	#Studies	%Studies
1	Improve the model/solution methodology by considering other factors	35	29.9%
2	Consider evacuees' behavior in the model	10	8.5%
3	Incorporate uncertainty and consider a large-scale network to make the model more realistic	10	8.5%
4	Consider shelter location and destination choice	9	7.7%
5	Assess performance of the model using different scenarios of traffic congestion	9	7.7%
6	Consider flexible evacuation route allocation	7	6.0%
7	Design a more reliable solution algorithm	6	5.1%
8	Apply the updated Geographical Information Systems (GIS) information for further analysis	4	3.4%
9	Miscellaneous	27	23.1%
	Total Number of Studies:	117	

A number of the studies underlined the importance of considering shelter and destination choice in assigning evacuees' at the hazard preparedness stage (a total of 9 studies or 7.7%), while 9 other studies suggested that there was a need to assess performance of the model using different scenarios of traffic congestion. Some of the studies stated the need to consider a flexible evacuation route allocation (a total of 7 studies or 6.0%), while 6 studies (or 5.1%) suggested that more reliable solution algorithms should be developed. Addressing the aforementioned limitations will further improve accuracy of the existing models used for the emergency evacuation planning optimization and also will allow development of the alternative models, which can facilitate the evacuation process.

2.3. Types of the Algorithms for Emergency Evacuation Planning

Throughout the literature review, the research team extracted the types of algorithms adopted by the collected studies. Figure 12 illustrates the distribution of studies by the types of algorithms. It was found that 32 studies (or 27.4% of the collected studies) developed the heuristic algorithms, while 31 studies (or 26.5% of the collected studies) developed the metaheuristic algorithms. Moreover, 21 studies (or 17.9% of the collected studies) adopted the exact solution algorithms. A relatively frequent implementation of the heuristic and metaheuristic algorithms indicates that many of the emergency evacuation planning problems, which were formulated, have a high complexity and cannot be solved using the exact optimization algorithms to the global optimality within an acceptable computational time.

Although most of the studies proposed a solution algorithm, some other studies focused on other methods such as simulation, statistical modeling, Markov chain, neural networks, and others. A total of 39 studies (or 33.3% of the collected studies) did not use any solution algorithm and focused on other modeling, analytical, or theoretical approaches, aiming to improve the emergency evacuation planning. The following sections provide description of the algorithms, which were developed by the collected studies.

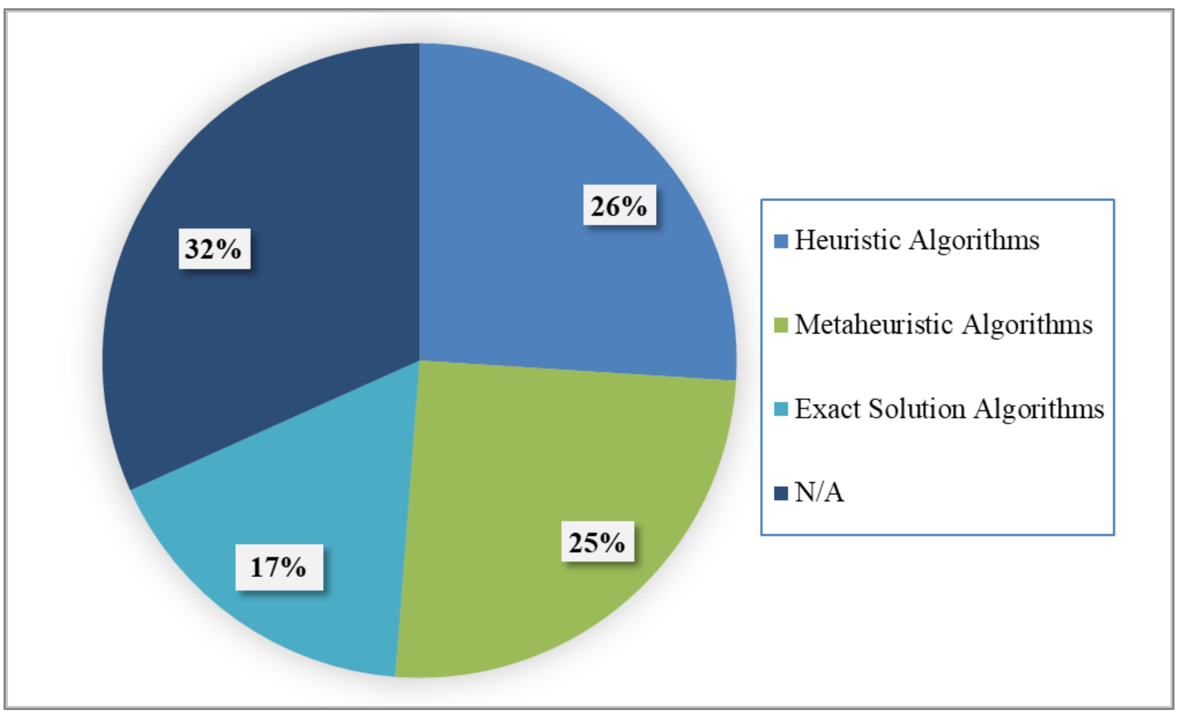

Figure 12 Distribution of studies by the algorithm type.

2.3.1. Heuristics

A heuristic is an algorithm designed to solve a specific problem within a reasonable computational (CPU) time at the expense of optimality or precision. Heuristics are mostly used for solving complex problems that cannot be solved in polynomial time (such as non-deterministic polynomial time (NP) problems, NP-complete problems, and NP-hard problems). Generally, the exact optimization algorithms require a lot of CPU time in order to solve NP-hard problems, which may not be feasible, especially for the large-size problem instances (i.e., the CPU time may become prohibitive). Thus, heuristics are the most suitable for such problems. Although heuristics do not guarantee optimality, they provide good quality solutions. Some of the heuristics, proposed by the reviewed studies, considered several types of assignments (such as routes, vehicles, evacuees, shelters, medical centers, and others) to facilitate the evacuation process. Heuristics are problem-specific algorithms (i.e., generally designed to solve certain problems, but may not be even applicable for other groups of problems) (Sheffi, 1985). The heuristic algorithms, which have been used frequently in literature for the user-equilibrium traffic assignment, are described throughout this section of the report.

The user equilibrium (UE) model is based on the assignment of travelers to the defined paths of the network. The UE assignment relies on the Wardrop's first principle, which states that no driver can unilaterally reduce his/her travel costs by changing the travel route. This assignment assumes that drivers have the perfect knowledge about the travel costs on a network and choose the best route. This assumption leads to the deterministic user equilibrium. The flow pattern on a UE assignment link is modeled such that no driver can better off by unilaterally changing routes. Other links of the traffic network will have either equal or larger travel times. There are three common heuristic methods used to determine the user-equilibrium flow pattern (Sheffi, 1985): 1) Capacity Restraint Method; 2) Modified Capacity Restraint Method; and 3) Incremental Assignment Method. These traffic assignment techniques are used to assign traffic flows to the links of the transportation network, aiming to achieve the user-equilibrium state. The Capacity Restraint, Modified Capacity Restraint, and Incremental Assignment Methods are described in sections 2.3.1.1 – 2.3.1.3 of the report.

2.3.1.1. Capacity Restraint Method

The Capacity Restraint Method is an iterative method, which involves a repetitive all-or-nothing assignment, with the aim of capturing the equilibrity of the traffic network. In this method, the approximate equilibrium solution is found by iterating between all-or-nothing traffic loadings and recalculating link travel times, based on a congestion function, which shows the link capacity. However, this method does not converge (due to the flow "flip-flows). The main steps of the Capacity Restraint Method are presented in **Pseudocode 1**.

2.3.1.2. Modified Capacity Restraint Method

The Modified Capacity Restraint Method attempts to approximate an equilibrium solution by iterating between all-or-nothing traffic loadings and recalculating the link travel times based on a congestion function that reflects the link capacity. This method attempts to solve the convergence problem, associated with the Capacity Restraint Method by using the link travel time, obtained from the previous iteration for the current iteration. The combination of travel times introduces a "smoothing" effect. Generally, since the algorithm does not converge, the number of iterations (N) is restricted (usually determined based on the number of links in the transportation network) in the Modified Capacity Restraint Method. Values for the weight of the averaging process are determined in the algorithm. The flow values from the last four iterations are averaged and selected as the equilibrium flows. The main steps of the Modified Capacity Restraint Method (using weights of 0.7 and 0.3 for the averaging process) are presented in **Pseudocode 2**.

Pseudocode 1: Capacity Restraint Method

Step 1. *Initialization*: Perform all-or-nothing assignment such that $t_l^0 = t_l(0)\ \forall l$, where t is the travel time and l is a link. The result is a set of link flows $\{x_l^0\}$. Set iteration counter $n = 1$.

Step 2. *Update the travel time*: $t_l^n = t_l(x_l^{n-1})\ \forall l$.

Step 3. *Network loading*: All-or-nothing assignment method is used to assign all trips to the network based on the travel time t_l^n. A set of link flows $\{x_l^n\}$ is obtained.

Step 4. *Convergence test*: If the maximum difference in link flows between two successive iterations is less than or equal to a predetermined value, STOP; else, set $n = n + 1$ and go to step 2.

Pseudocode 2: Modified Capacity Restraint Method

Step 1. *Initialization*: Perform all-or-nothing assignment such that $t_l^0 = t_l(0)\ \forall l$, where t is the travel time and l is a link. The result is a set of link flows $\{x_l^0\}$. Set iteration counter $n = 1$.

Step 2. *Update the travel time*: $t_l^n = t_l(x_l^{n-1})\ \forall l$.

Step 3. *Perform smoothing*: $t_l^n = 0.7 \cdot t_l^{n-1} + 0.3 \cdot t_l^n\ \forall l$.

Step 4. *Network loading*: All-or-nothing assignment method is used to assign all trips to the network based on the travel time t_l^n. A set of link flows $\{x_l^n\}$ is obtained.

Step 5. *Convergence test*: If $n = N$, go to step 6; else, set $n = n + 1$ and go to step 2.

Step 6. *Averaging*: The average over the last N iterations flow values are calculated for all links (and are considered as the link flows at equilibrium).

2.3.1.3. Incremental Assignment Method

Another heuristic method for solving a user-equilibrium traffic assignment problem is the Incremental Assignment Method. The Incremental Assignment Method involves the assignment of fractions of traffic volumes at each iteration. Based on all-or-nothing assignment, a fixed proportion of total traffic demand is assigned at each iteration. After each iteration, link travel times are recalculated based on the updated link volumes. When many increments are used, the flows may become similar to an equilibrium assignment; however, this method typically does not produce an equilibrium solution. Generally, the incremental assignment process is influenced by the order in which volumes for O-D pairs are assigned. The main steps of the Incremental Assignment Method are presented in **Pseudocode 3**.

Pseudocode 3: Incremental Assignment Method

Step 1. *Initialization*: All O-D entries are divided to N equal portions. Set iteration counter $n = 1$ and $x_l^0 = 0 \ \forall l$.

Step 2. *Update the travel time*: $t_l^n = t_l(x_l^{n-1}) \ \forall l$.

Step 3. *Incremental loading*: All-or-nothing approach is used to assign only the trip rates p_{rs}^n for each O-D pair based on the travel time on the link. A set of link flows $\{y_l^n\}$ is obtained.

Step 4. *Flow summation*: $x_l^n = x_l^{n-1} + y_l^n \ \forall l$.

Step 5. *Stopping criterion*: If $n = N$, STOP and return the current link flows as the solution; else, set $n = n + 1$ and go to step 2.

2.3.2. Metaheuristics

Metaheuristics are higher-level heuristics, which are designed to select or generate a heuristic, capable of providing a good quality solution to an optimization problem. Unlike heuristics, metaheuristics are problem-independent. Although they do not guarantee a globally optimal solution, compared to the exact optimization algorithms and other iterative methods, metaheuristics can provide good-quality solutions for a wide range of problems by efficiently exploring the search space to find the near-optimal solutions. Furthermore, metaheuristics guide the search process to find near-optimal solutions in a reasonable CPU time, using techniques ranging from simple search procedures to complex learning processes. Generally, metaheuristics are approximate and non-deterministic in nature. Findings from the review of the literature show that metaheuristics, such as Simulated Annealing, Evolutionary Algorithm, Ant Colony Optimization, Tabu Search, Particle Swarm Optimization, Greedy Randomized Adaptive Search Procedure, and others, have been frequently implemented in the state-of-the-art to solve the emergency evacuation planning problems. The metaheuristic algorithms, which have been used within the collected studies, are described in sections 2.3.2.1 – 2.3.2.8 of this report.

2.3.2.1. Simulated Annealing

Simulated Annealing (SA) is a metaheuristic algorithm, inspired by the process of annealing, which is widely used in metallurgy. The annealing technique involves cooling and heating a given material, aiming to achieve a specific structure of its crystals (which will determine the material properties). The temperature schedule allows modification of the structure of the material (i.e., the properties of the material, designed based on the fast cooling schedule, would be significantly different from the properties of the same material, which was designed based on the slow cooling schedule). The SA algorithm starts with generation of the initial state and enters an iterative procedure, where the current temperature is adjusted and a neighbor state is generated. After that, based on the acceptance probability function, the algorithm decides whether to stay in the current state or move on to the neighbor state. The acceptance probability function is dependent on the temperature value. In the beginning of the algorithmic run (when the temperature is high), the acceptance probability function even allows selecting the worse states. Towards convergence (when the temperature becomes lower), the acceptance probability function selects only the most favorable state at each iteration. The SA algorithm terminates, once certain convergence criterion is met (generally, the maximum number of iterations). The main steps of the SA algorithm are described in **Pseudocode 4**.

Pseudocode 4: Simulated Annealing Algorithm

Step 1. Generate the initial state.
Step 2. Adjust the current temperature.
Step 3. Generate randomly a neighbor state.
Step 4. Determine whether to stay in the current state or move on to the next state based on the acceptance probability function.
Step 5. If convergence criterion is met, STOP; else, go to step 2.

2.3.2.2. Evolutionary Algorithms (EA)

Evolutionary Algorithm (EA) is a generic population-based metaheuristic optimization algorithm. Charles Darwin's theory of evolution (which relies on reproduction, mutation, crossover, and selection) serves as an inspiration for EAs. The theory is based on the principle that in nature different species adapt to occupy different environmental niches, which usually contain finite resources; therefore, individuals compete with each other for resources in order to survive. Individuals that compete effectively and survive can mate and produce new offspring. Usually, individuals, who are better adapted to survive, are allowed to move on to the next generations (the latter phenomenon is called the evolutionary process). In an EA, candidate solutions encoded in the chromosomes (a set of solutions usually represented with a string of numbers) are represented in genotypic space to search for the global optimum. The initial population of individuals is randomly generated and the fitness is evaluated using a fitness function (an objective function that determines the quality of the solution). The fittest individuals are selected for reproduction, a process which involves the use of crossover and mutation functions to produce new individuals. Next, the fitness function is applied to evaluate the fitness of the new individuals. Once a certain convergence criterion is met (such as specific fitness value, maximum allowed number of generations, maximum number of generations without fitness improvement, etc.), the EA terminates the process and returns the best solution. Generally, EAs do not make any assumption about the fitness of the solution; hence, they produce good quality solutions for all types of problems. The main steps of the EA algorithm are described in **Pseudocode 5**.

Pseudocode 5: Evolutionary Algorithm (EA)

Step 1. Initialize chromosomes.
Step 2. Randomly generate the initial population of individuals.
Step 3. Evaluate the fitness of the individuals.
Step 4. Select the individuals for reproduction (parent selection).
Step 5. Generate new individuals through crossover and mutation operations (produce offspring).
Step 6. Evaluate the fitness of the new individuals.
Step 7. Identify the offspring chromosomes for the next generation (offspring selection).
Step 8. If convergence criterion is met, STOP and return the best solution; else, go to step 4.

2.3.2.3. NSGA-II

The Non-Dominated Sorting Genetic Algorithm II (NSGA-II), proposed by Kalyanmoy Deb (2002), is an extension of NSGA, developed by Srinivas and Deb (1995). This type of metaheuristic is applied in solving non-convex and non-smooth mathematical optimization problems, involving more than one objective function simultaneously. The NSGA-II is based on the structure of a typical EA; however, in addition to the generic operators (such as crossover and mutation) used in a typical EA, two multi-objective operators are applied, which include: 1) Non-Dominating Sorting (sorts the population and partitions it into Pareto Fronts. A Pareto Front is a set of non-dominated solutions, being chosen as optimal if no objective can be improved without sacrificing at least one other objective); and 2) Crowding Distance (a measure of how close an individual is to its neighbors). The NSGA-II algorithm starts with initialization of the population. Next, the population is sorted based on non-domination into Pareto Fronts. The first front is a completely non-dominant set in the population, while the second front is being dominated by individuals in the first front only, and the level of domination of the fronts is set in that order. The individuals are assigned fitness values based on the front they belong to, and the crowding distance is estimated for each individual. Afterward, the binary tournament selection operator and crowding distance values (an individual with a greater crowding distance in the rank is selected) are used in selecting parents. Offspring are generated using the crossover and mutation operators. The current population and the offspring generated are sorted based on non-domination. In addition, based on crowding distance and rank of the last front, the best individuals are selected. The offspring are merged with the current generation population, and selection is performed to determine the parents in the next generation. NSGA-II terminates, once certain convergence criterion is met and returns the best Pareto Front (Seshadri, 2000). The main steps of the NSGA-II algorithm are described in **Pseudocode 6**.

Pseudocode 6: NSGA-II Algorithm

Step 1. The population is initialized.
Step 2. The population is sorted based on non-domination and partitioned into Pareto Fronts.
Step 3. The crowding distance values are assigned to individuals.
Step 4. The binary tournament selection operator together with the crowding distance values are used in selecting parents.
Step 5. New individuals are generated using the crossover and mutation operators.
Step 6. The fittest individual is determined.
Step 7. Individuals are selected at the end of a generation.
Step 8. The offspring population is combined with the current generation population, and selection is performed to set the individuals of the next generation.
Step 9. If convergence criterion is met, STOP and return the Pareto Front; else, go to step 2.

2.3.2.4. Ant Colony Optimization

The Ant Colony Optimization (ACO) algorithm, proposed by Marc Dorigo in 1992, is a probabilistic method for solving the decision problems, which can be reduced to finding good paths on a graph. The behavior of ants, while travelling from their colony to a source of food, is an inspiration behind this metaheuristic optimization technique. Generally, when ants identify a source of food, they return to their colony, laying out a substance called “pheromone” along the path traversed. This behavior ensures that ants do not travel randomly. Moreover, as more ants use path to travel to the source of food, the pheromone density becomes higher. Over time, when ants do not use the path, the pheromone evaporates. The latter idea prevents convergence at the local optimal solution. The ACO algorithm iteratively constructs a solution for a problem. At each iteration, the ants move from one state to another (solutions are referred to as states). The probability of feasible states is computed based on the attractiveness value (desirability of that move) and the trail level value (estimate of efficiency of a particular move the ant was making in the past). The moves from the current state to another state occur based on the estimated probability value. Once all ants have completed selecting the states, the trails are updated. The ACO algorithm increases the trail level, when the solution is good, and decreases the trail level, when the solution is bad. Furthermore, the pheromone is deposited for the best solution at every iteration (the latter strategy is called "elitist ant system"). The main steps of the ACO algorithm are described in **Pseudocode 7**.

Pseudocode 7: Ant Colony Optimization Algorithm

Step 1. Construct ant solutions: A colony of ants that moves based on a stochastic decision through neighbor nodes to build solutions.
Step 2. Update pheromone: Once a solution is created, update the trail value (increase the trail value if solution is good or decrease the trail value if solution is poor).
Step 3. Pheromone evaporation: If the solution is sub-optimal, reduce the trail value to avoid too rapid convergence.
Step 4. Determine whether it is useful to deposit additional pheromone (increase the trail value) from a nonlocal perspective.
Step 5. If convergence criterion is met, STOP and return the best solution; else, go to step 2.

2.3.2.5. Greedy Randomized Adaptive Search Procedure

The Greedy Randomized Adaptive Search Procedure (GRASP) was proposed by Feo and Resende (1989). This type of metaheuristic algorithm is applied for combinatorial optimization problems. In GRASP, the iterative process consists of two phases: construction and local search. At the construction phase, a set of partial solutions is being developed by evaluating all candidate elements in the ground set, using the greedy randomized function. The greedy randomized function represents the increase in the cost function, due to the addition of an element in the solution set. The evaluation procedure leads to the creation of a list of elements, whose addition to the partial solution set gives the smallest incremental cost. Once an element is randomly selected from the ground set, the candidate list is updated and the incremental costs are reevaluated. If the greedy randomized construction procedure is unable to produce a feasible solution, a repair procedure is applied to achieve feasibility. After obtaining a feasible solution, the neighborhood of the search space is investigated using a local search algorithm. The local search algorithm iteratively investigates the search space and replaces the current solution, if a better solution is found. The local search heuristic terminates the search, when it fails to find a better solution. The GRASP algorithm does not reconsider its choices and subsequent solutions are the locally optimal solutions. This search method does not guarantee optimality. The main steps of the GRASP algorithm (Resende and Riberio, 1994) are described in **Pseudocode 8**.

2.3.2.6. Tabu Search

The Tabu Search (TS) algorithm, which relies on the local search methods, was proposed by Fred W. Glover (1986). The metaheuristic was designed to select a potential solution to a problem and check its immediate neighbors, with the aim of obtaining a better solution in the immediate neighborhood. The term "tabu" is a Tongan word, which means that something cannot be touched because it is sacred. This type of metaheuristic uses a local search procedure to iteratively move from a potential solution to an improved solution in the search space. Unlike other local search procedures, the TS algorithm explores the neighborhood of the current solution, and thus performs the search space exploitation better than other local search procedures. In a TS algorithm, the initial solution is determined and an empty Tabu list is initialized. The Tabu list stores the potential solutions from the states visited. To improve the local search, the TS procedure is restricted from going back to previously visited solutions based on the potential solutions in the Tabu list; hence, if a potential solution appears on the Tabu list, it cannot be revisited. A fitness function (generally, a mathematical function that represents objective of the optimization problem) is executed to determine if a current solution is better than the previous one. If a better solution is found, it is added to the Tabu list. When the Tabu list is full, some elements are removed, based on the order in which they were added. The process continues until a stopping criterion is met, and the best solution found during the search is returned. The main steps of the TS algorithm are described in **Pseudocode 9**.

Pseudocode 8: Greedy Randomized Adaptive Search Procedure

Step 1. Initialize a set of candidate elements.
Step 2. Initialize a set of partial solutions.
Step 3. Evaluate the incremental costs of the candidate elements randomly using the greedy randomized function.
Step 4. Update the partial solution set.
Step 5. Reevaluate the incremental costs and update the partial solution set.
Step 6. Repair infeasible solutions (if any).
Step 7. Perform a local search using the local search function to find the local optimal solution and update the solution.
Step 8. If convergence criterion is met, STOP and return the best solution; else, go to step 3.

Pseudocode 9: Tabu Search (TS) Algortihm

Step 1. Choose an initial solution randomly.
Step 2. Initialize an empty Tabu list.
Step 3. Check the local search space for a potential solution.
Step 4. Evaluate the fitness of the potential solution found using the fitness function.
Step 5. If the potential solution is better than the initial solution, add it to the Tabu list.
Step 6. Find other potential solutions based on the fitness function.
Step 7. If the Tabu list is full, remove some potential solutions by the order in which they were added.
Step 8. If a stopping criterion is met, STOP and return the best solution; else, go to step 3.

2.3.2.7. Artificial Immune System (AIS) Algorithm

The development of Artificial Immune System (AIS) Algorithm was inspired by the principles of the immune system of vertebrates from biology. Generally, the immune system of vertebrates learns about a type of disease, adapts, and stores the information about the disease. The information, stored by the immune system, is used in recognizing and defending the vertebrate if the disease reoccurs. The AIS algorithm applies this principle in learning (identification), memory, and associative retrieval. Specifically, the algorithm learns to recognize relevant patterns, remember patterns, which have been marked relevant, and use finite or countable discrete structures, to construct pattern detectors. Thus, the algorithm is effective in solving recognition and classification problems. The AIS algorithm starts with initializing a set of patterns to be recognized. Next, a set of potential detectors capable of classifying unseen patterns is randomly generated. The algorithm determines the affinity (a resemblance in structure) of each potential detector and each of the patterns initialized. The potential detectors with the highest affinity is stored in a memory set. The potential detectors in the memory set are cloned, and the cloned set undergoes the mutation operation. The affinity of the detectors from the mutation operation is determined, and detectors with the highest affinity are added to the memory set, while detectors with the lowest affinity are replaced with randomly generated detectors. A set of memory detectors with the highest affinity are returned after a stopping criterion is met. The main steps of the AIS algorithm are described in **Pseudocode 10**.

Pseudocode 10: Artificial Immune System (AIS) Algorithm

Step 1. Initialize the set of patterns to be recognized.
Step 2. Initialize a memory set to store detectors with the high affinity.
Step 3. Generate a set of potential detectors to classify the patterns to be recognized.
Step 4. Determine the affinity between each detector and each pattern.
Step 5. Store detectors with the highest affinity in a memory set.
Step 6. Clone the memory set.
Step 7. Apply the mutation operator to generate new detectors.
Step 8. Determine the affinity between the newly generated detectors and the set of patterns.
Step 9. Add the newly generated detectors with the highest affinity to the memory set.
Step 10. Replace the newly generated detectors with the lowest affinity with randomly generated detectors.
Step 11. If a stopping criterion is met, STOP and return a set of detectors with the highest affinity; else, go to step 3.

2.3.2.8. Particle Swarm Optimization

Kennedy et al. (1995) proposed the Particle Swarm Optimization (PSO) Algorithm. The PSO algorithm attempts to improve a candidate solution to an optimization problem iteratively, given a defined measure of quality. The PSO algorithm is inspired by the philosophy behind the movement of organisms, such as fish pool. This philosophy explains that fish swim together in the same direction in a coordinated fashion, deriving benefits, such as higher success of finding a mate, defense against predator, and others. The PSO algorithm starts the search process by initializing a population of candidate solutions, which are represented by dubbed particles. Next, the particles move in the search-space based on some defined mathematical formulae (generally, a function of the particle’s position and velocity). The movement of the particles is typically guided by their best known position and also the best known position in the entire swarm. The particles share the information about their position among themselves, using a “swarm communication structure”. This allows the whole swarm to share the best known position from a single particle. When the algorithm discovers a better position, the swarm movement is guided to the new position. Therefore, the movement of particles in the search space is dependent on the position of the best possible solution. The process is repeated until a stopping criterion is met (usually, when a specified number of iterations has been performed or when a desired objective function value is achieved). The main steps of the PSO algorithm are described in **Pseudocode 11**.

Pseudocode 11: Particle Swarm Optimization (PSO) Algorithm
Step 1. Initialize the particle's position with a uniformly distributed random vector.
Step 2. Initialize the particle's best-known position to its initial position.
Step 3. Initialize the particle's velocity.
Step 4. Update the particle's velocity.
Step 5. Update the particle's position.
Step 6. Search for a better particle's position.
Step 7. If a better particle's position is found, update the particle's best-known position.
Step 8. Update the swarm's best-known position.
Step 9. If a stopping criterion is met, STOP; else, go to step 4.

2.3.3. Exact Optimization Algorithms

The exact optimization algorithms are applied to solve a given optimization problem to the global optimality. Although these algorithms return the global optimal solution, the CPU time can be significant for the problems of a high complexity (i.e., which cannot be solved in polynomial time: NP problems, NP-complete problems, and NP-hard problems). Several exact optimization algorithms have been used in the past for solving different optimization problems (such as Simplex, Branch-and-Bound, CPLEX, Dijkstra Algorithm, etc.). Based on the analysis of the collected studies, Dijkstra and Branch-and-Bound Algorithms have been widely used for the emergency evacuation optimization problems. Both algorithms are described in sections 2.3.3.1 and 2.3.3.2.

2.3.3.1 Dijkstra Algorithm

The Dijkstra Algorithm (DA) was developed by Edsger W. Dijkstra in 1956. Given a node on the graph, the DA algorithm finds the shortest path between the node and any other node on the graph. This exact optimization algorithm is typically applied for the transportation problems, where nodes can be considered as the origins, destinations, or intermediate nodes, and the graph as a network of roads. For the DA algorithm, the nodes on a graph are assigned a tentative distance value of infinity, except the initial node selected, which is assigned a value of zero. The initial node selected by the algorithm is marked as the current node, while other nodes are marked as unvisited and stored in a set. A new tentative distance is calculated for all neighboring nodes, and the smaller value is assigned to each node after comparing the assigned distance value and the calculated distance. Afterwards, the current node is marked as visited and will never be visited again. When the neighboring nodes of the current node have been considered, they are removed from the unvisited set and marked as visited. The algorithm sets the unvisited node with the smallest tentative distance is set as the new current node and repeats the process. If a destination node has been marked visited or the smallest tentative distance among the nodes in the set of unvisited nodes is infinity, the algorithm stops and returns the shortest distance found. The main steps of the Dijkstra Algorithm are described in **Pseudocode 12**.

2.3.3.2 Branch and Bound Algorithm

A Branch and Bound (BB) algorithm was proposed by Land and Doig in 1960. The BB algorithm is designed for solving discrete mathematical optimization problems by systematically enumerating the candidate solutions provided from the state space search. A BB algorithm looks for a special solution among a set of solutions that minimizes or maximizes the objective function. A heuristic is used to find a solution to the optimization problem. The solution is stored in a set of best solutions. If no heuristic is available, the best solution value is assumed to be infinity. The best solution is selected as the upper bound on the candidate solution. Next, the BB algorithm initializes a queue to hold partial solutions, with none of the variables of the problem assigned. After that, a node is selected from the queue generated, and based on the objective of the model (to minimize or maximize the objective function) a candidate solution is compared with the best solution. For a minimization problem, if the candidate solution is less than the best solution, the candidate solution becomes the best solution; while for a maximization problem, if the candidate solution is higher than the best solution, the candidate solution is updated as the best solution. However, if the candidate solution does not provide a better solution, it is returned to the queue or discarded (since it will never give an optimal solution). The main steps of the BB algorithm are described in **Pseudocode 13**.

Pseudocode 12: Dijkstra Algorithm

Step 1. Assign a tentative distance to each node: Set the value for the initial node to zero and infinity for all other nodes.
Step 2. Select the initial node as the current node and tag other nodes as unvisited.
Step 3. Create a set of unvisited nodes.
Step 4. The distance between the current node and one of the other nodes is calculated and saved. This operation is repeated for the next neighboring node, and in comparison with the previous node a shorter distance is assigned to the current node.
Step 5. Repeat the process until all the nodes are tagged as visited.
Step 6. Do not check nodes that are marked as visited.
Step 7. If a node considered as destination and is marked as visited, or if the smallest distance in the unvisited set is infinity, STOP; else, select the node with the smallest distance in the unvisited set as the new current node and go back to step 4.

Pseudocode 13: Branch and Bound Algorithm

Step 1. A solution (e.g., $X1$) could be found using a heuristic, and its objective function value is stored $V = F(X1)$. If there is no heuristic available, set V to infinity. V is considered as the best solution found and as the maximum acceptable objective function value.
Step 2. A queue of a partial solution is generated, where none of the variables of the problem assigned. Until the queue is empty repeat steps 3-7.
Step 3. Pick a node I from the queue randomly.
Step 4. If the node I includes a solution with better objective function, update V.
Step 5. Else, in order to generate new nodes I_i, branch on I, then:
Step 6. If the objective function for I_i does not improve, skip.
Step 7. Else, store I_i in the queue.

2.3.4. Other Algorithms

Some other solution methods and custom algorithms have been developed in the literature for solving the emergency evacuation optimization problems, such as simulation methods, fuzzy logic, Markov chain, regression trees among others. Pourrahmani et al. (2015) used the fuzzy credibility theory in developing an EA-based algorithm, which was designed to solve the evacuation vehicle routing problem in urban areas. Fuzzy set theory permits the gradual assessment of the membership of elements in a set. The theory involves sets, which consist of elements assigned various degrees of membership. The fuzzy theory allows for easy estimation of an uncertain element in the fuzzy set based on experience, historical information, or expert judgment. Hence, it does not slow down the optimization process using iterative approaches. The algorithm designed considers the fuzziness of evacuation demand and vehicle's available capacity. The main steps of the algorithm are described in **Pseudocode 14**.

Pseudocode 14: Evacuation Simulation Model with Fuzzy Credibility

Step 1. Determine the number of pick-up points.
Step 2. Set the vehicle capacity and the number of available vehicles.
Step 3. Determine the credibility that a vehicle will be filled to capacity if assigned to a pick-up point (credibility-index).
Step 4. Assign a vehicle to pick-up point based on the credibility index.
Step 5. If the vehicle is filled to capacity, STOP; else, go to step 4.

Wang et al. (2015) applied the Markov route selection model for evacuees in quantifying the effects of psychological and physiological factors of a crowd on a large scale evacuation. The proposed Markov-process based evacuation model considered the distribution of a crowd in space and the change in a crowd density with time and used the transition probability formula in estimating the changes in crowd distribution, as well as the effects of the model parameters on randomness. Along with taking into account such factors as road network, type of vehicle used for evacuation, and real-time traffic information, the basic Markov model was modified to incorporate the crowd physiological and psychological factors for pedestrian evacuation. The developed Markov model was also characterized with the "no aftereffect" property. The latter property is based on the fact that the previous state of the model is irrelevant in predicting the future state.

Swamy et al. (2017) developed a dynamic simulation tool, aiming to improve efficiency of the emergency evacuation process. A Sweep Heuristic Algorithm was designed to determine the pick-up locations and assign evacuees to shelters in the event of a hurricane. The simulation tool dispatched a predefined number of buses, generated the stochastic arrival of evacuees, queueing effects at the pick-up locations, and the transportation of evacuees to shelters. The main steps of the emergency evacuation simulation model are described in **Pseudocode 15**, while the main steps of the Sweep Heuristic Algorithm are outlined in **Pseudocode 16**.

Pseudocode 15: Evacuation Simulation Model

Step 1. Identify pickup locations and assign vehicles to shelters.
Step 2. Generate route designs with shelters acting as destinations.
Step 3. Evaluate the performance of the route design using a realistic simulation model.
Step 4. Apply the Sweep Heuristic Algorithm to improve the route design.

Pseudocode 16: Sweep Heuristic Algorithm

t_{ij}= the time taken for a bus to travel link $(i, j) \in E$ in a network $G(N, E)$.
d_i= the rate of arrival of evacuees at a pickup location $I \in N \setminus \{0\}$, 0 indexing the shelter.
C = the capacity of a bus.
rem_cap = the remaining capacity of a bus during an iteration of the heuristic.
Step 1. Locate the nodes and shelter based on geographical coordinates.
Step 2. Choose one node i to start.
Step 3. Set $rem\_cap = C$. Add the link $(0, i)$. If $C \leq d_i * t_{0,i}$, add this link, and close this loop.
Step 4. Else, set $rem\_cap = rem\_cap - d_i * t_{0,i}$. Investigate the next node j in the clockwise direction with respect to the shelter. If $rem\_cap \leq d_j * (t_{i,j} + t_{0,i})$, add the link $(i, 0)$ and proceed to step 3 with $i = j$. Else, add the link (i, j) and update $rem\_cap = rem\_cap - d_j * \left(t_{i,j} + t_{0,i}\right)$. Investigate the next node after j in the clockwise direction with respect to the shelter, and so on until the route is closed.
Step 5. Repeat steps 3 and 4 and terminate, when all the nodes have been added to the graph.

2.4. Summary of Findings and Future Research Extensions

The review of scientific literature, conducted under this project, reveals that the development of efficient solution algorithms, aiming to facilitate emergency evacuation, considering various types of hazards, has received an increasing attention from the scientific community over the last decade. Findings from the state-of-the-art indicate that researchers and transportation agencies are still seeking for new transportation planning models, which will assist State authorities with efficient natural hazard preparedness (assignment of evacuating individuals to evacuation routes and emergency shelters) especially in the areas with vulnerable population groups. Based on the conducted comprehensive literature review, the following findings were revealed to address the research questions posed:

- **<u>Finding 1:</u>** The review of literature reveals that many of the studies focused on modeling disruptive driving conditions (such as emergency evacuation). The major types of hazards considered include natural and man-made hazards, general chaotic condition, hurricane, wildfire, earthquake, flood, aircraft emergency, and tsunami. Other types of hazards, such as nuclear plant radiation, radioactive propagation, terrorist attack, and toxic cloud releases, were considered by some of the studies. A few studies did not consider specific hazards, but proposed the traffic assignment algorithms, which can be generally applied for emergency evacuation.
- **<u>Finding 2:</u>** The literature review indicates that many studies modeled the effects of roadway capacity and travel demand on emergency evacuation. Some studies underlined the effects of number of lanes and number of evacuation routes in the network on the efficiency of the evacuation process. Other studies suggested that during emergency evacuation, there is an increase in the travel demand (as population aims to evacuate the area, expecting the greatest impact); thus, those studies focused on maximizing the travel demand during emergency evacuation, considering the capacity of the evacuation routes in the network.
- **<u>Finding 3:</u>** The number of lanes, road length, road alignment, shoulder width, surface condition of the roadway, median width, lane width, and road class were found to be the major evacuation route characteristics discussed in literature that affect the emergency evacuation process. A significant number of studies highlighted the effects of number of lanes (which

determines the evacuation route capacity) and road length (evacuation distance) on the evacuation time.

➢ **Finding 4:** The review of scientific literature indicates that many studies have considered the shelter capacity as an important factor in emergency evacuation planning. A significant number of studies focused on maximization of the shelter coverage, while some studies aimed to minimize the shelter overload capacity in their objectives. Findings suggest that achieving the aforementioned objectives would increase the shelter capacity and facilitate the emergency evacuation process.

➢ **Finding 5:** Many of the reviewed studies underlined the effects of shelter location on emergency evacuation. A substantial portion of studies proposed the mathematical models, aiming to minimize the evacuation distance (the distance from the hazard location to a shelter). The review of literature suggests that minimizing the evacuation distance would reduce the evacuation time and allow more evacuees to reach the shelters on time (before the hazard strikes). The latter increasing the efficiency of emergency evacuation.

➢ **Finding 6:** Age, driving experience, gender, health condition, reaction time, residency, education, income, marital status, race, and physiological condition were found to be the key driver characteristics, discussed in the reviewed studies that affect the driving ability during emergency evacuation. Although the effects of individual driver characteristics on emergency evacuation were not explicitly modeled in some studies (e.g., using optimization or simulation models), the correlation between the driver characteristics and the driving performance during emergency evacuation was found by analytical methods.

➢ **Finding 7:** Some studies discussed the effects of some other factors, which might influence emergency evacuation and decision of individuals to evacuate. The majority of studies highlighted the effects of factors, such as evacuation time, number of vehicles available for passenger pick-up, traffic flow, evacuation demand, evacuation cost, and route disruption on the efficiency of the evacuation process. Also, some studies suggested that shelter type (such as special needs shelter, pet-friendly shelter), presence of children, evacuation risk, congestion, vehicle type, hazard type, household size, route disruption, population density, hazard awareness, and weather could affect the decision of evacuees to evacuate.

➢ **Finding 8:** The review of studies revealed various types of mathematical models that have been used in the state-of-the-art for the emergency evacuation optimization problems. Most of the studies used mixed integer programming and linear programming models. Furthermore, a number of studies used mixed integer nonlinear programming models, nonlinear programming models, integer programming models, and mixed integer quadratic programming models. Some studies proposed other solution approaches for the emergency evacuation problems without using mathematical models.

➢ **Finding 9:** A detailed review of the collected studies indicates that most of the proposed mathematical models aimed to minimize the total evacuation time. A large number of studies focused on maximizing the total number of evacuees. A significant number of models aimed to minimize the total evacuation distance and the total cost, associated with emergency evacuation.

➢ **Finding 10:** The heuristic and metaheuristic algorithms were the key algorithm types adopted for solving the emergency evacuation optimization problems based the conducted literature review. Some of the heuristic algorithms proposed include the user-equilibrium traffic assignment algorithms, sweep heuristic, and the problem specific local search heuristics, designed for the emergency evacuation optimization problems. A significant number of studies also used metaheuristics, some of which include Tabu Search, Simulated Annealing, Ant Colony Optimization, Artificial Immune System, Greedy Randomized Adaptive Search Procedure, and Evolutionary Algorithms. Furthermore, a few studies also used the exact optimization methods, such as Branch and Bound Algorithm, Djikstra Algorithm, and CPLEX. A wide use of heuristics and metaheuristics is based on the fact that those solution algorithms can solve complex optimization problems and achieve good quality solutions within an acceptable computational time, while the exact optimization methods cannot solve complex problems to optimality within an acceptable computational time.

➢ **Finding 11:** A total of five research methods have been used for addressing various emergency evacuation problems, including the following: 1) theoretical method; 2) analytical method; 3) survey method; 4) literature review method; and 5) modeling method. A significant number of the reviewed studies adopted the modeling method (≈92.3% of studies), followed by the theoretical method (≈3.4% of studies). Only a very few studies adopted the analytical, survey, and literature review methods (a total of 5 studies).

➢ **Finding 12:** Some of the major challenges, associated with the emergency evacuation planning and identified from the literature review, include the following: 1) forecasting evacuation demand; 2) shelter location and destination choice of evacuees; 3) flexible evacuation route allocation; 4) modeling the effects of driver, roadway and traffic characteristics; 5) overload capacity of shelters; and 6) evacuation route risks.

The following gaps were identified from a detailed review of the collected studies on the solution methodologies that have been proposed for emergency evacuation, as well as various driver, roadway, and other attributes that could affect the emergency evacuation process:

1) The majority of the reviewed studies highlight the drawbacks of the proposed solution methodologies based on the limited number of factors captured in the models. The future research should attempt to incorporate some other important factors that affect emergency evacuation (such as traffic attributes, hazard awareness, weather, household size, shelter type, and others) to improve the accuracy of the presented mathematical models.

2) The literature review suggests that majority of the solution methodologies, proposed by the studies, do not consider the behavior of evacuees. The future research should focus on modeling the behavior of evacuees (such as driver aggressiveness) during the evacuation process as it may affect traffic flow, travel speed, route density, etc.

3) Generally, the emergency evacuation process is subject to uncertainty, considering the fact that a lot of individuals evacuate in unorganized manner. The nature of the uncertainties that can arise during the emergency situations may significantly impact the efficiency of the evacuation process. Future work should account for uncertainties in the models, when considering emergency evacuations, and also implement the models on a large-scale evacuation network (as the impact of uncertainties is expected to be more significant for the large-scale evacuation networks).

4) Approximately 7.7% of the reviewed studies highlight limitations of the proposed solution methodologies based on the fact that the evacuee choice of destination and shelter locations were not considered. Many studies suggested that in the event of a hazard some of the evacuees do not use the assigned shelter but travel to other destinations (e.g., some evacuees travel to the alternative destinations with friends and families). The future research should

attempt to obtain more accurate data about shelter locations and other destination choices to validate the proposed methodologies.

5) The literature review indicates that the solution approaches proposed by certain studies are specific to the hazard type and/or the location. There is a need to assess performance of the presented mathematical models and solution algorithms using different evacuation scenarios. A detailed analysis should be conducted to assess changes in the results from applying the developed solution approaches for different types of hazards and in various geographical locations.

6) Certain studies propose the solution algorithms for the traffic assignment during evacuation, which do not capture the effects of flexible evacuation route allocation on emergency evacuation (e.g., due to traffic congestion or crashes the evacuees can shift to alternative routes). Future research should consider alternative approaches, which permit flexible evacuation route allocation, to improve the efficiency of the evacuation process.

7) About 5.1% of the reviewed studies highlight the limitations of the presented solution algorithms. The future research should focus on the development of more advanced solution algorithms, which address the existing drawbacks.

8) Approximately 3.4% of the reviewed studies highlight limitations of the proposed solution methodologies due to the outdated version of the Geographical Information Systems (GIS) datasets used. The future research should attempt to obtain an updated version of the GIS datasets to validate the proposed methodology or model.

2.5. Literature Review Conclusions

The literature review, conducted as a part of this project, focused on analysis of the existing mathematical models and solution algorithms, which have been developed in order to facilitate the emergency evacuation planning. It was found that the emergency evacuation planning receives an increasing attention from the research community. A large number of different hazards have been considered in the reviewed studies, including natural and man-made hazards, hurricane, wildfire, tsunami, flood, nuclear plant radiation, radioactive propagation, terrorist attacks, and others. Moreover, an increasing amount of studies started considering certain important factors, including driver characteristics (such as age, driving experience, gender, reaction time, health condition, etc.), evacuation route characteristics (such as number of lanes, lane width, median width, surface condition, etc.), shelter location, shelter capacity, evacuation demand, and others, on the efficiency of the evacuation process. A substantial amount of the reviewed studies highlighted the effects of age, driving experience, gender, reaction time, and health condition on the driving performance of individuals under emergency evacuation, while the number of lanes was the most critical roadway geometric feature, affecting the efficiency of the evacuation process. Several studies also accounted for the effects of some other factors, such as evacuation time, shelter type, vehicle type, traffic flow, evacuation cost, and the evacuation route disruptions.

Results of the conducted literature review show that the majority of the reviewed studies focused on modeling disruptive driving conditions and adopted the modeling research method. A large number of mathematical models were presented for different emergency evacuation optimization problems, including mixed integer programming models, linear programming models, mixed integer nonlinear programming models, nonlinear programming models, and other models. Different types of assignments were considered in the proposed mathematical models, including the assignment of evacuees to evacuation routes, the assignment of evacuees to emergency shelters, the assignment of vehicles to pick-up locations, the assignment of evacuees to medical centers, and others. Certain studies also modeled allocation of additional resources, such as ambulances, police vehicles, fire trucks, relief materials, aiming to improve the efficiency of the evacuation process and preserve safety of human lives. The presented mathematical models captured a wide range of objectives (e.g., minimization of the total travel time of evacuees along the evacuation routes; minimization of the evacuation distance; maximization of the number of evacuees; maximization of the shelter coverage; minimization of network clearance time, minimization of the evacuation cost, etc.). Certain studies proposed multi-objective mathematical models. Due to complexity of the considered emergency evacuation optimization problems, the reviewed studies primarily focused on development of the problem specific heuristic and metaheuristic algorithms (e.g., Evolutionary Algorithms, Ant Colony Optimization, Simulated Annealing, Tabu Search, etc.). Several studies used the exact optimization algorithms, including Branch-and-Bound Algorithm, CPELX, and Dijkstra Algorithm.

The gaps in the state-of-the-art were identified based on the critical analysis of findings from the conducted literature review. The work, conducted in this study, could be extended in several directions. First, a more comprehensive literature survey may be performed to collect additional studies relevant to the research questions posed. Second, the literature search could be expanded by relaxing some of the delimitations (e.g., include the conference papers and articles from on-line transportation and hazard journals, include relevant technical reports to capture more information about solution methodologies being used, as well as the practical effects of other factors on emergency evacuation). Third, additional scientific publishers can be considered (e.g., Transportation Research Record – www.trrjournalonline.trb.org, Emerald Insight – www.emeraldinsight.com; SAGE – journals.sagepub.com; Taylor and Francis – taylorandfrancis.com; and others). The latter three extensions would allow a more detailed evaluation of the current published work on the natural hazard preparedness and the solution approaches, which have been used for solving various emergency evacuation optimization problems.

3. PROBLEM DESCRIPTION

This section of the report presents a detailed description of the emergency evacuation planning optimization problem and the main assumptions, which were adopted throughout this study. In case of approaching natural hazards, the population, inhabiting areas that would be affected by the hazards, is advised to evacuate. When the potential impact is expected to be devastating, State authorities announce a mandatory evacuation. Let $I = \{1, \dots, n\}$ denote a set of evacuating individuals. Throughout the evacuation process, some routes are designated as evacuation routes. Denote $R = \{1, \dots, o\}$ as a set of evacuation routes. Using the dedicated evacuation routes, evacuees can travel to one of the available emergency shelters $S = \{1, \dots, u\}$. A set of the available emergency shelters for the considered metropolitan area is illustrated in Figure 13. Each evacuation route has a certain capacity during a given time period, and individuals are instructed to evacuate the emergency area during a certain time period (when the assigned emergency evacuation route has a sufficient capacity). Let $P = \{1, \dots, m\}$ be a set of time periods for the considered evacuation planning horizon. Denote $C^1_{pr}, p \in P, r \in R$ as the capacity of route r during time period p (vehicles).

In this study, the evacuation route capacity will be set, taking into consideration the important features of emergency evacuation. Specifically, the nominal capacity of a given route segment may be higher under emergency evacuation as compared to the normal driving conditions due to the fact that the route shoulders can be used as additional lanes to accommodate evacuees. In the meantime, it will be necessary to account for the additional demand due to the fact that some individuals will be willing to evacuate for extra safety precaution, even if they were not advised to do so (the latter phenomenon is generally referred to as "*shadow evacuation*"). The additional demand will be assessed based on communication with the appropriate representatives of States that often experience emergency evacuation. Similar to the evacuation routes, the available emergency shelters also have a limited capacity. Let $C^2_s, s \in S$ be the capacity of shelter s (evacuees). Furthermore, this study takes into consideration other passengers, who will be traveling with a given individual to the assigned emergency shelter (e.g., the whole family is trying to evacuate in one vehicle). Denote $q_i, i \in I$ as the total number of individuals, traveling in the vehicle, which is driven by individual i (evacuees).

The available emergency shelters can be classified in two categories, including: a) general type shelters; and b) special needs shelters. Certain vulnerable population groups (e.g., individuals with disabilities) should be assigned to the special needs shelters to ensure that these individuals will have the adequate accommodations until the given metropolitan area will be able to recuperate from the natural hazard effects and return to the normal or close to normal operating conditions. However, other evacuees (i.e., the ones, who do not require special accommodations) can be assigned to both general type and special needs shelters. Based on the literature review, it was found that the driving ability of individuals under normal and disruptive driving conditions (e.g., emergency evacuation) can be affected with a wide range of factors, including socio-demographic characteristics of drivers (e.g., age, gender, racial group, driving experience, marital status, health condition, etc.), evacuation route characteristics (number of travel lanes), driving conditions (time of the day, day of the week), traffic characteristics (space headway, time headway), and others. This study accounts for the potential effects of the aforementioned factors on the driving ability of individuals under emergency evacuation (which will be further discussed in the following section of the report). The objective of the emergency evacuation planning optimization problem studied herein is to assign evacuees to the available evacuation routes and emergency shelters, aiming to minimize the total travel time of the individuals, evacuating from a given metropolitan area that expects an approaching natural hazard.

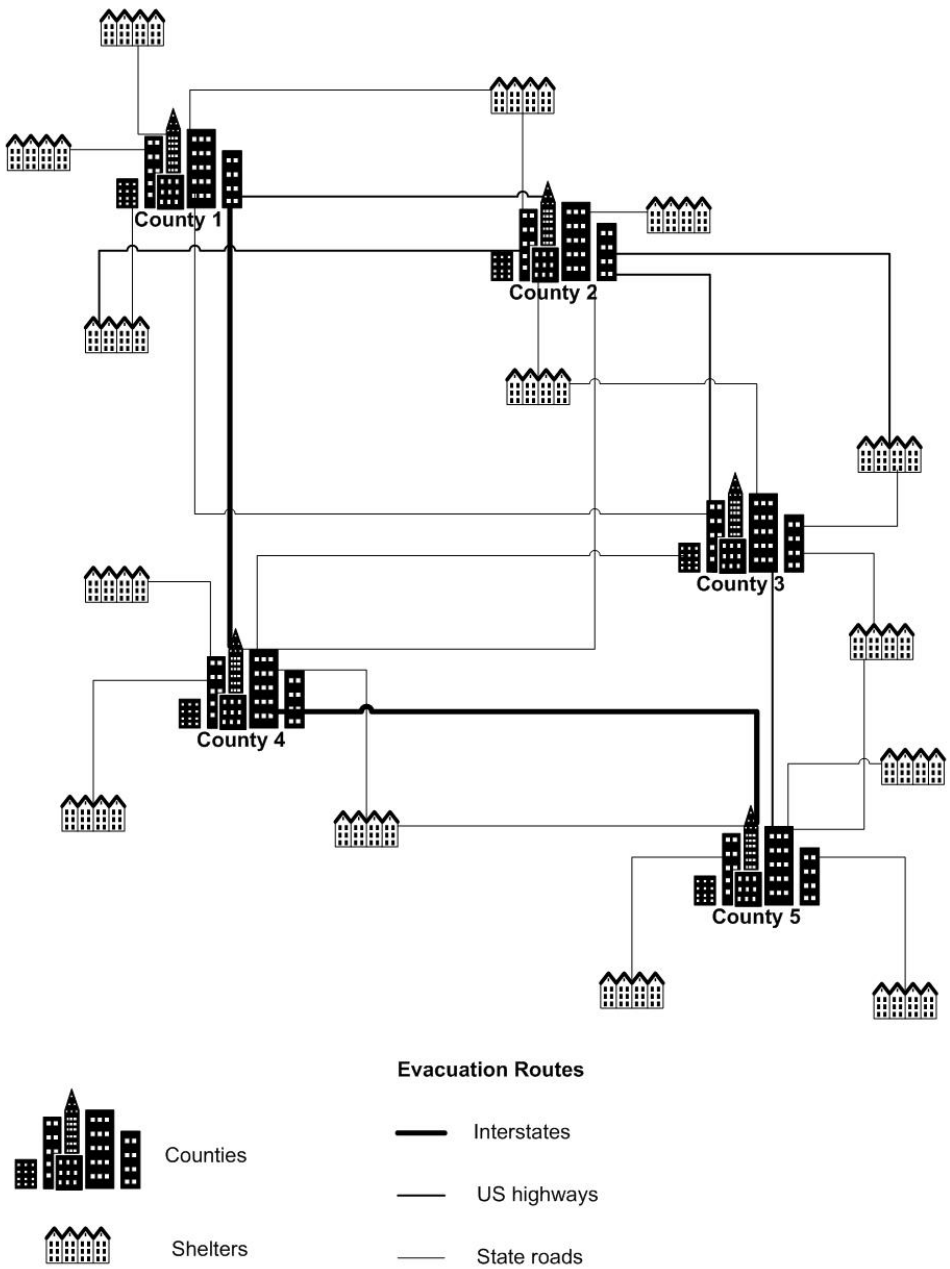

Figure 13 Emergency evacuation planning problem.

4. MATHEMATICAL MODEL DEVELOPMENT

The emergency evacuation planning optimization problem (**EEPOP**), described in the previous section of the report, is formulated as a mixed integer programming model. Table 5 presents the main components of the **EEPOP** mathematical model and their description.

Table 5 Nomenclature adopted for the **EEPOP** mathematical model.

Model Component		Description
Type	**Nomenclature**	
Sets	$I = \{1, \dots, n\}$	set of evacuees (evacuees)
	$P = \{1, \dots, m\}$	set of time periods (time periods)
	$R = \{1, \dots, o\}$	set of available evacuation routes (evacuation routes)
	$S = \{1, \dots, u\}$	set of available shelters (shelters)
	$J_i = \{1, \dots, a_i\}, i \in I$	set of socio-demographic characteristics for individual i (socio-demographic characteristics)
	$K_r = \{1, \dots, b_r\}, r \in R$	set of characteristics for route r (routes characteristics)
	$D_{pr} = \{1, \dots, c_{pr}\}$, $p \in P, r \in R$	set of driving conditions on route r during time period p (driving conditions)
	$F_{pr} = \{1, \dots, h_{pr}\}$, $p \in P, r \in R$	set of traffic characteristics on route r during time period p (traffic characteristics)
Decision Variables	$\boldsymbol{x}_{ipr}, i \in I, p \in P, r \in R$	=1 if individual i is assigned to evacuate via route r during time period p (=0 otherwise)
	$\boldsymbol{z}_{is}, i \in I, s \in S$	=1 if individual i is assigned to emergency shelter s (=0 otherwise)
Auxiliary Variables	$\boldsymbol{t}_{ir}, i \in I, r \in R$	total evacuation time required by individual i assigned to route r (hours)
Parameters	$y_{is}, i \in I, s \in S$	=1 if individual i can be assigned to shelter s (=0 otherwise)
	$w_{rs}, i \in I, s \in S$	=1 if evacuation route r leads to emergency shelter s (=0 otherwise)
	$C^1_{pr}, p \in P, r \in R$	capacity of route r during time period p (vehicles)
	$C^2_s, s \in S$	capacity of shelter s (evacuees)
	$q_i, i \in I$	total number of individuals traveling in the vehicle, driven by individual i (evacuees)

Emergency Evacuation Planning Optimization Problem (EEPOP)

$$min \sum_{i \in I} \sum_{r \in R} q_i \boldsymbol{t}_{ir} \tag{1}$$

Subject to:

$$\sum_{p \in P} \sum_{r \in R} \boldsymbol{x}_{ipr} = 1 \ \forall i \in I \tag{2}$$

$$\sum_{s \in S} \boldsymbol{z}_{is} = 1 \ \forall i \in I \tag{3}$$

$$\boldsymbol{z}_{is} \le y_{is} \ \forall i \in I, s \in S \tag{4}$$

$$\boldsymbol{x}_{ipr} \le \sum_{s \in S} w_{rs} \boldsymbol{z}_{is} \ \ \forall i \in I, p \in P, r \in R \tag{5}$$

$$\sum_{i \in I} \boldsymbol{x}_{ipr} \leq C_{pr}^{1} \; \forall p \in P, r \in R \tag{6}$$
$$\sum_{i \in I} q_i \boldsymbol{z}_{is} \leq C_{s}^{2} \; \forall s \in S \tag{7}$$
$$\boldsymbol{t}_{ir} = f\left(J_i, K_r, D_{pr}, F_{pr}, \boldsymbol{x}_{ipr}\right) \; \forall i \in I, p \in P, r \in R \tag{8}$$
$$\boldsymbol{x}_{ipr}, \boldsymbol{z}_{is}, y_{is}, w_{rs} \in \{0,1\} \; \forall i \in I, p \in P, r \in R, s \in S \tag{9}$$
$$C_{pr}^{1}, C_{s}^{2}, q_i \in N \; \forall i \in I, p \in P, r \in R, s \in S \tag{10}$$
$$\boldsymbol{t}_{ir} \in R^{+} \; \forall i \in I, r \in R \tag{11}$$

The objective function (1) of the **EEPOP** mathematical model aims to minimize the total travel time of the individuals, evacuating from a given metropolitan area that expects a devastating natural hazard. Constraint set (2) guarantees that each individual is assigned to one of the available evacuation routes during one of the time periods in the considered planning horizon. Constraint set (3) ensures that each individual will be assigned to only one of the available emergency shelters. Constraint set (4) guarantees that each individual will be assigned to the specific shelter based on the individual needs (e.g., vulnerable population groups may require additional accommodations, and, therefore, should be assigned to special needs shelters; on the other hand, general population groups can be assigned to either general shelters or special needs shelters). Constraint set (5) indicates that the selected evacuation route should lead to the emergency shelter, assigned for a given individual. Constraint set (6) guarantees that the total number of vehicles, traveling along each evacuation route, will not exceed the evacuation route capacity during a given time period. Constraint set (7) ensures that the total number of evacuees, assigned to a given emergency shelter, will not exceed the shelter capacity. Constraint set (7) includes term $q_i, i \in I$ to account for other passengers, who will be traveling with a given individual to the assigned emergency shelter. As discussed earlier, in certain instances, the whole family will be evacuating the emergency area in a one vehicle. Constraint set (8) estimates the total travel time of each individual (and other passengers carpooling with that individual) along the selected evacuation route based on the driver socio-demographic characteristics (J_i, $i \in I$), evacuation route characteristics ($K_r, r \in R$), driving conditions ($D_{pr}, p \in P, r \in R$), and traffic characteristics ($F_{pr}, p \in P, r \in R$). Constraint sets (9)-(11) define the nature of parameters and variables of the **EEPOP** mathematical model.

The nature of function for estimating the travel time of individuals (i.e., $f\left(J_i, K_r, D_{pr}, F_{pr}, \boldsymbol{x}_{ipr}\right)$) will determine complexity of the **EEPOP** mathematical model (e.g., mixed integer linear programming model vs. mixed integer nonlinear programming model). The travel time function will be designed based on the study, which was previously conducted by Dulebenets et al. (2017). Specifically, Dulebenets et al. (2017) performed a comprehensive pilot study, where 115 participants of different age groups, gender, driving experience, racial groups, education, income level, marital status, employment status (e.g., students, part-time employees, full-time employees, retirees), and health conditions were requested to drive the Drive Safety driving simulator (DriveSafety, 2018), illustrated in Figure 14. Different emergency evacuation scenarios were developed by changing the evacuation route characteristics (e.g., two-lane evacuation route vs. three-lane evacuation route), and participants were requested to imagine a real-life situation, when they were required to evacuate as a result of approaching natural hazard.

Figure 14 The Drive Safety driving simulator used in the pilot study.

Based on the collected data, a number of statistical models were developed to estimate various driving performance indicators, including the total travel time required to evacuate the virtual emergency area, which will be adopted under this project. A large number of different factors were considered, when estimating various driving performance indicators, including driver characteristics (e.g., age, gender, racial group, driving experience, marital status, health condition, etc.), evacuation route characteristics (number of travel lanes), driving conditions (time of the day, day of the week), and traffic characteristics (space headway, time headway). A set of candidate statistical models (including a large variety of linear and polynomial regression models) were evaluated for the travel time response variable, and the linear regression model demonstrated the best fit (as it yielded the highest log-likelihood [LL] value). Detailed information for the coefficients of statistically significant predictors (i.e., predictors with p-value $\leq$ 0.0500), retrieved from the final travel time regression model, is presented in Table 6 (Dulebenets et al., 2017).

Table 6 Coefficient information for predictors of the final travel time regression model LN1.

	Coefficient	S.E.	*t*-stat	*p*-value
Intercept	11.9658	0.5605	21.3473	< 0.0001
Age	0.0107	0.0038	2.8175	0.0053
Driving frequency (Dr_Freq)	-0.0649	0.0260	-2.4916	0.0136
Distance driven per week ($Dist\_Dr$)	-0.0286	0.0123	-2.3240	0.0212
Difficulty evacuating ($Diff\_Ev$)	-0.4187	0.2019	-2.0732	0.0395
Ability to make quick decisions (Ab_QDec)	-0.2555	0.0903	-2.8279	0.0052
Driving simulator experience (Sim_Exp)	-0.0625	0.0119	-5.2682	< 0.0001
Average space headway (Avg_SpHead)	0.0015	0.0008	1.9069	0.0480

Notes: S.E. – standard error; *t*-stat – *t*-statistic.

*Final model LL = -244.0834; Final model *p*-value < 0.0001.

Based on the results from the conducted regression analysis, the total travel time of evacuees was found to be significantly influenced with age (greater travel time was typically observed for aging individuals), driving frequency (greater travel time was typically observed for individuals, who drive less frequently), distance driven per week (greater travel time was typically observed for individuals, who do not drive far), difficulties evacuating in the past (greater travel time was typically observed for individuals, who previously experienced difficulties during emergency evacuation), the self-reported ability of drivers to make quick decisions (greater travel time was typically observed for individuals with lower rating for the self-reported ability to make quick decisions), driving simulator experience (greater travel time was typically observed for individuals, who have less experience driving the simulator), and average space headway (greater travel time was typically observed for individuals, who prefer to keep greater average space headway). Let $l_r, r \in R$ be the length of emergency evacuation route r (measured in miles). Taking into consideration findings from the previously conducted statistical analysis, the original **EEPOP** mathematical model can be reformulated as a mixed integer linear programming model (which will be further referred to as **EEPOP-L**) as follows:

Emergency Evacuation Planning Optimization Problem with Linear Travel Time Function (EEPOP-L)

$$min \sum_{i \in I} \sum_{r \in R} q_i \boldsymbol{t}_{ir} \tag{12}$$

Subject to:

Constraint sets (2)-(7), (9)-(11)

$$\boldsymbol{t}_{ir} = \sum_{p \in P} [(11.9658 + 0.0107 \cdot Age_i - 0.0649 \cdot Dr\_Freq_i - 0.0286 \cdot Dist\_Dr_i - 0.4187 \cdot Diff\_Ev_i \\ -0.2555 \cdot Ab\_QDec_i - 0.0625 \cdot Sim\_Exp_i + 0.0015 \cdot Avg\_SpHead_i) \cdot (\frac{l_r}{10}) \cdot \boldsymbol{x}_{ipr}] \ \forall i \in I, r \in R \tag{13}$$

Similar to the **EEPOP** mathematical model, the objective function (12) for the **EEPOP-L** mathematical model aims to minimize the total travel time of the individuals, evacuating from a given metropolitan area that expects a devastating natural hazard. Constraint set (13) estimates the total travel time of each individual (and other passengers carpooling with that individual) along the selected evacuation route based on the major factors, which could influence the emergency evacuation process, including age, driving frequency, distance driven per week, difficulty evacuating, ability to make quick decisions, simulator experience, and average space headway. Note that length of emergency evacuation route r ($l_r, r \in R$) is used in constraint set (13), as the travel time regression model was developed for a 10-mile evacuation route (Dulebenets et al., 2017). This study assumes that the travel time of evacuees will be increasing proportionally to the evacuation route length.

5. SOLUTION ALGORITHM DEVELOPMENT

A large number of studies, reviewed under this project (see section 2 of the report), have adopted various solution approaches (such as heuristics, metaheuristics, and exact optimization approaches) to solve different emergency evacuation planning optimization problems. Since the travel time function $f\left(J_i, K_r, D_{pr}, F_{pr}, \boldsymbol{x}_{ipr}\right)$ is linear, the **EEPOP-L** mathematical model becomes a mixed integer linear programming model, which can be solved to the global optimality using the exact optimization methods. Commercial mixed integer linear programming optimization solver packages (e.g., CPLEX, Gurobi, FICO-Xpress, MOSEK, and others) can solve this type of optimization problems. However, finding the optimal solution, given the number of decision variables and constraints, may require a significantly large computational time for the realistic size problem instances (e.g., when 1,000,000 individuals are expected to evacuate from the area, expecting a devastating natural hazard). Therefore, along with the exact optimization approach, some heuristic algorithms will be developed in this project as well. The heuristic algorithms are expected to obtain good quality solutions and significantly reduce the computational time, required to solve the **EEPOP-L** mathematical model. The latter aspect can be considered as critical, taking into account that all emergency evacuation decisions have to be made in a timely manner in case of approaching devastating natural hazard. The following sections of the report describe the exact optimization approach and a set of heuristic algorithms, which were developed to solve the **EEPOP-L** mathematical model.

5.1. Exact Optimization Approach

The exact optimization algorithms are the algorithms capable to solve the optimization problem to the global optimality (i.e., obtain the best possible solution to a given problem of interest). Since the **EEPOP-L** mathematical model is a mixed integer linear programming model, CPLEX will be adopted as the exact solution approach. CPLEX was developed in 1988 by Robert E. Bixby (Lima, 2010). CPLEX is able to solve different types of mathematical models, including linear programming models, integer programming models, mixed integer programming models, quadratic programming models, mixed integer quadratic programming models, quadratic constrained programming models, and mixed integer quadratic constrained programming models (Lima, 2010). CPLEX is based on the Brach-and-Cut (B&C) algorithm, which is an extension of the Branch-and-Bound (B&B) algorithm. The idea behind the Branch-and-Bound algorithm is to solve a sequence of linear relaxation problems (i.e., where the integrality constraints are relaxed) and provide certain bounds. However, the B&B algorithm generally does not perform well for the large size problem instances, as the number of iterations grows exponentially with the number of variables in the mathematical model.

Unlike the B&B algorithm, the B&C algorithm applies a pre-processing step and additional cutting planes in order to facilitate the search process (Lima, 2010). Throughout the pre-processing step, the following techniques are used: (1) identification of the infeasibility; (2) identification of the redundancy; (3) improvement of the bounds; and (4) rounding (primarily for the mixed integer programming models). Along with the aforementioned techniques, CPLEX also deploys the probing techniques at the pre-processing stage, which allow fixing binary variable to either 0 or 1 and check the logical implications (Lima, 2010). Along with the pre-processing step, CPLEX applies a set of cutting planes, aiming to obtain a tighter linear relaxation of the mixed integer programming problem. The following cutting planes have been deployed within CPLEX: Knapsack covers, flow covers, cliques, implied bounds, Gomory mixed integer cuts, mixed integer rounding cuts, disjunctive cuts, and others. The number of cutting plane types used depends on the version of CPLEX. Also, throughout the search process, CPLEX applies a set of heuristics. The purpose of using heuristics consists in the fact that they allow exploring additional domains of the search space and identify good solutions fairly quickly. Two types of heuristics are used within CPLEX (Lima, 2010): (a) node heuristics; and (b) neighborhood exploration heuristics. The node heuristics aim to fix a set of integer infeasible variables, strengthen bounds, and solve the linear relaxation. The neighborhood exploration heuristics aim to explore a given neighborhood for superior solutions. The neighborhood exploration heuristics include Local Branching, Relaxation Induced Neighborhood Search, Guided Dives, and Evolutionary Algorithms for solution polishing.

Throughout this project, CPLEX will be executed via the General Algebraic Modeling System (GAMS). GAMS includes a library of different optimization solvers, which can be applied for different types of mathematical models, such as: (1) LP – linear programming; (2) QCP – quadratic constraint programming; (3) NLP – nonlinear programming; (4) DNLP – nonlinear programming with discontinuous derivatives; (5) MIP – mixed integer programming; (6) MIQCP – mixed integer quadratic constraint programming; and others. GAMS allows compact representation of large and complex models (GAMS, 2018). Furthermore, the user is able to easily make changes in the mathematical model within the GAMS environment. GAMS relies on fairly simple statements and algebraic relationships. One of the major advantages of using GAMS consists in the fact that it does not require for the user to select any specific optimization solver. The user is required to specify only the mathematical model type, and GAMS will select and the appropriate optimization solver for that problem. CPLEX is typically deployed by GAMS for solving large scale MIP mathematical models.

5.2. Heuristic Approaches

A set of heuristic algorithms were also developed along with the exact optimization approach. The need for developing heuristic algorithms can be explained by the fact that the exact optimization algorithm (i.e., CPLEX) may require a significant computational time to solve the **EEPOP-L** mathematical model for the large size problem instances (e.g., 1,000,000 evacuees; 20 evacuation routes; 4,000 emergency shelters). Although the heuristic algorithms may not be able solve the **EEPOP-L** mathematical model to the global optimality, they should be able to obtain the good quality solutions to the **EEPOP-L** mathematical model within a reasonable computational time. The computational time for solving the **EEPOP-L** mathematical model is critical from the practical standpoint, as State authorities generally have a very limited time to organize the evacuation process (instruct evacuees to use a specific evacuation route and travel to specific emergency shelters). A total of four heuristic algorithms were developed under this study, including the following: (1) the Most Urgent Evacuee First heuristic; (2) the Most Urgent Evacuee Last heuristic; (3) the Most Urgent Evacuee Group First heuristic; and (4) the Most Urgent Evacuee Group Last heuristic. All the proposed heuristic algorithms are described in the following sections of the report. Note that the term “the most urgent evacuee” was applied to the evacuee, who required the greatest time to travel from the emergency area to the nearest available emergency shelter (e.g., individuals with disabilities, aging adults, or other individuals, belonging to the vulnerable population groups, which require greater evacuation time).

5.2.1. The Most Urgent Evacuee First heuristic

The Most Urgent Evacuee First (MUEF) heuristic assumes that the individuals, who require the greatest time to travel from the emergency area to the nearest available emergency shelter, should receive a priority and evacuate the emergency area first. The main steps of the MUEF heuristic are outlined in **Algorithm 1**.

Algorithm 1. The Most Urgent Evacuee First (MUEF) heuristic

Step 1: Assign priorities to evacuees.
Step 2: Sort evacuees based on their priorities and initialize set E.
Step 3: Determine the closest available shelter s.
Step 4: Determine the shortest evacuation route r leading to shelter s, which has the available capacity during time period p.
Step 5: Assign evacuee e with the highest priority to route r, leading to shelter s, during time period p.
Step 6: Update set E: $E = E - \{e\}$. Update capacity of route r during time period p: $C_{pr}^1 = C_{pr}^1 - 1$. Update capacity of shelter s: $C_s^2 = C_s^2 - q_e$.
Step 7: Is set E empty? If yes, STOP; else, go to step 3.

In step 1, the MUEF heuristic assigns priorities to the evacuees, where higher priorities will have those individuals, who require the greatest time to travel from the emergency area to the nearest available emergency shelter. Note that the priority will be assigned to each evacuee, considering not only the travel time required to evacuate the emergency area, but also the number of other individuals carpooling with that individual (in order to account for the travel time of all individuals in a given vehicle) as follows: $priority_e = min_{r \in R}(q_e \boldsymbol{t}_{er})$, where $priority_e$ – is the priority of evacuee e. In step 2, the evacuees are sorted based on their priorities in the descending order. Set E is initialized for the evacuees, sorted based on their priorities to evacuate the emergency area. In step 3, the closest available shelter is identified, considering the shelter requirements of the evacuees (certain evacuees may have to be assigned to the special needs shelters). In step 4, the MUEF heuristic determines the shortest route, which leads to the closest available shelter and has the available capacity for a given time period. In step 5, the evacuee with the highest priority (i.e., the most urgent evacuee) is assigned to travel via the evacuation route, leading to the closest available shelter, during a given time period. If the shortest route does not have enough capacity at the given time period, the evacuee will be assigned to evacuate the emergency area during the next time period. In step 6, the MUEF heuristic updates the set of evacuees sorted based on their priorities, capacities of the evacuation routes, and capacities of the emergency shelters. In step 7, the MUEF heuristic checks whether all evacuees have been assigned to travel to one of the available emergency shelters along one of the evacuation routes during a certain time period (i.e., either set E is empty or not). If all evacuees have been assigned, the MUEF heuristic is terminated; otherwise, the MUEF heuristic will go to step 3 and will start searching for the closest available shelter for the next evacuee in the priority list.

5.2.2. The Most Urgent Evacuee Last heuristic

The Most Urgent Evacuee Last (MUEL) heuristic assumes that the individuals, who require the least time to travel from the emergency area to the nearest available emergency shelter, should receive a priority and evacuate the emergency area first. The main steps of the MUEL heuristic are the same as the main steps of the MUEF heuristic. The only difference between the MUEL and MUEF heuristic algorithms consists in the priority assignment procedure. Specifically, in step 1, the MUEL heuristic assigns priorities to the evacuees, where higher priorities will have those individuals, who require the least time to travel from the emergency area to the nearest available emergency shelter. Note that the MUEL heuristic may cause the infeasibility, when assigning evacuees to the available emergency shelters. Specifically, the individuals, who do not require special accommodations, can be assigned to the special needs shelters, and the remaining capacity of the special needs shelters may not be sufficient for all individuals, who require special accommodations. In order to avoid the latter shortcoming, the MUEL heuristic will re-assign the individuals, who do not require special accommodations, to the general type shelters in order to create a sufficient capacity of the special needs shelters for all individuals, who require special accommodations.

5.2.3. The Most Urgent Evacuee Group First heuristic

Similar to the MUEF heuristic, the Most Urgent Evacuee Group First (MUEGF) heuristic assumes that the individuals, who require the greatest time to travel from the emergency area to the nearest available emergency shelter, should receive a priority and evacuate the emergency area first. However, unlike the MUEF heuristic, the MUEGF heuristic does not assign evacuees one by one to the emergency shelters, evacuation routes, and time periods. The MUEGF heuristic groups the evacuees based on the total travel time, required to evacuate the emergency area, and assigns the group of evacuees to travel to one of the available emergency shelters along one of the evacuation routes during a certain time period. Denote $G = \{1, \dots, f\}$ as a set of evacuee groups. Let $\widetilde{\boldsymbol{x}}_{ig}, i \in I, g \in G$ be the evacuee to group decision variable (=1 if individual i is assigned to group of evacuees g; =0 otherwise). The main steps of the MUEGF heuristic are outlined in **Algorithm 2**.

Algorithm 2. The Most Urgent Evacuee Group First (MUEGF) heuristic

Step 1: Assign priorities to evacuees.
Step 2: Sort evacuees based on their priorities.
Step 3: Group the evacuees, sorted based on their priorities, and initialize set G.
Step 4: Determine the closest available shelter s.
Step 5: Determine the shortest evacuation route r leading to shelter s, which has the available capacity during time period p.
Step 6: Assign group of evacuees g with the highest priority to route r, leading to shelter s, during time period p.
Step 7: Update set G: $G = G - \{g\}$. Update capacity of route r during time period p: $C_{pr}^1 = C_{pr}^1 - \sum_{i \in I} \widetilde{\boldsymbol{x}}_{ig}$. Update capacity of shelter s: $C_s^2 = C_s^2 - \sum_{i \in I} q_i \widetilde{\boldsymbol{x}}_{ig}$.
Step 8: Is set G empty? If yes, STOP; else, go to step 4.

In step 1, the MUEGF heuristic assigns priorities to the evacuees, where higher priorities will have those individuals, who require the greatest time to travel from the emergency area to the nearest available emergency shelter. In step 2, the evacuees are sorted based on their priorities in the descending order. In step 3, the evacuees, sorted based on their priorities, are grouped, and a set of grouped evacuees G is initialized. Note that the evacuee group size (parameter gr_size) will be set based on the available capacity of the emergency evacuation routes during the available time periods and capacity of the available emergency shelters. In step 4, the closest available shelter is identified, considering the shelter requirements of the evacuees within a given group (certain evacuee groups may have to be assigned to the special needs shelters). In step 5, the MUEGF heuristic identifies the shortest route, which leads to the closest available shelter and has the available capacity for all evacuees within the considered group (including the individuals, carpooling with each evacuee in a one vehicle) for a given time period. In step 6, the evacuee group with the highest priority (i.e., the most urgent evacuee group) is assigned to travel via the evacuation route, leading to the closest available shelter, during a given time period. If the shortest route does not have enough capacity at the given time period, the evacuee group will be assigned to evacuate the emergency area during the next time period. In step 7, the MUEGF heuristic updates the set of evacuee groups sorted based on their priorities, capacities of the evacuation routes, and capacities of the emergency shelters. In step 8, the MUEGF heuristic checks whether all evacuee groups have been assigned to travel to one of the available emergency shelters along one of the evacuation routes during a certain time period (i.e., either set G is empty or not). If all evacuee groups have been assigned, the MUEGF heuristic is terminated; otherwise, the MUEGF heuristic will go to step 4 and will start searching for the closest available shelter for the next evacuee group in the priority list.

The "grouping effect", deployed within the MUEGF heuristic, is expected to outperform the MUEF heuristic in terms of the computational time, especially for the realistic size problem instances (i.e., assigning evacuees one by one is expected to be more computationally intensive as compared to assigning groups of evacuees). However, the "grouping effect" may negatively affect the solution quality, as at the optimal/near-optimal solution two individuals of the same group can be assigned to different evacuation routes and emergency shelters. Evaluation of the "grouping effect" within the MUEGF heuristic will be conducted throughout the numerical experiments.

5.2.4. The Most Urgent Evacuee Group Last heuristic

Similar to the MUEL heuristic, the most urgent Most Urgent Evacuee Group Last (MUEGL) heuristic assumes that the individuals, who require the least time to travel from the emergency area to the nearest available emergency shelter, should receive a priority and evacuate the emergency area first. However, unlike the MUEL heuristic, the MUEGL heuristic does not assign evacuees one by one to the emergency shelters, evacuation routes, and time periods. The MUEGF heuristic groups the evacuees based on the total travel time, required to evacuate the emergency area, and assigns the group of evacuees to travel to one of the available emergency shelters along one of the evacuation routes during a certain time period. The main steps of the MUEGL heuristic are the same as the main steps of the MUEGF heuristic. The only difference between the MUEGL and MUEGF heuristic algorithms consists in the priority assignment procedure. Specifically, in step 1, the MUEGL heuristic assigns priorities to the evacuees, where higher priorities will have those individuals, who require the least time to travel from the emergency area to the nearest available emergency shelter. Similar to the MUEL heuristic, the MUEGL heuristic may cause a situation, when the individuals, who do not require special accommodations, can be assigned to the special needs shelters, and the remaining capacity of the special needs shelters may not be sufficient for all individuals, who require special accommodations. In order to avoid the latter shortcoming, the MUEGL heuristic will re-assign the individuals, who do not require special accommodations, to the general type shelters in order to create a sufficient capacity of the special needs shelters for all individuals, who require special accommodations.

5.3. Solution Algorithm Conclusions

Under this project, the research team focused on development of the mathematical model for the emergency evacuation planning optimization problem. The objective of the proposed mixed integer mathematical model aimed to assign individuals to evacuate the emergency area using one of the available emergency evacuation routes to one of the emergency shelters during a specific time period, aiming to minimize the total travel time of evacuees. The developed mathematical model captured realistic features of emergency evacuation, including the following: (1) limited capacity of the available emergency evacuation routes; (2) limited capacity of the available emergency shelters; (3) potential carpooling of individuals (e.g., the whole family is evacuating; (4) shelter requirements for vulnerable population groups (e.g., individuals with disabilities should be assigned to the special needs shelters to ensure that these individuals will have the adequate accommodations; however, other evacuees can be assigned to both general type and special needs shelters); (5) major socio-demographic characteristics of drivers, evacuation route characteristics, driving conditions, and traffic characteristics, which may affect the driving ability of individuals under emergency evacuation; and others.

Two groups of algorithms were developed to solve the proposed mathematical formulation for the emergency evacuation planning optimization problem, including: (a) exact solution approach; and (2) heuristic solution approaches. CPLEX will be used as the exact solution approach to solve the proposed mathematical model to the global optimality. A total of four heuristic algorithms were developed under this project: (1) the Most Urgent Evacuee First heuristic; (2) the Most Urgent Evacuee Last heuristic; (3) the Most Urgent Evacuee Group First heuristic; and (4) the Most Urgent Evacuee Group Last heuristic. The heuristics are differed in terms of how individuals are prioritized to evacuate the emergency area. Furthermore, the Most Urgent Evacuee First and the Most Urgent Evacuee Last heuristics assign evacuees one by one to the emergency shelters, evacuation routes, and time periods. On the other hand, the Most Urgent Evacuee Group First and the Most Urgent Evacuee Group Last heuristics group the evacuees based on the total travel time, required to evacuate the emergency area, and assign the group of evacuees to travel to one of the available emergency shelters along one of the evacuation routes during a certain time period. Performance of the proposed solution approaches in terms of both solution quality and the computational time required will be assessed throughout the numerical experiments.

6. METHODOLOGY DESCRIPTION

This section of the report presents: 1) the process of gathering the data required to conduct the numerical experiments; 2) major assumptions for the Emergency Evacuation Planning Optimization Problem (**EEPOP**); and 3) description of various evacuation scenarios considered. Specifically, the present work shall consider emergency evacuation of Broward County, Florida (a coastal area in the U.S.), as a result of approaching devastating natural hazard.

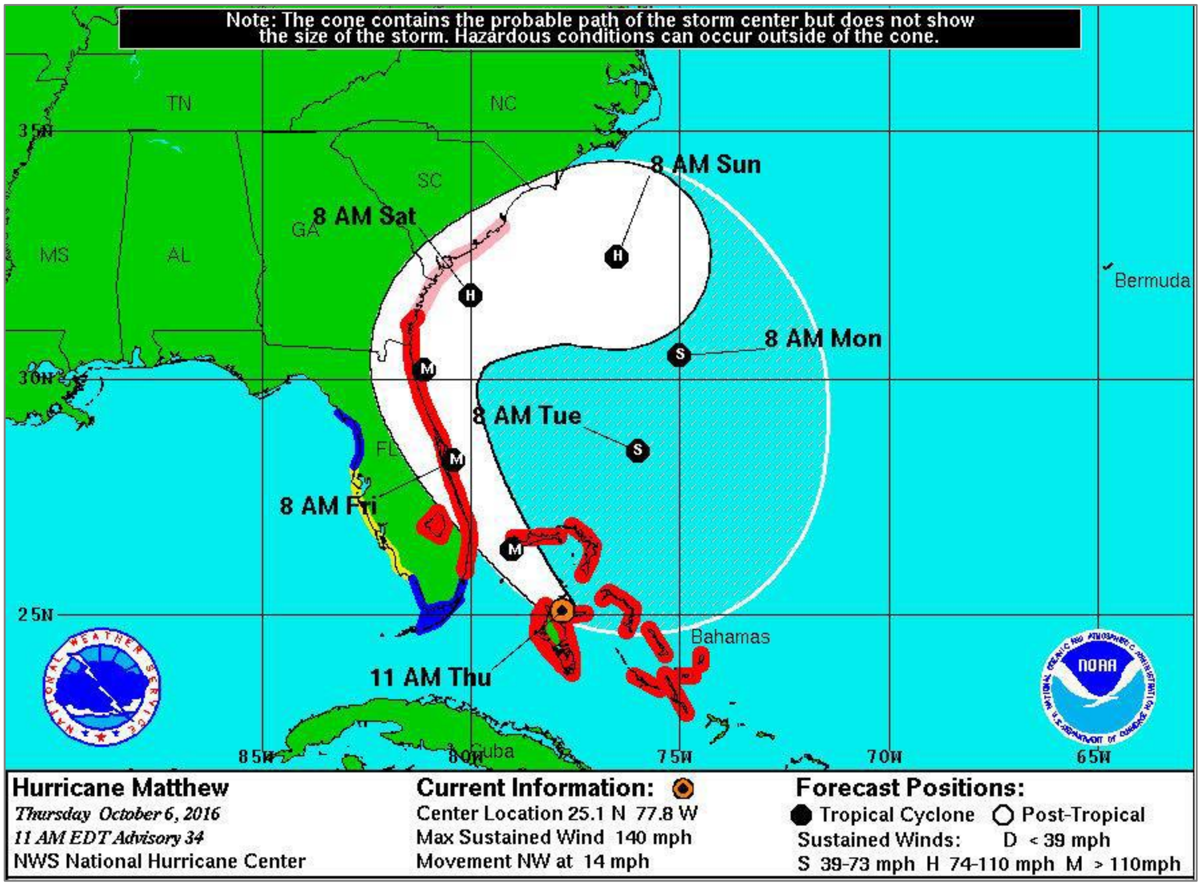

Figure 15 Areas affected by hurricane Matthew in September – October, 2016
Source: National Hurricane Center, 2016. Hurricane Matthew.

All the coastal areas of the United States (U.S.), including East Coast, West Coast, and Gulf of Mexico, are characterized with a frequent occurrence of natural hazards (such as hurricanes, severe storms, tropical storms, straight-line winds, severe thunderstorms, and others). For example, hurricane Matthew, which made a landfall near Les Anglais (Haiti) around 11:00 UTC on 4 October 2016 with winds of 150 mph, significantly affected the States of Florida, Georgia, South Carolina, and North Carolina (see Figure 15). More than 1.5 million Floridians were required to evacuate from the following areas: 1) Palm Beach County; 2) Broward County; 3) St. Johns County; 4) Duval County; 5) Brevard County; 6) St. Lucie County; 7) Flagler County; 8) Miami-Dade County; and others (The Weather Company, 2017).

6.1. Data Collection

In order to conduct the numerical experiments, a set of input parameters are required for the **EEPOP** mathematical model and the optimization algorithms (see sections 3,4, and 5 of this report for detailed problem description and the proposed optimization algorithms). To ensure credible and valid results, the research team ensured accuracy and reliability of external data sources. Furthermore, the ArcGIS software (ArcMap 10.3.1) was used in preparing all maps for this report. ArcGIS is a geographic information system (GIS) for creating, compiling, editing, analyzing, and sharing maps. The tool effectively allows the user to manage geographic information in a database. Sections 6.1.1 – 6.1.5 of this report provides detailed information regarding the following aspects: 1) emergency shelters and shelter selection process; 2) evacuation routes and route selection process; 3) route capacity estimation; 4) evacuation time periods; and 5) sampling evacuee age values (based on the Broward County population).

6.1.1. Emergency Shelters

An emergency shelter is a facility, which temporarily accommodates individuals evacuating until the hazard will pass a given metropolitan area. Generally, emergency shelters provide basic life sustaining amenities such as food, water, medicine, and basic sanitary facilities. However, when a mandatory evacuation order is announced, evacuees are advised to travel to shelters with their disaster supply kit, which may comprise of the following (Weather Underground, 2018): 1) Water (one gallon of water per person per day, for 3 to 7 days); 2) Food (at least a three-day supply of non-perishable food, cooking tools / fuel, paper plates / plastic utensils); 3) Battery-powered radio and a National Oceanic and Atmospheric Administration (NOAA) Weather Radio with tone alert and extra batteries for both; 4) Flashlight and extra batteries; 5) First Aid kit; 6) Whistle to signal for help; 7) Infant formula and diapers (for evacuees with an infant); 8) Moisture wipes, garbage bags and plastic ties for personal sanitation; 9) Dust mask or cotton t-shirt (to help filter the air); 10) Plastic sheeting and duct tape to shelter-in-place; 11) Wrench or pliers to turn off utilities; 12) Can opener for food (if kit contains canned food); 13) Clothing and Beddings; 14) Medications; 15) Lawn chair and/or bed roll; and 16) cash. Evacuees travelling to shelters with their pets are also advised to make a customized emergency kit for their pets. The emergency kit for pets may include: 1) non-perishable food; 2) water; 3) medications; 4) sturdy cage or carrier; 5) collar; 6) leash; and 7) most recent vaccine record. Emergency shelters do not provide any conveniences or luxuries for individuals.

After the event of Hurricane Andrew in 1986, which killed more than 65 people and displaced more than 200,000 families (Rapaport, 1993), the State of Florida recognized the necessity of providing safe emergency shelter space for its population and prepared a "statewide emergency plan" (SEP), which identified strategic locations for building emergency shelters. The SEP is based on a forecast of emergency evacuation demand over a period of five (5) years. Furthermore, the SEP is revised every two years to ensure that adequate spaces are available to accommodate evacuees, due to the rapid growth of population especially in urban areas. According to the SEP, emergency shelters are classified into: 1) General Population shelters (otherwise called regular shelters); and 2) Special Needs Shelters.

6.1.1.1. General Population Shelters (GP)

In practice, GP shelters are designed to accommodate the population (children and adults) with access and functional needs, and do not necessarily have medical conditions or any other vulnerability. Specifically, individuals with and without disabilities who have access and functional needs are accommodated in the general population shelters (FEMA, 2010). Individuals, who request accommodation due to disabilities, are provided with special accommodation while they are sheltered. General population shelters provide individuals with food, water, medicine, and basic sanitary facilities, although these services are limited. In addition, GP shelters may have pet shelter spaces which are usually separated from the GP shelter spaces (as certain individuals may have allergies for pets). These shelters are referred to as pet-friendly shelters. These shelters typically require pet owners to take care of their own animals. However, GP shelters accommodate every service animals whether the shelter is designated as pet-friendly or not. Also, service animals are never separated from their owners under any circumstance (FEMA, 2007). According to the Florida Division of Emergency Management (FDEM, 2018), there are 1,422 GP shelters in Florida, with a total of 1,039,468 shelter spaces.

6.1.1.2. Special Needs Shelters (SpNS)

SpNS are designed to meet the needs of individuals with special medical conditions and vulnerable population. SpNS provide individuals with disabilities or limitations with the best sheltering accommodations during a hazard. Usually, individuals who require assistance in the event of a hazard are advised to register in order to effectively plan for resource allocation, and to meet their needs. The Florida Department of Health and Bureau of Preparedness and Response design standardized and comprehensive protocols, as well as technical assistance (also known as the SpNS Operations Plan), which is integrated into the SEP. Furthermore, the SpNS Operations Plan ensures continuity in services and quality care to evacuees, caregivers and staff during their stay in a special needs shelter. According to FDEM (2018), there are 111 SpNS in Florida, with a combined capacity of 36,648 shelter spaces.

6.1.1.3. Emergency Shelter Data Preparation

To evacuate Broward County, the GP shelters and SpNS in Florida were considered. A GIS shapefile containing the ID number, name, address, and geographical location of all GP shelters in Florida was obtained from the American Red Cross (ARC). First, the "*find centroid*" tool in GIS was used to identify the centroid of the County. Next, the "*buffer*" tool was used to create a 155-mile buffer from the centroid of Broward County, to identify all GP shelters within 155-mile radius of the County in the GIS data environment. The information was used to create a map showing GP shelters within 155-mile radius of Broward County (see Figure 16). GP shelters within 155-mile radius were considered to ensure that individuals evacuating from Broward County are assigned to the shelters, which are closer to the evacuation zone.

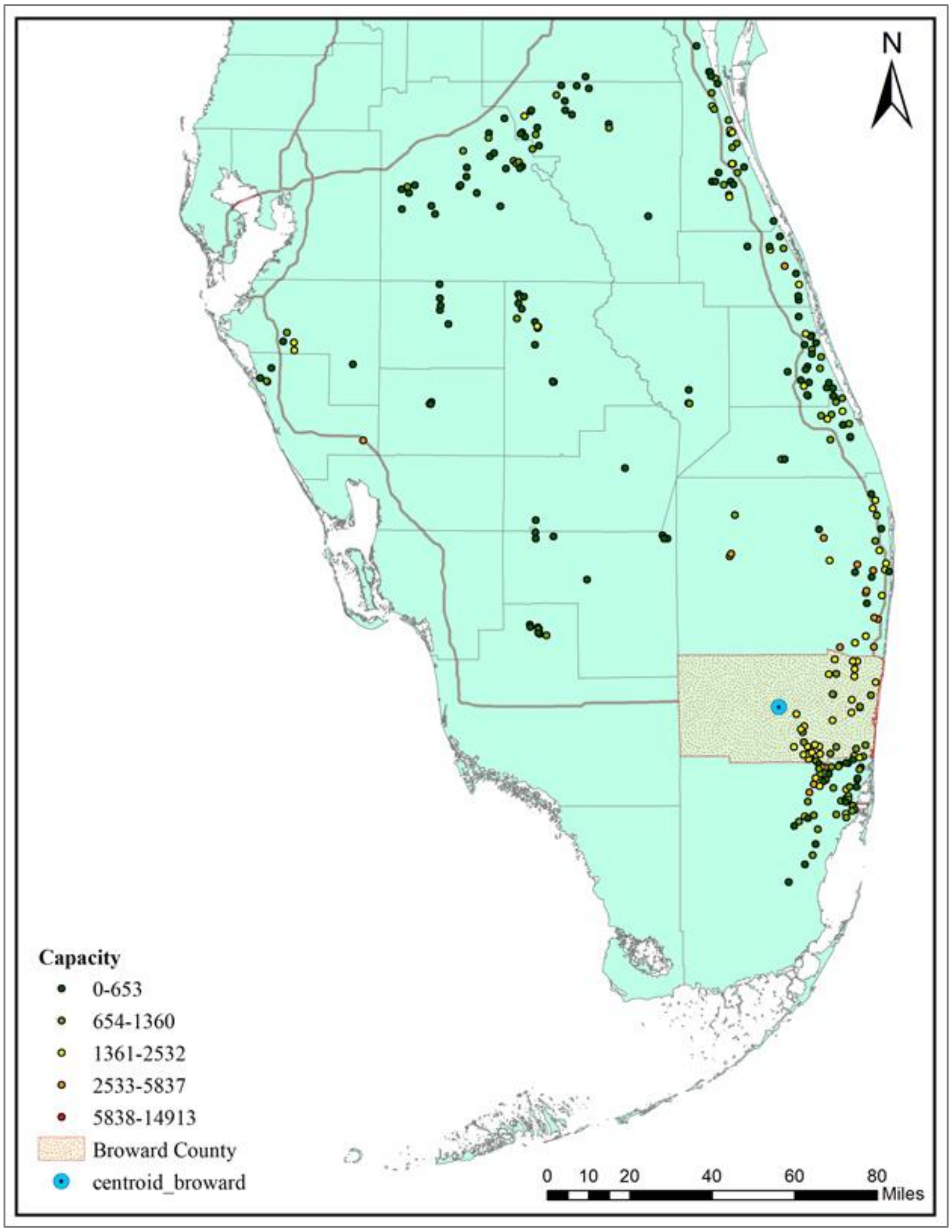

Figure 16 General population shelters within 155-mile radius of Broward County, Florida.

In order to accommodate the surge in evacuation demand due to a hazard, high capacity GP shelters located outside the 155-mile buffer in the State of Florida were considered as well. A 155-mile buffer was created from the established centroid of Broward County using the "*buffer*" tool in the GIS environment. High capacity GP shelters were identified and selected, using the "*select by location*" tool in the GIS environment. This feature allowed the selection of GP shelters having high capacities outside the defined 155-mile radius of Broward County. A GIS shapefile was created from the shelters selected and a map showing the shelters was prepared (see Figure 17). A total of 486,346 regular shelter spaces were reserved for the general population evacuating from Broward County.

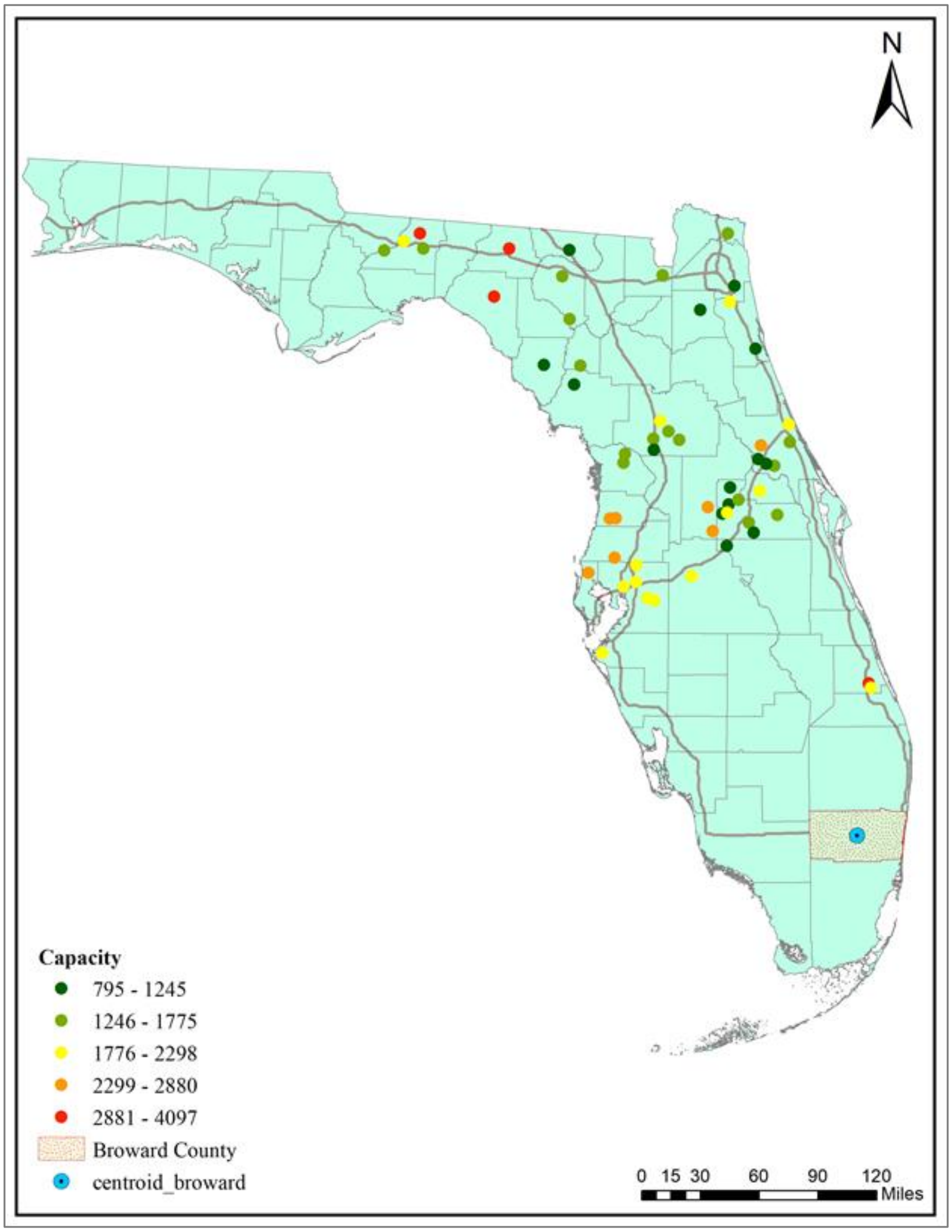

Figure 17 High capacity general population shelters outside 155-mile radius of Broward County, Florida.

Furthermore, the SpNS in Florida were considered. Although there was a GIS shapefile for GP shelters in Florida, the research team was unable to obtain an existing GIS shapefile for SpNS in Florida. Using the up-to-date shelter information provided by FDEM (2018), a shapefile which consisted of the required data was developed by the research team for this study. First, a GIS shapefile showing the counties in Florida and the boundaries was obtained from the Florida Geographic Data Library (FGDL) (FGDL, 2018). The "*Create Feature Class*" tool in GIS was used to create a shapefile for the SpNS in Florida and coordinate system of the shapefile was set using the defined coordinates of the Florida County GIS shapefile. Next, the attribute of the feature (SpNS shelters to be created) was defined as "*points*" and the attributes were edited using the "*editor*" tool in GIS. Each shelter was inserted in the map using the "*Create Feature*" tool in GIS. To ensure precision and accuracy in locating the shelters on the base map, the X and Y coordinates (latitude and longitude values) obtained from Google map was used in creating candidate SpNS in GIS. Information about shelter ID number, shelter name, shelter address, latitude and longitude, shelter type, and shelter capacity for all SpNS were entered in the attributes table. All the SpNS (a total of 111) in Florida were considered. The SpNS considered has a total capacity of 36,648 spaces. A map which depicts the SpNS in Florida is presented in Figure 18.

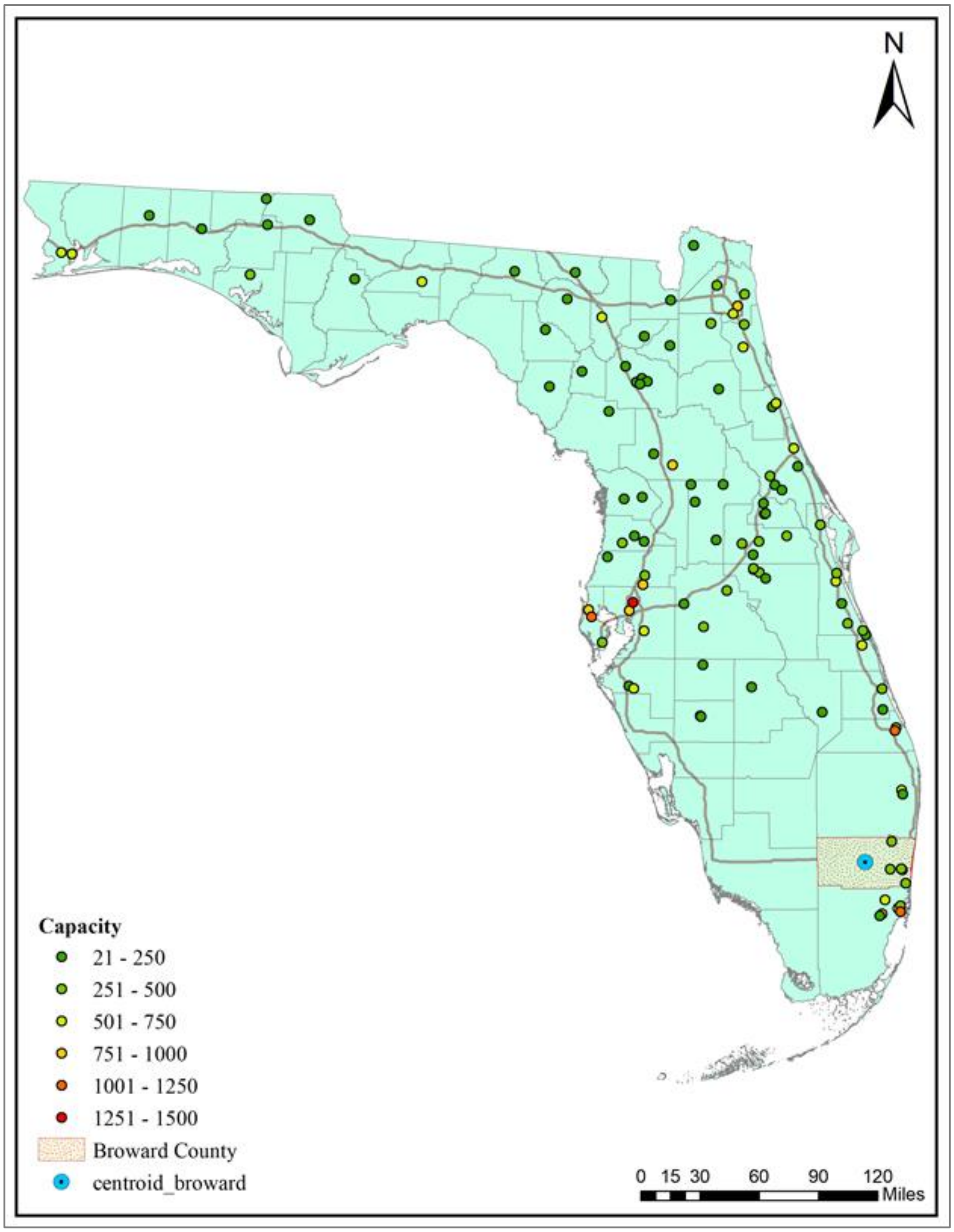

Figure 18 Special needs shelters in Florida.

6.1.2. Emergency Evacuation Routes

The population, inhibiting areas where the impact of the hazard is expected to be devastating, are advised by State authorities to evacuate to shelters using dedicated evacuation routes (which include Interstates, U.S. highways, and State roads). Emergency evacuation routes are designated roadways, which carry traffic of evacuating individuals from a hazard zone, where an emergency evacuation order has been issued to a shelter. Driving to the main evacuation routes can sometimes require traveling through residential areas and streets with lower capacities. Throughout the evacuation process, the major Interstate highways are designated as evacuation routes (CBS News, 2016). Usually, evacuees attempt to use the same evacuation route. The latter often results in route congestion (due to the limited capacity of evacuation routes) and significantly delays the evacuation process.

6.1.2.1. Evacuation Route Selection

The procedure for selecting potential evacuation routes was based on the GIS maps and Google maps (Google, 2018). The GIS shapefiles which consist of: 1) Interstates; 2) U.S. highways; 3) State roads; and 4) Local roads in Florida, were obtained from FGDL (FGDL, 2018). Also, an up-to-date GIS shapefile, which includes the name of all roadways in Florida, number of lanes, road length, road class and roadway ID number, was acquired from FGDL. Both files were imported into the ArcMap 10.3.1, and the layers were turned off. The map showing all the shelters considered in the previous section for the numerical experiments was imported into the data environment as the base map, afterwards all layers were turned on. For this task, the centroid of Broward County was assumed as the origin of all trips.

Next, the research team identified the shortest route and least one other route from the centroid of Broward County to each of the shelters considered. Information about the number of lanes, types of road (Interstates, U.S. highways, and State roads) leading to each shelter from the centroid of Broward County, and evacuation route length was recorded for each evacuation route. To expedite the process, Google map was also used in identifying evacuation routes. To accomplish the latter, the location of the centroid of Broward County was entered in Google map as well as the location of the shelter considered. Google map returned the shortest route to the shelter and at least one other route. Specifically, five evacuation routes were considered for shelters closest to the centroid of Broward County, majority of which can be reached by local roads. Moreover, two to three evacuation routes were considered from the centroid of Broward County to farther shelters (majority of which include highways and Interstate roads). The aim was to generate a sufficiently large set of candidate evacuation paths from the centroid of Broward County to emergency shelters. Furthermore, the research team selected more than one evacuation route to all shelters to reduce or eliminate congestion on evacuation routes, and significantly reduce the travel time of evacuees. A total of 1,314 evacuation routes were selected. Throughout the emergency evacuation process, an individual can be assigned to any of the routes identified.

6.1.3. Evacuation Route Capacity Estimation

Route capacity is defined as the maximum number of vehicles, people, or amount of freight than can move along a given route within a certain time period (usually an hour). The procedure for estimating road capacity, which was presented in the Highway Capacity Manual (HCM) 2010 (HCM, 2010) was adopted for all roadways considered. The HCM is published by the

Transportation Research Board (TRB) of the National Academies of Science in the United States. The manual contains concepts, guidelines, and computational procedures for estimating the capacity and level of service for various highway facilities (including freeways, highways, arterial roads, rural highways, signalized and unsignalized intersections, and others). For the present work, the capacities of the following roadways were estimated: a) Freeways; b) Multilane highways; and 3) Two-lane highways.

6.1.3.1. Freeway capacity estimation

The free-flow speed of 55 mi/h was selected from the HCM to determine the traffic flow on freeways. From the speed−flow curve (**Exhibit 11-2**), the range of flows for the selected free-flow speed was 0–2,250 pc/h/ln. Since the service measure for basic freeway segments is density, the density value at a level of service (LOS) was used in selecting the range of flows at the selected free flow speed. This is because the speed maintains a constant value for a wide range of flow values and the volume to capacity ratio (v/c) cannot be easily perceived by road users. The LOS D with density values between 26–35 pc/mi/ln (**Exhibit 11-5**) was selected for all freeways. The latter assumption can be justified based on the fact that the traffic characteristics at the LOS D emulate the traffic conditions during emergency evacuations. At LOS D, the speed reduces with increasing flow and density; thus, drivers have limited opportunities to change lanes. In addition, there is a decline in the physical and psychological comfort of drivers, and an incident on the freeway can result in congestion due to limited ability of the freeway to absorb traffic disruptions. Using the speed-flow curves (**Exhibit 11-6**) for basic freeway segment at the selected LOS, as well as the selected free flow speed and density values, the range of flows was 1,400-1,900 pc/h/ln.

6.1.3.2. Multilane highway capacity estimation

The descriptions of LOS for basic freeway segments given in Chapter 11 of the HCM (2010) for basic freeway segments are also generally applicable to multilane highways. For multilane highways, the free-flow speed was assumed to be 45 mi/h, while the LOS was assumed to be D. Using exhibit (**Exhibit 14-5**) of the HCM 2010 the range of flows was identified to be 1,180-1,550 pc/mi/ln.

6.1.3.3. Two-lane highway capacity estimation

The capacity of a two-lane highway under base conditions is 1,700 veh/h in one direction. However, when both directions are considered, the capacity is 3,200 veh/h. For two-lane highways, the directional split during emergency evacuation was assumed to be 80/20, and the percent time spent following (PTSF) another vehicle was assumed to be greater than 80%. The latter assumption can be justified based on the fact that passing maneuvers on two-lane highways are made in the opposing direction of flow, thus, the ability to pass is limited by the distribution of gaps in both directions. The Speed–Flow curve PTSF relationships for directional Segments with base Conditions (**Exhibit 15-2**) was used in selecting the directional flow rate. Based on the assumptions a value of 1,050 veh/h was selected. The research team assumed that the directional flow before emergency evacuation was 60/40 with a flow of 550 pc/h in the direction of evacuation.

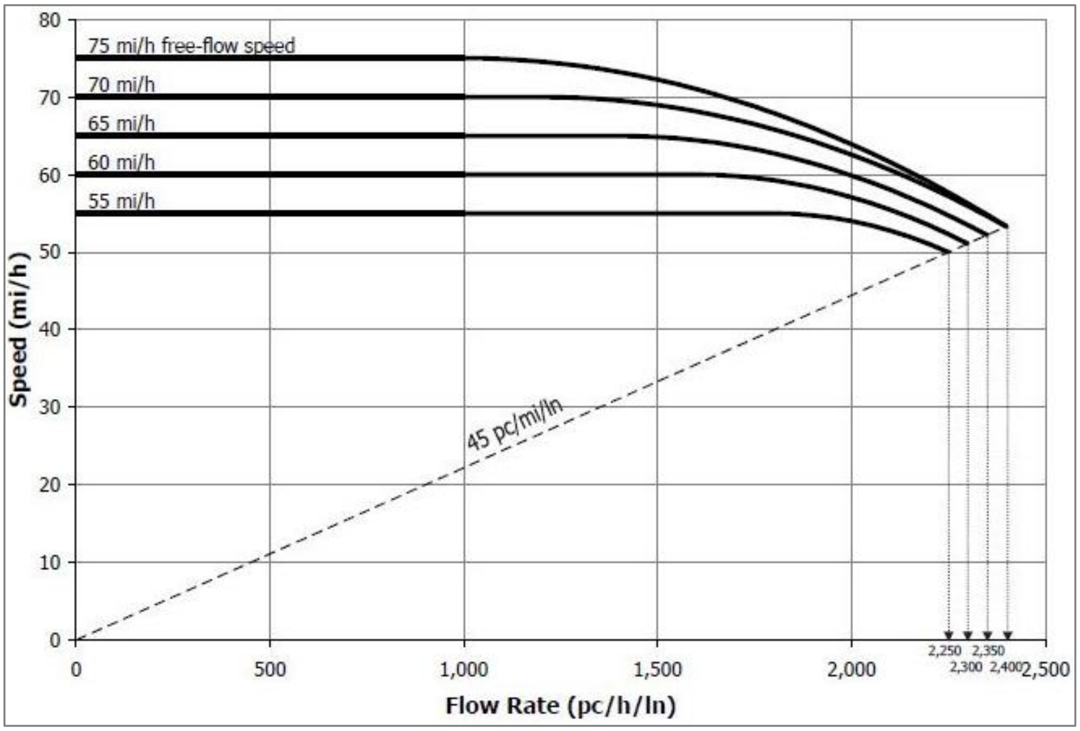

Exhibit 11-2 Speed – Flow Curves for Basic Freeway Segments under Base Conditions
Source: HCM (2010)

Exhibit 11-5 LOS Criteria for Basic Freeway Segments

LOS	Density (pc/mi/ln)
A	≤11
B	>11-18
C	>18-26
D	>26-35
E	>35-45
F	Demand exceeds capacity >45

Source: HCM (2010)

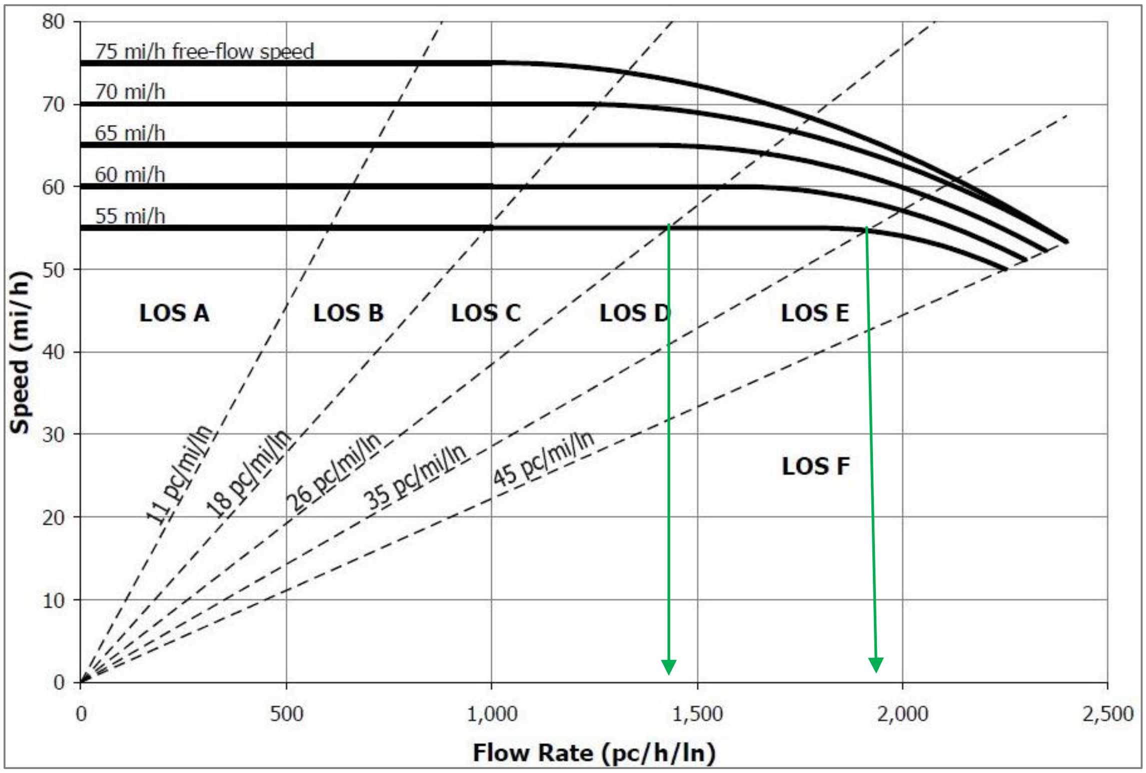

Exhibit 11-6 LOS for Basic Freeway Segments

Source: HCM (2010)

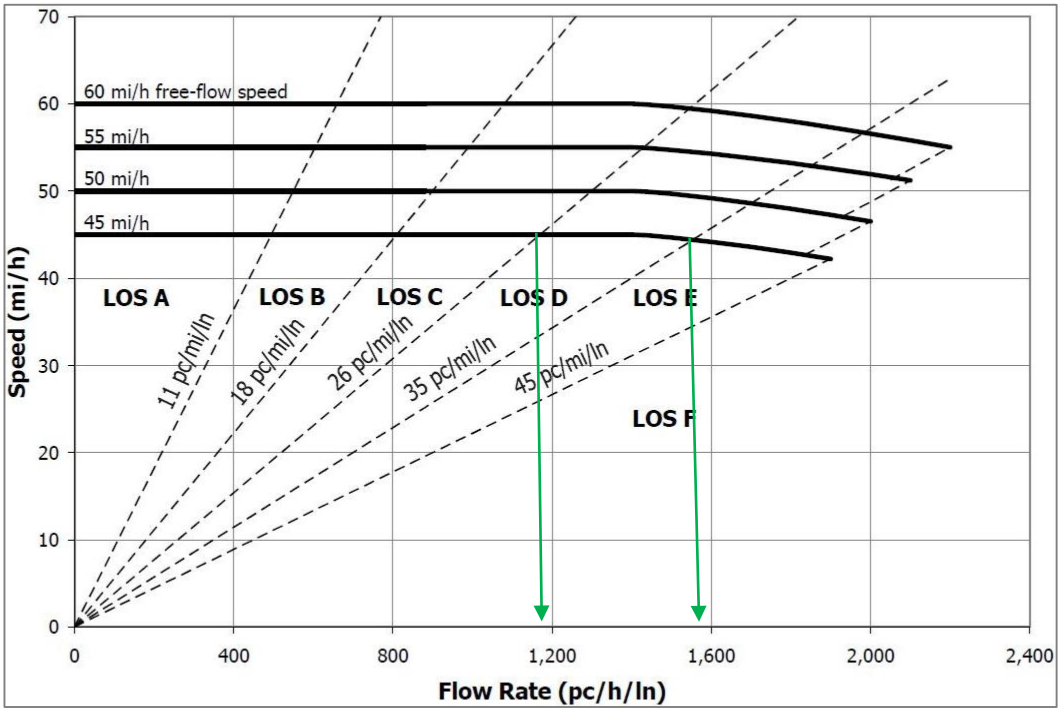

Exhibit 14-5 LOS on Base Speed – Flow Curves

Source: HCM (2010)

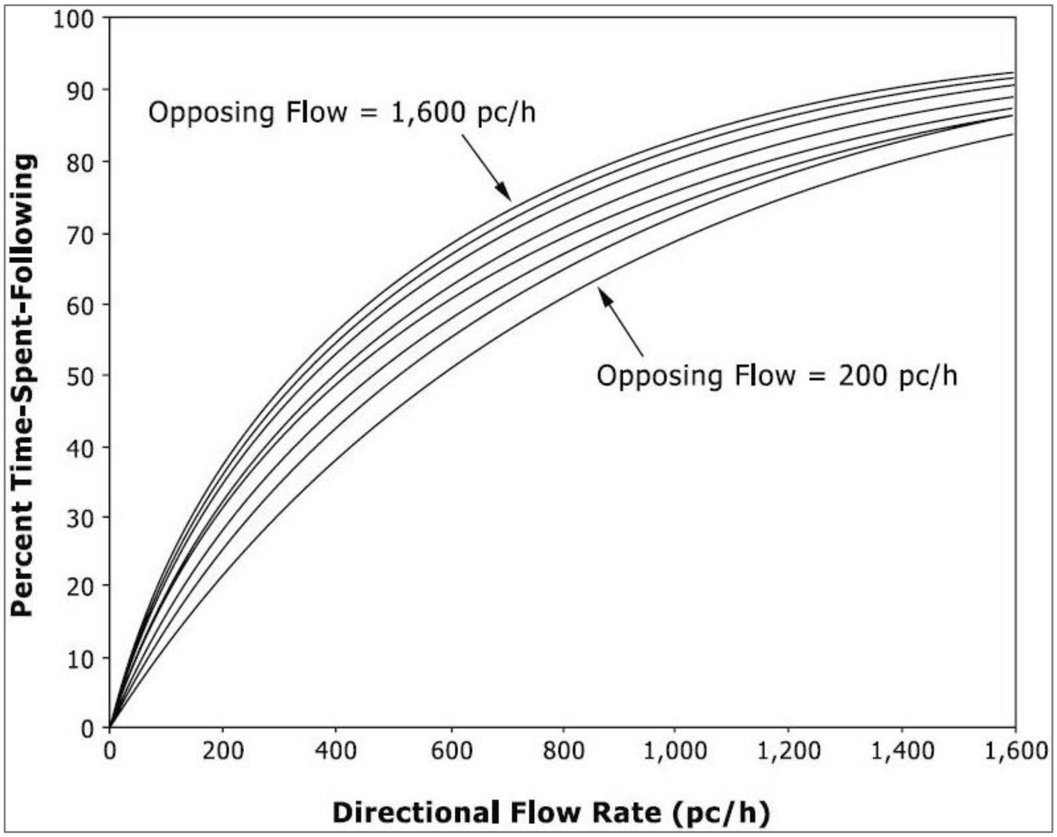

Exhibit 15-2 PTSF versus Directional Flow Rate

Candidate evacuation routes have multiple segments, which may comprise of freeways, multilane highways, and/or two-lane highways. Although the range of flow was estimated for all roadways, the capacity of all evacuation routes was assumed to be the lower value for range of flows on the two-lane highways (550 veh/hr). The latter assumption was made based on the fact that traffic demand during emergency evacuation is always high. Also, a large number of potential evacuation routes considered have two-lane freeway segments. Usually, traffic is expected to operate within the defined range of flows for the two-lane highway on all evacuation routes during emergency evacuation.

6.1.4. Evacuation Time Periods

Generally, when a mandatory emergency evacuation is announced, evacuees travel to shelters almost immediately. The latter action results in congestion on evacuation routes due to an instantaneous increase in traffic demand. The present work accounts for the aforementioned challenge by proposing a time period-based emergency evacuation throughout the planning horizon. Allocating time periods for evacuating individuals will reduce the congestion on the roadway and ensure the best use of the available facility. Furthermore, evacuation by time periods will facilitate adequate planning in terms of capacity of the evacuation routes, which is estimated per hour. For the numerical experiments, a sufficiently large number of time periods were considered in order to evacuate all individuals from the hazard location.

6.1.5. Sampling Evacuee Age Values

The population of individuals within the age groups defined in the Broward County demographics database was extracted. Next, the population groups were further divided into five classes which included: 1) number of individuals not older than 17 years; 2) individuals aged between 18-34 years; 3) individuals aged between 35-54 years; 4) individuals aged between 55-64 years; and 5) individuals aged 65 years and above. Figure 19 presents the distribution of population by age groups.

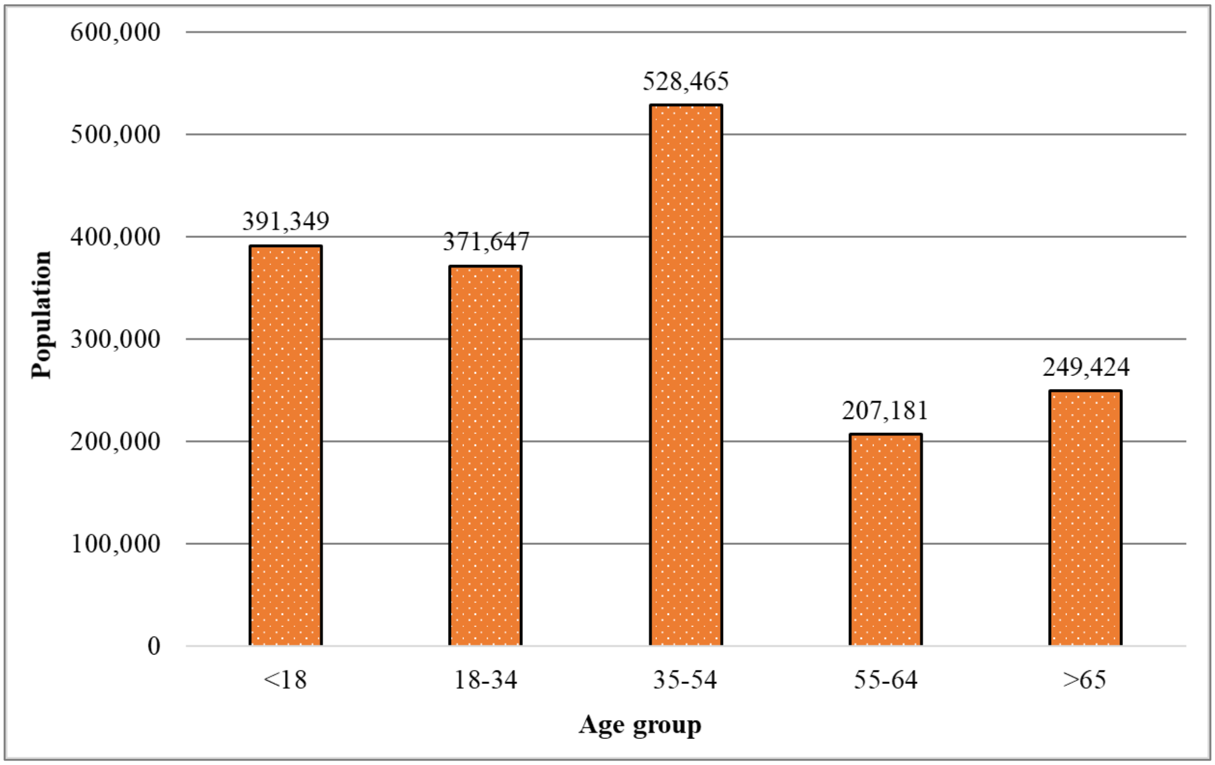

Figure 19 Distribution of Broward County population by age groups.

The age group data was imported into MATLAB workspace, and a matrix which consisted of the age group values was created. Random numbers (integers) were generated uniformly for the total number of individuals within each age group and a matrix which consists of the random numbers (which represents the ages of individuals living in Broward County) was created. The "*distribution fitting*" tool was used to create a normal distribution for the values of the age groups, and a cumulative distribution was generated for the data from the normal distribution.

The evacuee data was prepared at the household level. It was assumed that every household in Broward County has at least one vehicle, which can be used to evacuate not more than four individuals. The County demographic data, obtained from the U.S. Census Bureau (2018) indicated that the total population of Broward County (TP) in 2010 was 1,748,066, while the total number of households (TH) were 686,047. The average number of individuals in each vehicle (AIV) was computed using Equation 1 as follows:

$$AIV = \frac{TP}{TH} = \frac{1{,}748{,}066}{686{,}047} \approx 2.5\ individuals/vehicle \qquad (1)$$

The estimated AIV value was used in assigning the number of individuals in each vehicle. For every household, the number of individuals in each vehicle was assumed to range between 1 and 4. The latter assumption can be supported by the fact that for the most of vehicle types, only four individuals can be seated conveniently, while other items (such as important documents, food, water, toiletries, etc.) may be stored in any unoccupied space. The number of passenger(s) in each vehicle was assigned using uniformly distributed random integers between 1 and 4 in MATLAB.

Afterwards, the "*normrand"* function in MATLAB was used to generate normally distributed random numbers representing the age of the individuals. The function requires the user to input the mean and standard deviation values from a normal distribution to produce a predefined number of values. The mean and standard deviation values obtained from the normal distribution of the age of individuals in Broward County was used in generating the age of evacuee(s) in each vehicle evacuating for each household. The values generated were rounded off to the nearest whole number and the absolute values were estimated to represent the sample of the age of individuals in each vehicle. If a vehicle is occupied by individuals not older than 18, MATLAB was programmed to replace at least one individual in the vehicle with another individual older than 18 years. The latter measure was adopted to ensure that there is at least one experienced driver in vehicles with only young individuals (who are inexperienced and ineligible to drive).

Furthermore, the driver selection procedure involved identification of an individual who can be considered as the most experienced in order to safely maneuver the vehicle to a shelter. To achieve the latter task, the following constraints were imposed:

1. For every vehicle with more than one individual younger than 65 years and older than 17 years, select an individual younger than 64 years but older than other individuals as the driver.
2. If there exists a vehicle with only one individual younger than 64 years and older than 17 years, select that individual younger than 64 years and older than 18 years as the driver.
3. If there exists a vehicle in which all individuals are older than 64 years, select the youngest individual as the driver.

Moreover, age prioritization strategy was adopted in the selection of drivers (selection of the most experienced younger adult drivers) where applicable, imposed in constraints 1 and 2, can be supported by the fact that substantial perceptual and cognitive changes (such as vision disorders, hearing impairment, decreasing attention, reduced speed of processing of the basic information and responsiveness, presence of chronic diseases, and others) that occur with age have been reported to affect the ability of elderly drivers during emergency evacuation. The effects of those perceptual and cognitive changes on driving ability of an elderly driver may significantly increase during emergency evacuation due to a disruptive nature of emergency evacuation.

6.2. Major Assumptions

A number of assumptions were made in order to solve the **EEPOP** mathematical model. The assumptions were critical to prepare the input data for the **EEPOP** mathematical model and directly affect the suggested evacuation routes, emergency shelters, and time periods that were assigned to evacuees. The assumptions are presented as follows:

- The research team assumed that the evacuation demand (i.e., the number of individuals that need to travel to the assigned shelter) originated at the centroid of Broward County.
- After receiving an evacuation order, individuals living in Broward County evacuate based on time periods (each time period is equal to one hour). An evacuee must evacuate within the time period assigned.
- Each household drive to the assigned emergency shelter using one vehicle. Individuals or households without a private vehicle may rely on a variety of alternatives including riding with friends, neighbors, or other family members.
- Throughout the evacuation process, the capacity of all evacuation routes was assumed to be the minimum capacity of two-lane highways. The conservative value was selected to ensure that a surge in evacuation demand will not result in traffic congestion. Technically, the available real-time capacity of evacuation routes can be set by State troopers or other agencies responsive for the emergency evacuation planning, which have information regarding traffic conditions on each one of the evacuation routes.
- At least two candidate evacuation routes were considered for each emergency shelter.
- Only ARC-approved shelters were considered throughout the numerical experiments (while locally recognized shelters were ignored)
- All emergency shelters are opened immediately, once the evacuation order has been announced.
- Emergency shelters have a limited capacity for accommodating the demand assigned to them. Hence, once a shelter is full, individuals cannot be assigned to the shelter.
- Vulnerable population groups (e.g., aging adults, individuals with disabilities and/or chronic diseases) have to be assigned to SpNS. However, the capacity information was not available for some of SpNS; and, the research team had to assign certain capacity values (within acceptable ranges as compared to SpNS, for which the capacity information was available).
- If a family is evacuating in a one vehicle and one of the family members is an aging adult, the whole family would be assigned to SpNS (to make sure that the aging adult will have access to adequate accommodations).

Throughout the hypothetical emergency evacuation, individuals were assigned to shelters based on their needs. From the population data generated, individuals who were assumed to have special medical conditions were assigned to SpNS, while individuals without special medical conditions could be assigned to either GP or SpNS shelters. An example of evacuee to shelter assignment, based on individual needs is presented in Table 7.

6.3. Description of the Considered Scenarios

A total of 40 problem instances were developed for evaluation of the developed solution algorithms (including CPLEX, MUEF, MUEL, MUEGF, and MUEGL algorithms). The developed problem instances can be divided in two groups, including:

1) Small size problem instances, where the total number of evacuees ($\sum_{i \in I} q_i$) was changed from 20 evacuees to 400 evacuees with an increment of 20 evacuees (the small size problem instances will be referred to as S1-S20); and
2) Large size problem instances, where the total number of evacuees was changed from 5,000 evacuees to 100,000 evacuees with an increment of 5,000 evacuees (the large size problem instances will be referred to as L1-L20).

Note that the rest of the values for remaining parameters of the **EEPOP** mathematical model (i.e., the number of available evacuation routes, the number of available shelters, the number of time periods for evacuation, capacities of the available evacuation routes, capacities of the available shelters, etc.) were set to be the same for the small size and large size problem instances. The main objective of the numerical experiments was to determine how performance of the proposed solution algorithms (in terms of the quality of obtained solutions and the computational time required) would be affected with increasing number of evacuees. Two sets of problems instances were required, as it was found throughout the numerical experiments that the exact optimization algorithm (i.e., CPLEX) was not able to solve the problem instances with more than 400 evacuees and returned a memory error (i.e., CPLEX memory was not sufficient for solving the problem instances with more than 400 evacuees).

Table 7 Needs-based evacuee to shelter assignment.

	Shelter 1 (GP)	**Shelter 2 (GP)**	**Shelter 3 (GP)**	**Shelter 4 (GP)**	**Shelter 5 (GP)**	**Shelter 6 (SpNS)**	**Shelter 7 (SpNS)**
Evacuee 1*	0	0	0	0	0	1	1
Evacuee 2	1	1	1	1	1	0	0
Evacuee 3*	0	0	0	0	0	1	1
Evacuee 4*	0	0	0	0	0	1	1
Evacuee 5	1	1	1	1	1	0	0
Evacuee 6	1	1	1	1	1	0	0
Evacuee 7	1	1	1	1	1	0	0
Evacuee 8	1	1	1	1	1	0	0
Evacuee 9	1	1	1	1	1	0	0

* - *An evacuee with a medical condition.*

Cell value equals 1 if an evacuee can be assigned to a shelter, otherwise 0.

7. METHODOLOGY APPLICATION

7.1. Evaluation of the Developed Solution Approaches

A set of numerical experiments were conducted to evaluate the developed solution algorithms. The numerical experiments were divided into three steps, including the following: (1) sensitivity analysis for the group size parameter; (2) analysis of the small size problem instances; and (3) analysis of the large size problem instances. The first step aimed to assess performance of the MUEGF and MUEGL heuristics for different values of the group size parameter (gr_size) for the small size and large size problem instances. The second step focused on a comparative analysis of all the developed solution algorithms in terms of the objective function and computational time values for the small size problem instances. The third step aimed to conduct a comparative analysis of all the developed solution algorithms in terms of the objective function and computational time values for the large size problem instances. A detailed description of each step is presented in the following sections of the report.

7.1.1. Sensitivity Analysis for the Group Size Parameter

Unlike the MUEF and MUEL heuristics, the MUEGF and MUEGL heuristics do not assign evacuees one by one to the emergency shelters, evacuation routes, and time periods. The MUEGF and MUEGL heuristics group the evacuees based on the total travel time, required to evacuate the emergency area, and assign the group of evacuees to travel to one of the available emergency shelters along one of the evacuation routes during a certain time period. The evacuee group size (gr_size) may significantly affect performance of both MUEGF and MUEGL heuristics. The first step of the numerical experiments focused on evaluating different gr_size values and their effects on performance of the MUEGF and MUEGL heuristics in terms of the objective function and computational time values for the small size and large size problem instances. A total of 20 scenarios for gr_size values were considered, where gr_size was changed from 20 evacuees to 400 evacuees with an increment of 20 evacuees. All the developed scenarios for gr_size values are presented in Table 8.

Table 8 Considered scenarios for gr_size values.

Scenario	gr_size	Scenario	gr_size
1	20	11	220
2	40	12	240
3	60	13	260
4	80	14	280
5	100	15	300
6	120	16	320
7	140	17	340
8	160	18	360
9	180	19	380
10	200	20	400

The MUEGF and MUEGL heuristics were executed for all the considered gr_size value scenarios for both small and large size problem instances. A total of 5 replications were performed for each scenario and each problem instance to estimate the average computational time (while the objective function value did not change from one replication to another, as both heuristic algorithms are deterministic in their nature). The average MUEGF and MUEGL objective function and computational time values over the small size problem instances for the considered group size scenarios are presented in Figure 20.

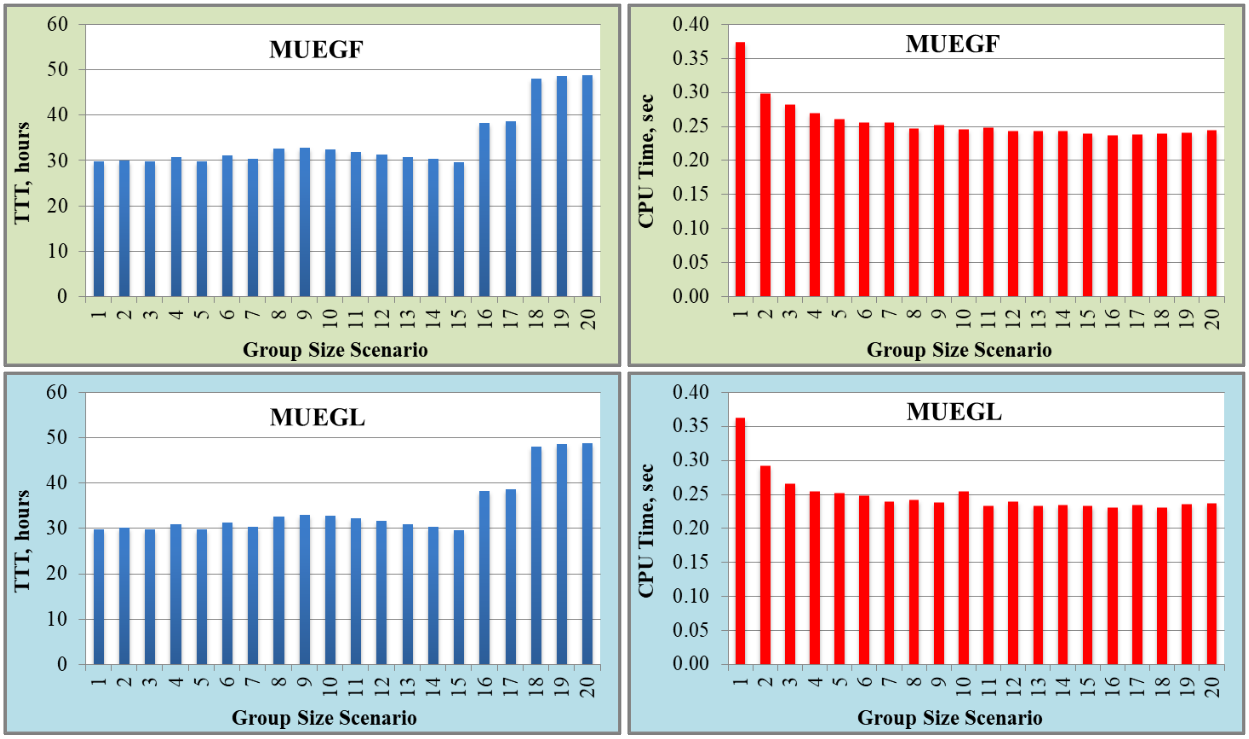

Figure 20 Average MUEGF and MUEGL objective function and computational time values over the small size problem instances for the considered group size scenarios.

It can be observed that increasing group size negatively affects the objective function values, but reduces the computational time required to solve the **EEPOP** mathematical model. The latter finding can be explained by the fact that two individuals of the same group can be assigned to different evacuation routes and emergency shelters at the optimal/near-optimal solution. A reduction in the MUEGF and MUEGL computation time with increasing group size can be explained by the fact that assigning evacuees in smaller groups is more computationally intensive (i.e., requires more iterations) as compared to assigning larger groups of evacuees. Based on the results from the numerical experiments, the gr_size value will be set to 300 evacuees (i.e., gr_size scenario 15) for both MUEGF and MUEGL heuristics for the small size problem instances. The average objective function values comprised 29.62 hours and 29.65 hours for the MUEGF and MUEGL heuristics over the small size problem instances, when the gr_size value was set to 300 evacuees. The average computational time values comprised 0.29 sec and 0.23 sec for the MUEGF and MUEGL heuristics over the small size problem instances, when the gr_size value was set to 300 evacuees.

The average MUEGF and MUEGL objective function and computational time values over the large size problem instances for the considered group size scenarios are presented in Figure 21 and in Figure 22. Similar to the results from the numerical experiments that were conducted for the small size problem instances, it was found that increasing group size negatively affected the objective function values, but reduced the computational time required to solve the **EEPOP** mathematical model for the large size problem instances. Based on the results from the numerical experiments, the gr_size value will be set to 380 evacuees (i.e., gr_size scenario 19) for both MUEGF and MUEGL heuristics for the large size problem instances. The average objective function values comprised 99,026.57 hours and 108,387.72 hours for the MUEGF and MUEGL heuristics over the large size problem instances, when the gr_size value was set to 380 evacuees. The average computational time values comprised 563.23 sec and 562.90 sec for the MUEGF and MUEGL heuristics over the large size problem instances, when the gr_size value was set to 380 evacuees.

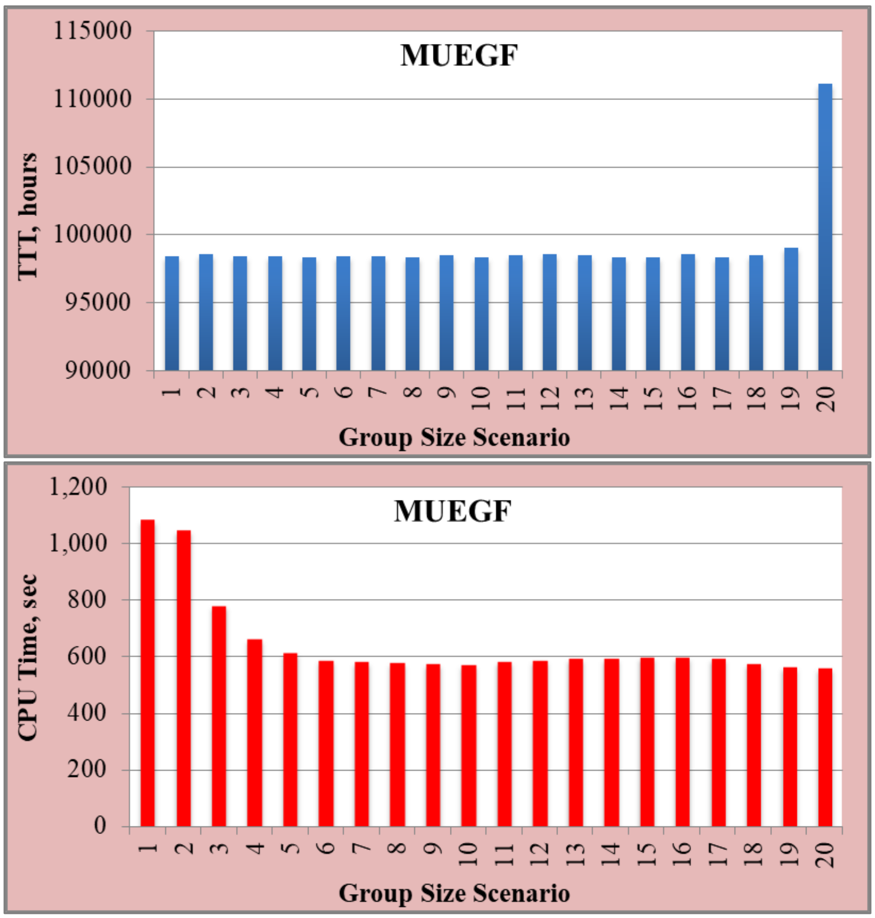

Figure 21 Average MUEGF objective function and computational time values over the large size problem instances for the considered group size scenarios.

7.1.2. Analysis of the Small Size Problem Instances

The second step of the numerical experiments focused on a detailed comparative analysis of the developed solution algorithms for the small size problem instances. All the proposed solution algorithms (i.e., CPLEX, MUEF, MUEL, MUEGF, and MUEGL algorithms) were executed for all the generated small size problem instances. A total of 5 replications were performed for each algorithm and each problem instance to estimate the average computational time values. The results from the conducted numerical experiments are provided in Table 9, which includes the following data: (1) instance number; (2) total number of evacuees ($\sum_{i \in I} q_i$); (3) objective function values (i.e., total travel time of evacuees – $\boldsymbol{TTT}$) for each solution algorithm; and (4) average computational time (CPU) values over 5 replications for each solution algorithm.

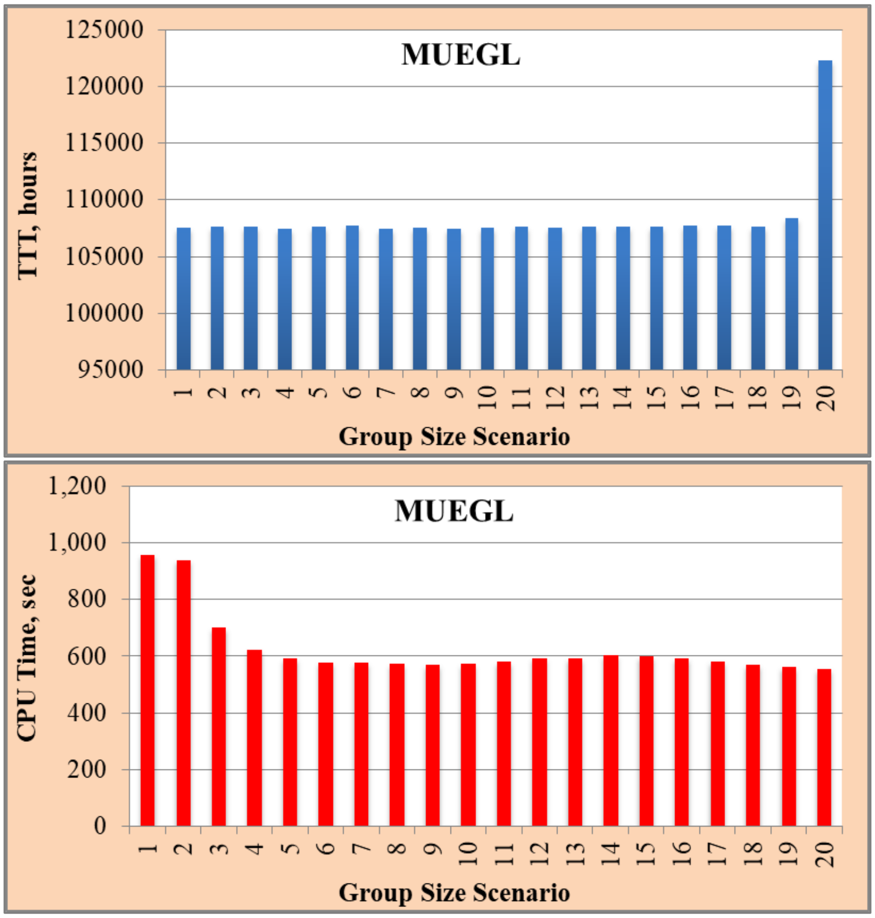

Figure 22 Average MUEGL objective function and computational time values over the large size problem instances for the considered group size scenarios.

Findings from the conducted analysis indicate the CPLEX computational is significantly affected with the problem size. Specifically, the CPLEX computational time is exponentially increasing with the total number of evacuees. The average computational time comprised 339.23 sec, 3.63 sec, 2.94 sec, 0.29 sec, and 0.23 sec over the generated small size problem instances for the CPLEX, MUEF, MUEL, MUEGF, and MUEGL algorithms respectively. The "grouping effect" (i.e., assignment of evacuees in groups to the emergency shelters, evacuation routes, and time periods) allowed the MUEGF and MUEGL heuristics solving the **EEPOP** mathematical model significantly faster as compared to the MUEF and MUEL heuristics.

Table 9 Analysis results for the small size problem instances: average objective function and computational time values, obtained by the developed solution algorithms.

Instance	$\sum_{i \in I} q_i$	CPLEX		MUEF		MUEL		MUEGF		MUEGL	
		$\boldsymbol{TTT}$, hours	CPU time, sec	$\boldsymbol{TTT}$, hours	CPU time, sec	$\boldsymbol{TTT}$, hours	CPU time, sec	$\boldsymbol{TTT}$, hours	CPU time, sec	$\boldsymbol{TTT}$, hours	CPU time, sec
S-1	20	2.69	30.57	2.69	0.58	2.69	0.52	2.69	0.27	2.69	0.24
S-2	40	5.36	60.76	5.36	0.90	5.36	0.89	5.36	0.23	5.36	0.26
S-3	60	8.03	85.10	8.03	1.10	8.03	1.14	8.03	0.24	8.03	0.24
S-4	80	10.73	110.52	10.73	1.47	10.73	1.40	10.73	0.30	10.73	0.24
S-5	100	13.38	138.69	13.38	1.79	13.38	1.74	13.38	0.49	13.38	0.29
S-6	120	16.05	169.47	16.05	2.23	16.05	2.04	16.05	0.24	16.05	0.22
S-7	140	18.74	198.96	18.74	2.52	18.74	2.26	18.74	0.24	18.74	0.21
S-8	160	21.41	228.30	21.41	2.80	21.41	2.27	21.41	0.27	21.41	0.21
S-9	180	24.07	258.75	24.07	3.25	24.07	2.54	24.07	0.28	24.07	0.21
S-10	200	26.75	287.51	26.75	3.45	26.75	2.79	26.75	0.27	26.75	0.21
S-11	220	29.44	316.79	29.44	3.80	29.44	3.00	29.44	0.28	29.44	0.21
S-12	240	32.12	347.70	32.12	4.05	32.12	3.27	32.12	0.28	32.12	0.22
S-13	260	34.81	378.06	34.81	4.47	34.81	3.89	34.81	0.30	34.81	0.23
S-14	280	37.46	411.06	37.46	4.66	37.46	4.11	37.46	0.29	37.46	0.22
S-15	300	40.12	442.51	40.12	5.10	40.12	4.01	40.12	0.29	40.12	0.23
S-16	320	43.90	568.03	43.90	5.35	43.99	4.09	44.36	0.31	44.47	0.24
S-17	340	48.74	630.90	48.74	5.99	48.98	4.35	49.27	0.35	49.39	0.25
S-18	360	53.62	671.74	53.62	6.09	54.00	4.61	54.20	0.33	54.34	0.24
S-19	380	58.50	703.95	58.50	6.42	58.99	4.87	59.22	0.31	59.29	0.24
S-20	400	63.39	745.29	63.39	6.67	63.98	5.05	64.18	0.31	64.27	0.25
Average:		29.47	339.23	29.47	3.63	29.55	2.94	29.62	0.29	29.65	0.23

Furthermore, it was found that the proposed solution algorithms were able to obtain the solutions, which were close to the optimal ones (suggested by CPLEX) for all the generated small size problem instances. The optimality gap values for each one of the developed solution algorithms are presented in Figure 23. Note that the optimality gap for algorithm alg ($\boldsymbol{Gap}_{alg}$) was estimated as follows: $Gap_{alg} = \frac{\boldsymbol{TTT}_{alg} - \boldsymbol{TTT}_{CPLEX}}{\boldsymbol{TTT}_{CPLEX}}$, where $\boldsymbol{TTT}_{alg}$ – is the average objective function value, obtained by algorithm alg; and $\boldsymbol{TTT}_{CPLEX}$ – is the optimal objective function value, obtained by CPLEX. It can be observed that the maximum optimality gap did not exceed 1.38% over the proposed heuristic algorithms, which demonstrates their accuracy. Smaller optimality gaps were generally recorded for the MUEF and MUEL heuristics, which can be explained by the fact that they assign evacuees one by one to the emergency shelters, evacuation routes, and time periods. On the other hand, the "grouping effect", adopted within the MUEGF and MUEGL heuristics, negatively affected the solution quality, as at the optimal/near-optimal solution two individuals of the same group can be assigned to different evacuation routes and emergency shelters. However, the "grouping effect" still did not cause a substantial increase in the objective function values, as the maximum optimality gap did not exceed 1.38%.

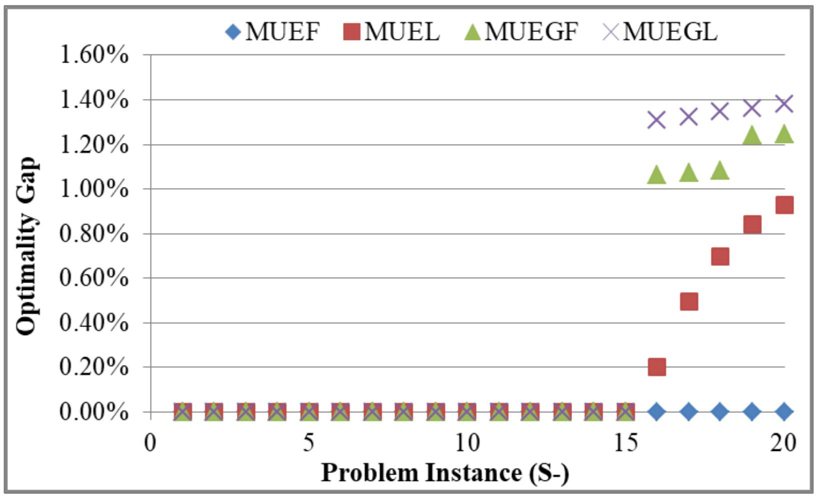

Figure 23 Optimality gap values for the developed solution algorithms.

7.1.3. Analysis of the Large Size Problem Instances

The third step of the numerical experiments focused on a detailed comparative analysis of the MUEF, MUEL, MUEGF, and MUEGL algorithms for the large size problem instances. As discusses earlier, CPLEX was not able to solve the problem instances with more than 400 evacuees, as its memory was not sufficient to load the input data. The MUEF, MUEL, MUEGF, and MUEGL algorithms were executed for all the generated large size problem instances. A total of 5 replications were performed for each algorithm and each problem instance to estimate the average computational time values. The results from the conducted numerical experiments are provided in

Table 10, which includes the following data: (1) instance number; (2) total number of evacuees ($\sum_{i \in I} q_i$); (3) objective function values (i.e., total travel time of evacuees – $\boldsymbol{TTT}$) for each solution algorithm; and (4) average computational time (CPU) values over 5 replications for each solution algorithm. Based on the conducted numerical experiments, the average computational time comprised 1,111.91 sec, 1,000.48 sec, 563.23 sec, and 562.90 sec over the generated large size problem instances for the MUEF, MUEL, MUEGF, and MUEGL algorithms respectively. Similar to the results from the numerical experiments that were conducted for the small size problem instances, the "grouping effect" allowed the MUEGF and MUEGL heuristics solving the **EEPOP** mathematical model significantly faster as compared to the MUEF and MUEL heuristics for the large size problem instances. It can be observed that the MUEGF and MUEGL computational time savings over the MUEF and MUEL heuristics increase with increasing problem size. The latter finding highlights importance of the "grouping effect", considering the fact that all emergency evacuation decisions have to be made in a timely manner in case of approaching devastating natural hazard.

The average objective function values comprised 94,558.54 hours, 105,395.20 hours, 99,026.57 hours, and 108,387.72 hours for the MUEF, MUEL, MUEGF, and MUEGL algorithms respectively over the generated large size problem instances. Therefore, the MUEF heuristic outperformed the MUEL, MUEGF, and MUEGL algorithms on average by 11.46%, 4.73%, and 14.62% respectively. Contrary to the results from the numerical experiments that were conducted for the small size problem instances, the MUEGF heuristic outperformed the MUEL heuristic in terms of the obtained objective function values for all the developed large size problem instances. The latter finding can be supported by the fact that assigning higher priorities to the individuals, who require the greatest time to travel from the emergency area to the nearest available emergency shelter, is critical, especially for the large scale emergency evacuations (i.e., with a significant number of evacuees).

7.2. Discussion

Throughout the numerical experiments, it was found that the exact solution algorithms would not be applicable for solving large scale emergency evacuation problems (formulated using the **EEPOP** mathematical model). Specifically, the exact optimization approach used in this study (i.e., CPLEX) was not able to solve the problem instances with more than 400 evacuees and returned a memory error (i.e., CPLEX memory was not sufficient for solving the problem instances with more than 400 evacuees). Moreover, the CPLEX computational time was growing exponentially with increasing problem size even for the small size problem instances. It was found that the developed heuristic algorithms (i.e., MUEF, MUEL, MUEGF, and MUEGL heuristics) were able to obtain the solutions, which were close to the optimal ones (obtained by CPLEX), for the small size problem instances. Specifically, the maximum optimality gap did not exceed 1.38% over the proposed heuristic algorithms. The analysis of large size problem instances demonstrated that the MUEF heuristic outperformed the MUEL, MUEGF, and MUEGL algorithms on average by 11.46%, 4.73%, and 14.62% respectively. However, the MUEF computational time was significantly greater as compared to the MUEGF computational time (i.e., 1,111.91 sec vs. 563.23 sec). The MUEF computational time was increasing with the problem size. Therefore, the MUEGF heuristic will be further used for the analysis of the managerial insights, as it was able to provide solutions of an acceptable quality within a reasonable computational time.

Table 10 Analysis results for the large size problem instances: average objective function and computational time values, obtained by the developed solution algorithms.

Instance	$\sum_{i \in I} q_i$	MUEF		MUEL		MUEGF		MUEGL	
		$\boldsymbol{TTT}$, hours	CPU time, sec	$\boldsymbol{TTT}$, hours	CPU time, sec	$\boldsymbol{TTT}$, hours	CPU time, sec	$\boldsymbol{TTT}$, hours	CPU time, sec
L-1	5000	6881.92	75.13	7350.06	77.08	7082.35	9.25	7462.67	9.32
L-2	10000	25140.42	179.61	26984.33	175.88	25934.00	38.22	27466.70	38.47
L-3	15000	48953.98	305.74	52993.26	309.94	50808.49	93.98	54344.77	89.70
L-4	20000	75501.02	442.56	81873.11	441.13	78377.47	162.10	83903.08	157.57
L-5	25000	77155.57	613.87	83742.11	618.68	80128.33	261.64	85817.44	256.22
L-6	30000	78467.84	688.28	85376.60	671.80	81567.41	260.69	87383.16	260.68
L-7	35000	79896.67	692.20	87175.87	676.82	83095.86	310.64	89394.53	310.24
L-8	40000	92463.95	763.87	101024.53	752.00	96186.36	374.15	103756.23	366.00
L-9	45000	95908.75	847.37	105187.35	831.26	99769.85	430.37	108360.03	420.77
L-10	50000	99548.01	914.45	109966.79	926.21	103566.39	483.86	112628.45	488.41
L-11	55000	102155.09	1060.50	112881.96	1000.26	106311.88	545.77	116252.04	551.82
L-12	60000	105216.05	1296.02	116846.81	1097.16	110035.60	616.37	120896.12	608.12
L-13	65000	108707.83	1379.04	121407.13	1189.98	113997.31	677.68	125340.04	685.50
L-14	70000	112483.03	1451.53	125751.05	1277.53	118042.85	765.32	129988.79	749.53
L-15	75000	117896.07	1561.72	132391.49	1385.90	123892.46	832.70	136566.66	833.47
L-16	80000	122762.99	1673.81	138045.39	1507.56	129183.40	904.75	142721.83	904.31
L-17	85000	127926.91	1774.60	144256.29	1596.57	134730.82	986.65	149133.54	1016.79
L-18	90000	132625.07	2033.56	150840.03	1713.67	139899.86	1075.95	155079.00	1084.45
L-19	95000	137915.62	2137.96	157353.49	1819.70	145711.17	1171.37	161987.10	1164.11
L-20	100000	143564.06	2346.38	166456.38	1940.53	152209.57	1263.13	169272.26	1262.47
Average:		94558.54	1111.91	105395.20	1000.48	99026.57	563.23	108387.72	562.90

8. MANAGERIAL INSIGHTS

This section of the report discusses managerial insights that were revealed using the developed mathematical model and heuristics. Although the research team applied all heuristics developed (including MUEF, MUEL, MUEGF, and MUEGL) to solve the **EEPOP** mathematical model, only managerial insights, provided by the MUEGF heuristic, will be considered because the results from the numerical experiments indicated that it is superior to other heuristics.

8.1. Shelter Utilization

8.1.1. Total utilization of shelters

The total utilization of available shelters throughout the evacuation process is presented in Figure 24 for each one of the generated large size problem instances. For example, the outmost top left chart shows utilization of available shelters for large size problem instance L-1. Based on the conducted numerical experiments, the MUEGF heuristic assigned 5,000 evacuees to 11 shelters for large size problem instance L-1. The top five shelters with maximum capacity utilization include: 1) Dunedin Highland Middle School (ID number 505); 2) David L. Anderson Middle School (ID number 496); 3) Booker T. Washington Senior High (ID number 485); 4) South Mainland (Micco) (ID number 521); and 5) John Hopkins Middle School (ID number 506). Note that based on the input data prepared for the numerical experiments, the first 476 shelters (i.e., ID number 1 - ID number 476) are GP shelters, while shelters 477 through 587 are SpNS.

GP shelters and SpNS were listed in an increasing order of their distance from the centroid of Broward County; hence, the closest shelters are listed first in both categories. Furthermore, the utilization of available shelters for large problem size instance L-20 is illustrated in the outmost bottom right chart of Figure 24. The MUEGF heuristic assigned 100,000 evacuees to 99 shelters for large problem size instance L-20. The charts, presented in Figure 24 for large size problem instances, indicate that an increase in the number of evacuees assigned by the MUEGF heuristic resulted in an increase in the number of shelters utilized. Moreover, the results demonstrated that the MUEGF heuristic generally assigned evacuees to the closest shelters with high capacities. The maps, showing the total utilization of GP shelters and SpNS, are presented in Figure 25 and Figure 26 respectively. From Figures 24 and 25, some shelters, which are closer to Broward County were not fully utilized, while the shelters farther from the centroid of Broward County were utilized. The latter finding may be justified based on the fact that the MUEGF heuristic assigned evacuees in groups to high capacity shelters, while the smaller capacity shelters were used to accommodate the remaining evacuees, who were not assigned to the larger shelters due to the capacity constraints.

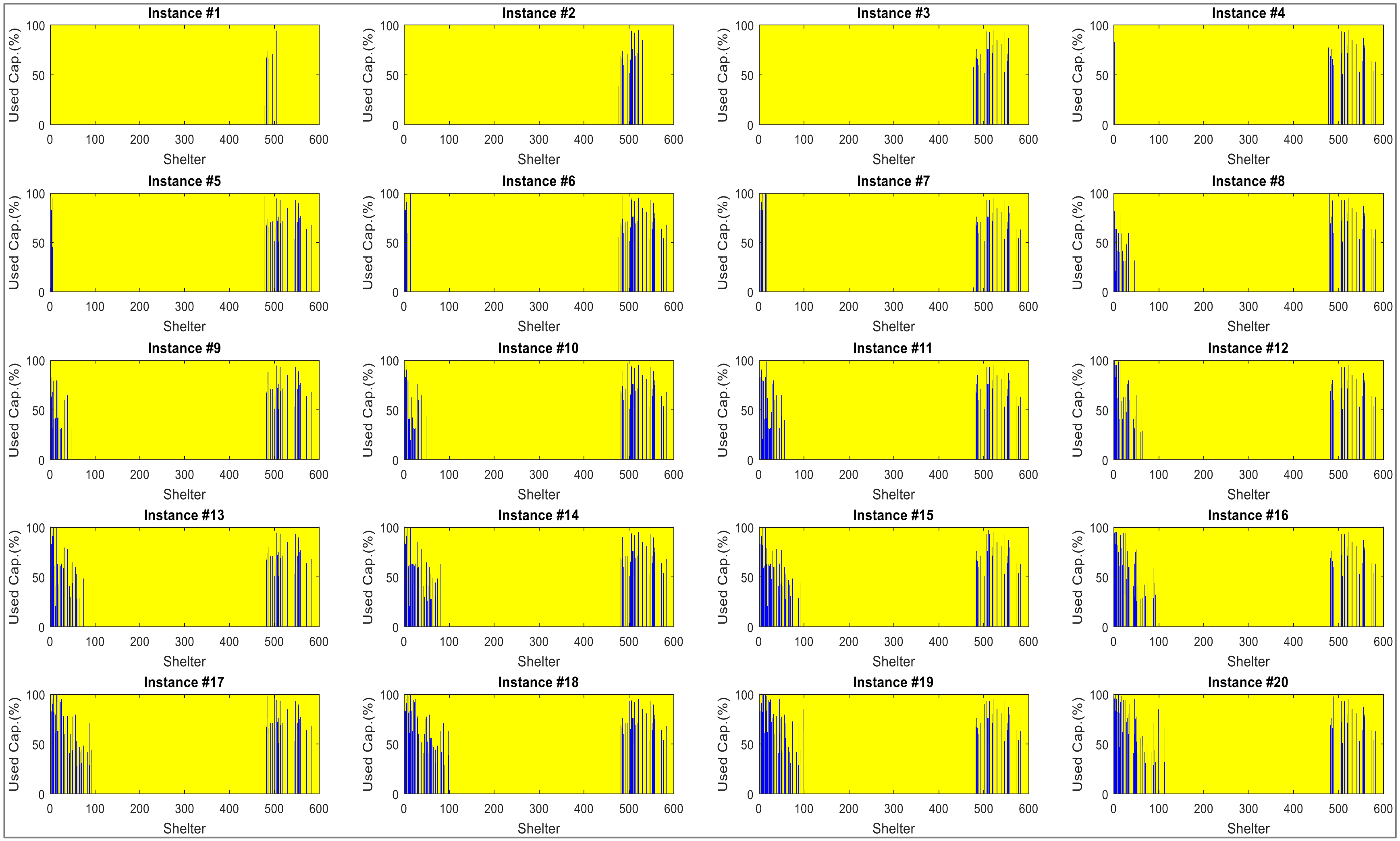

Figure 24 Total utilization of the available shelters throughout the evacuation process for large size problem instances (L-1 through L-20).

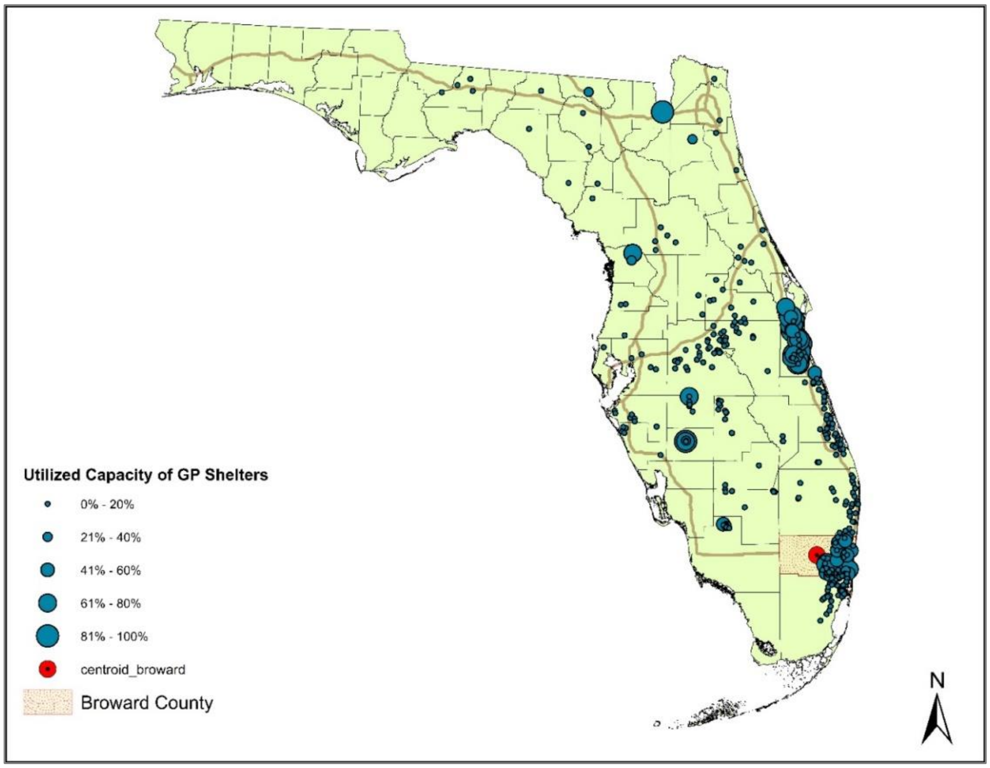

Figure 25 The total utilization of GP shelter capacity for large size problem instance L-20.

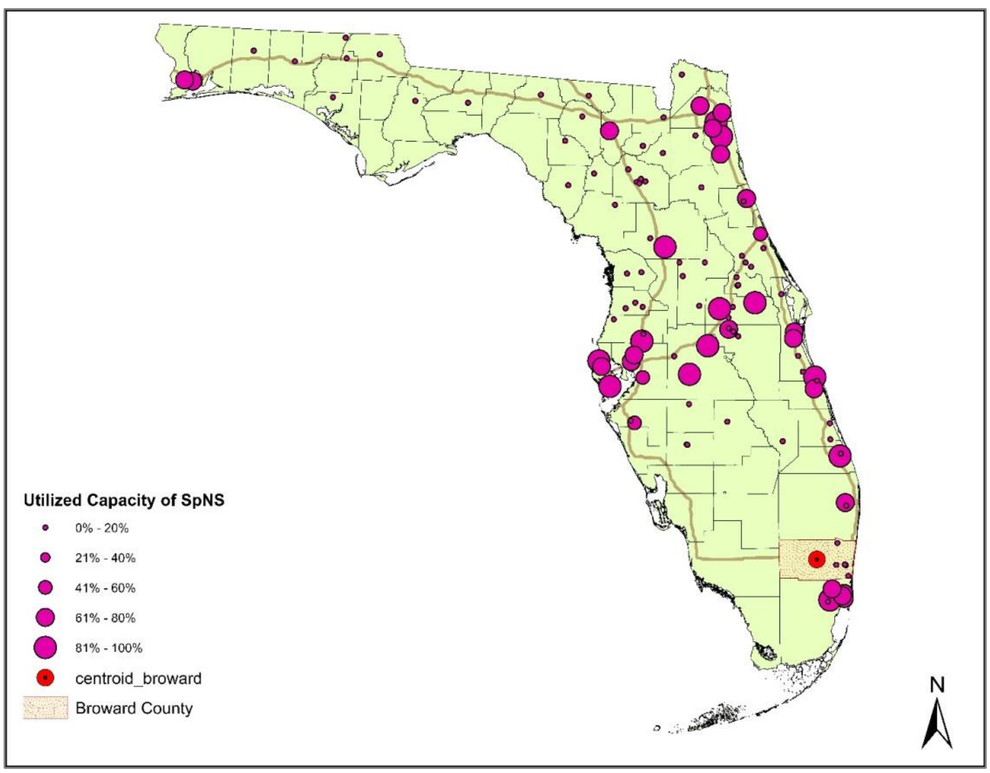

Figure 26 The total utilization of SpNS for large size problem instance L-20.

8.1.2. Utilization of assigned shelters by time period

Figure 27 illustrates the utilization of assigned shelters by time period throughout the evacuation process for large size problem instances. For example, the outmost top left chart shows the utilization of assigned shelters by time period for large size problem instance L-1. Based on the conducted numerical experiments the MUEGF heuristic assigned 5,000 evacuees to shelters within two time periods (or 2 hours). However, for large problem size instance L-20 (see the outmost bottom right chart), the MUEGF heuristic assigned 100,000 evacuees to shelters within 18 time periods. The results from computational experiments indicated that the number of time periods, utilized by the MUEGF heuristic, increased with increasing problem size. In the event of a hazard, State authorities seek to evacuate the population affected to shelters in the shortest possible time. The results for problem size instances L1-L20 demonstrated that the MUEGF heuristic utilized the capacity of available high capacity shelters within the first time periods (see Figure 27); thus, the majority of evacuees were evacuated within the first time period.

8.1.3. Cumulative utilization of available shelters by time period

Figure 28 presents the cumulative utilization of available shelters by time period throughout the evacuation process for large size problem instances L1-L20. For example, the outmost top left chart shows the utilization of available shelters for large size problem instance L-1. The chart shows that the MUEGF heuristic assigned 3860 evacuees out of 5000 evacuees within the first time period and the remaining 1140 evacuees were assigned during the second time period. Furthermore, the chart presented in the outmost bottom right of Figure 28 for large problem size instance L-20 (with 100,000 evacuees), shows that the MUEGF heuristic assigned 70,133 evacuees within the first time period and a total of 84,800 were evacuated after the second time period. The remaining evacuees were assigned over 16 time periods for problem size instance L-20. The findings demonstrate the efficiency of the algorithm in assigning the majority of the evacuees to emergency shelters within the first few hours of evacuation.

The utilized capacity of GP shelters after 6-hour time periods was estimated for large problem size instance L-20. The maps, showing the total utilization of GP shelters after 2 time periods, 4 time periods, and 6 time periods, are presented in Figure 29, Figure 30, and Figure 31 respectively for large size problem instance L-20 to illustrate the increase in utilized capacity of the available shelters after 2 hours, 4 hours, and 6 hours of emergency evacuation. A comparative analysis of the three maps suggests that the majority of the evacuees were assigned to shelters within the first 2 hours of emergency evacuation. The percent utilization of GP shelters for some of the available shelters increased within 2 to 4 hours of emergency evacuation. Moreover, utilization of certain GP shelters slightly increased after 4 hours of emergency evacuation as well.

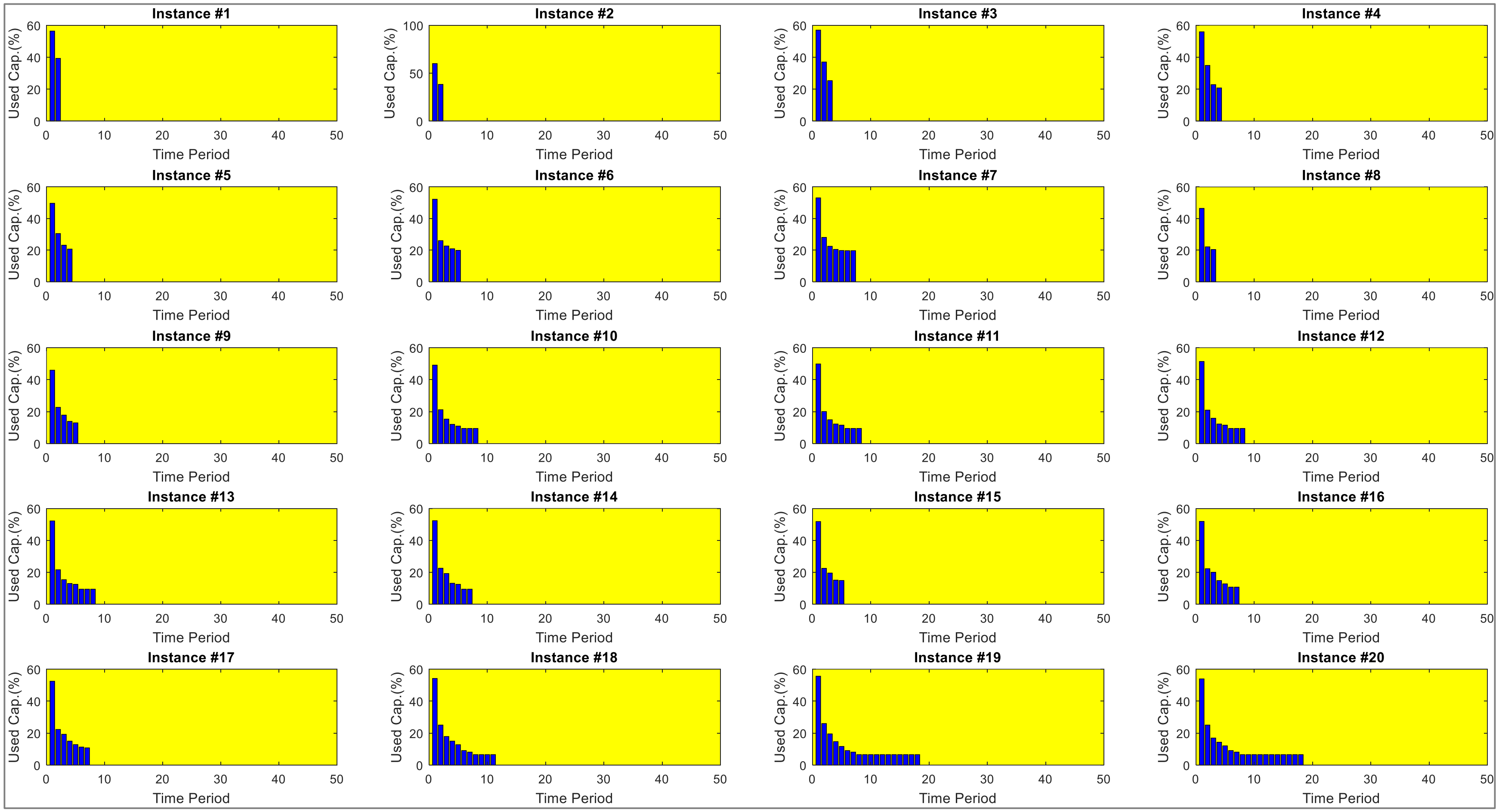

Figure 27 Utilization of the assigned shelters by time period throughout the evacuation process for large size problem instances (L-1 through L-20).

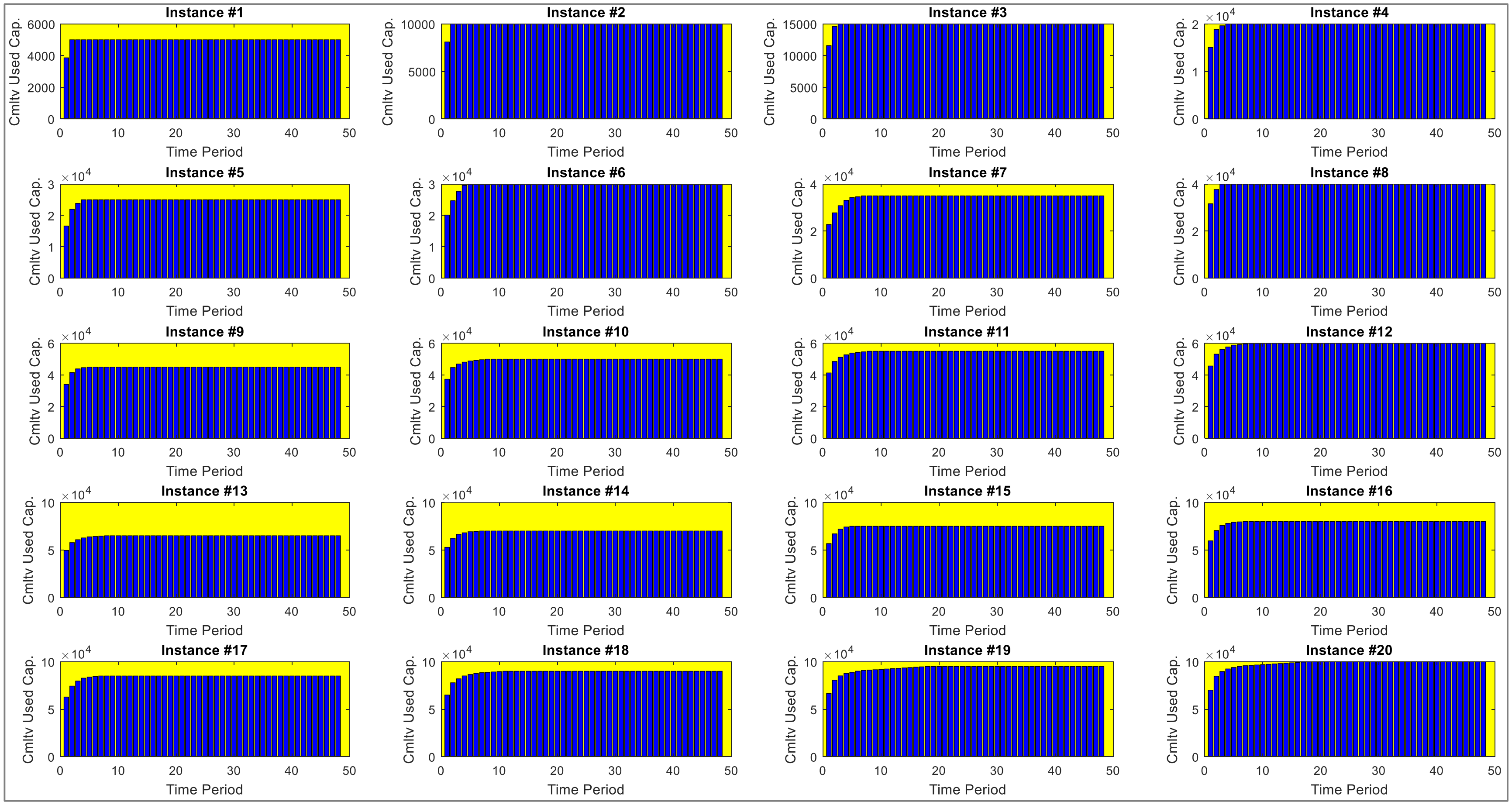

Figure 28 Cumulative utilization of the available shelters by time period throughout the evacuation process for large size problem instances (L-1 through L-20).

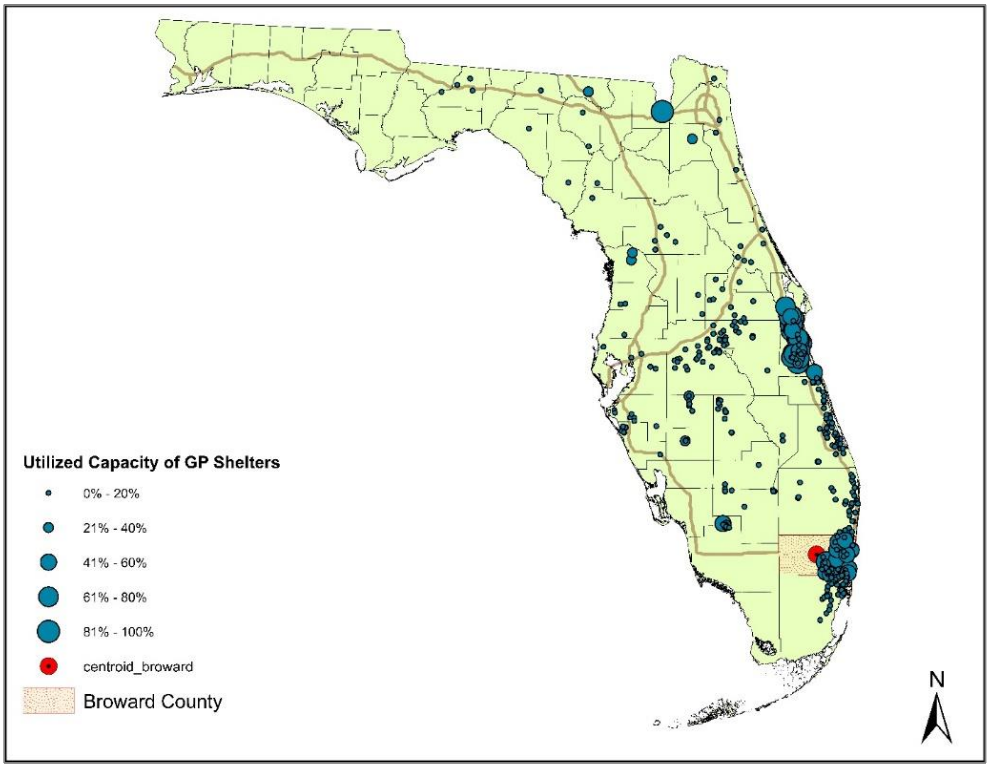

Figure 29 The total utilization of GP shelters after 2 time periods for large size problem instance L-20.

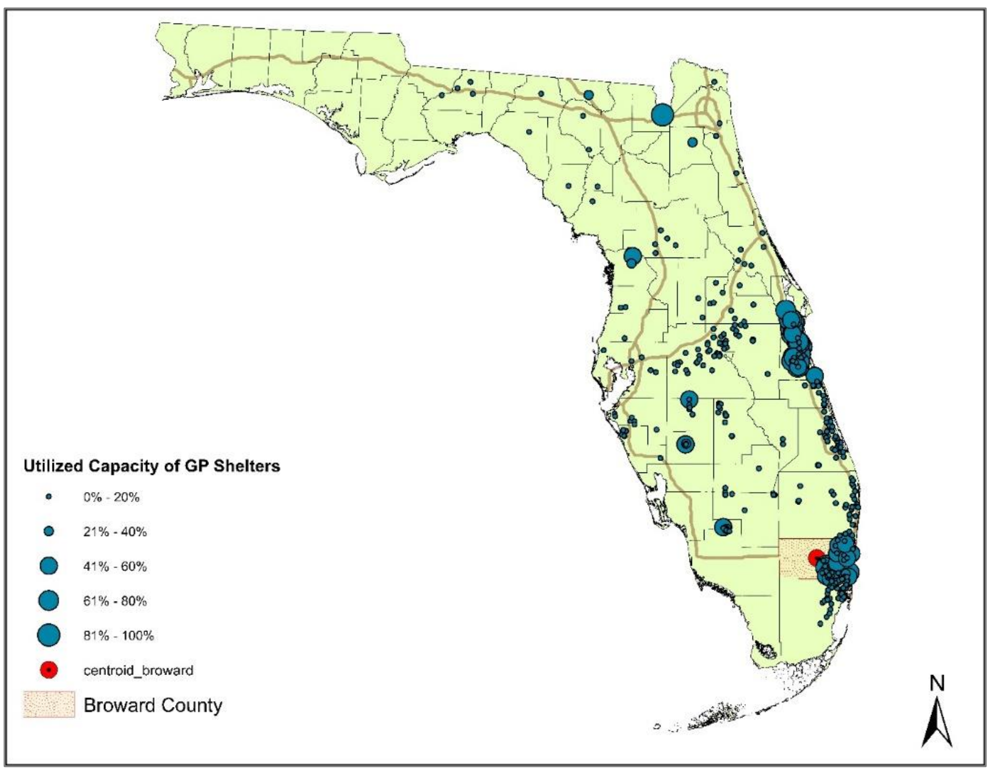

Figure 30 The total utilization of GP shelters after 4 time periods for large size problem instance L-20.

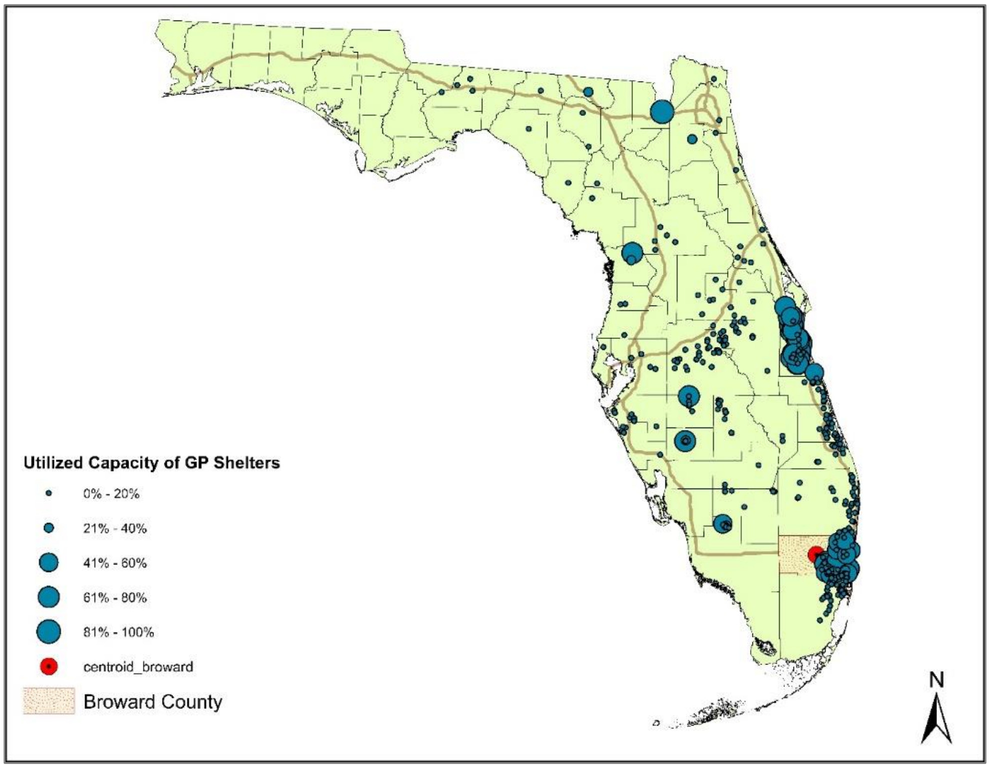

Figure 31 The total utilization of GP shelters after 6 time periods for large size problem instance L-20.

8.2. Utilization of evacuation routes

8.2.1. Average utilization of evacuation routes

The average utilization of evacuation routes over time periods throughout the evacuation process for large size problem instances is shown in Figure 32. For example, the outmost top left chart shows the utilization of available evacuation routes for large size problem instance L-1. Based on the conducted numerical experiments, it was found that the MUEGF heuristic assigned 5,000 evacuees to the shortest evacuation routes leading to SpNS for large size problem instance L-1. The latter finding may be supported by the fact that, there is at least one evacuee in each group created for the large problem instance L-1, who needed to be assigned to a SpNS. Note that based on the input data prepared for the numerical experiments, the first 904 evacuation routes lead to GP shelters, while evacuation routes 905 through 1314 lead to SpNS. Also, the evacuation routes leading to GP shelters and SpNS were listed in an increasing order of route lengths from the centroid of Broward County; thus, the shortest evacuation routes were listed first in both categories. As the problem size instance increased, the MUEGF heuristic assigned evacuees to the shortest evacuation routes, which lead to both GP shelters and SpNS. Furthermore, the average utilization of all evacuation routes did not exceed 80% throughout the evacuation process.

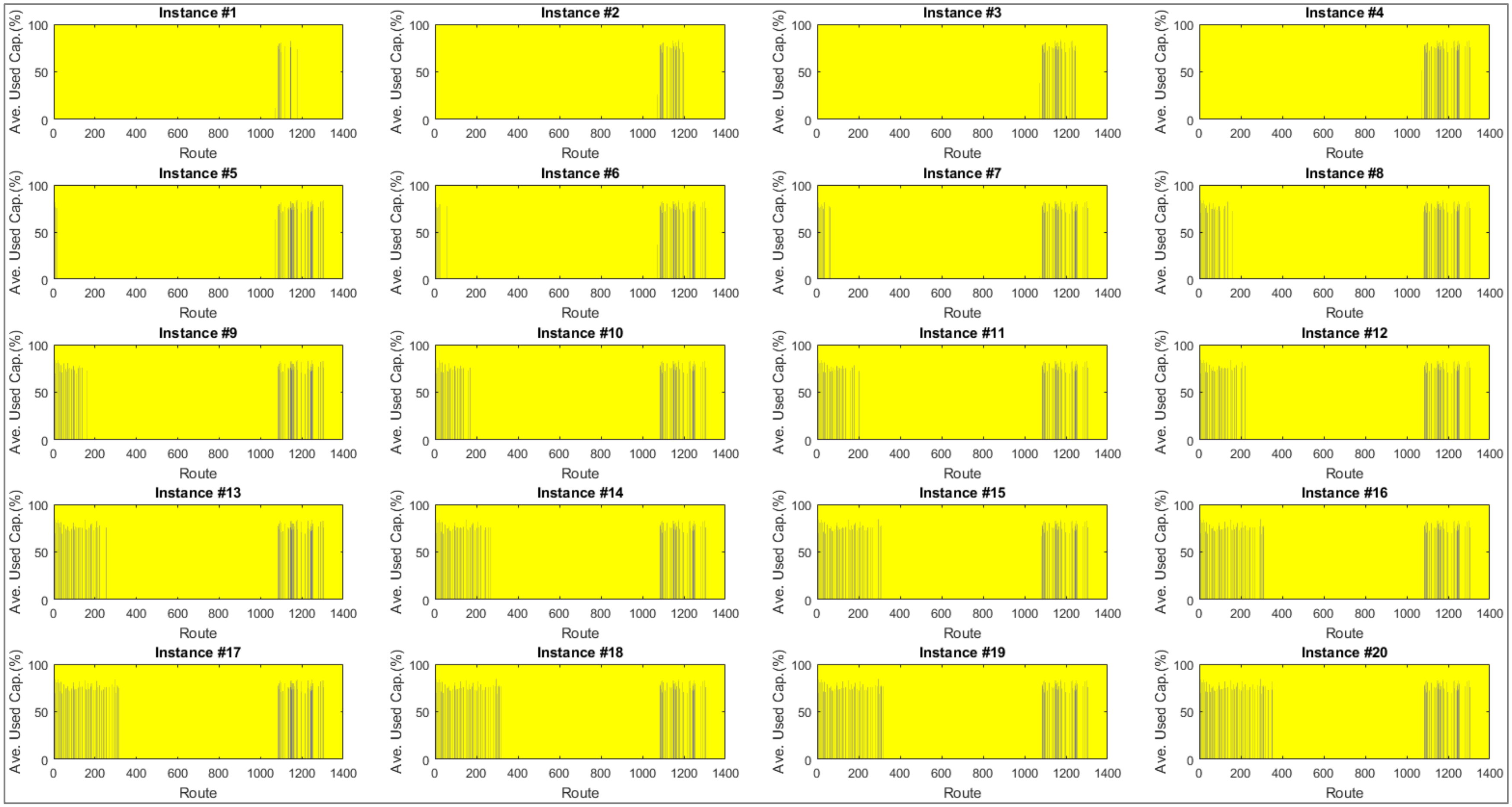

Figure 32 Average utilization of the evacuation routes over time periods throughout the evacuation process for large size problem instances (L-1 through L-20).

8.2.2. Total utilization of the available evacuation routes by time period

The total utilization of the available evacuation routes by time period throughout the evacuation process for large size problem instances is illustrated in Figure 33. For example, the outmost bottom right chart shows the total utilization of the available evacuation routes by time period for large size problem instance L-20, where 100,000 evacuees were assigned using the MUEGF heuristic. The results from conducted numerical experiments indicate that less than 1% of the total capacity of the available evacuation routes was utilized at each time period for all large size problem instances (L-1 through L-20). The total utilization of the available evacuation routes is expected to significantly increase for a large scale emergency evacuation.

8.2.3. Average utilization of the assigned evacuation routes by time period

The average utilization of the assigned routes in each time period throughout the evacuation process for large size problem instances is presented in Figure 34. For example, the outmost top left chart shows the average utilization of assigned routes in each time period for large size problem instance L-1. Based on the conducted numerical experiments, the MUEGF heuristic did not utilize more than 75% of capacity of the assigned evacuation routes during the first and second time periods for large size problem instance L-1. Generally, throughout the evacuation process, it was found the MUEGF heuristic did not utilize more than 80% of capacity of the assigned evacuation routes at each time period. The latter finding suggests that the MUEGF heuristic is conservative and avoids making use of the maximum route capacity to avoid congestion of emergency evacuation routes.

8.3. Average travel time of evacuees

Figure 35 presents the average travel time of evacuees in each time period throughout the evacuation process for large size problem instances. For example, the outmost bottom right chart shows the average travel time of evacuees in each time period for large size problem instance L-20, where 100,000 evacuees were assigned using the MUEGF heuristic. The results presented in Figure 35 indicate that the average travel time of evacuees may vary from one evacuation time period to another for all large problem size instances (L-1 through L-20) considered. The latter finding can be explained by the fact that the travel time function encoded in the MUEGF heuristic is dependent on various human characteristics (which varies among individuals), as well as length of the evacuation routes.

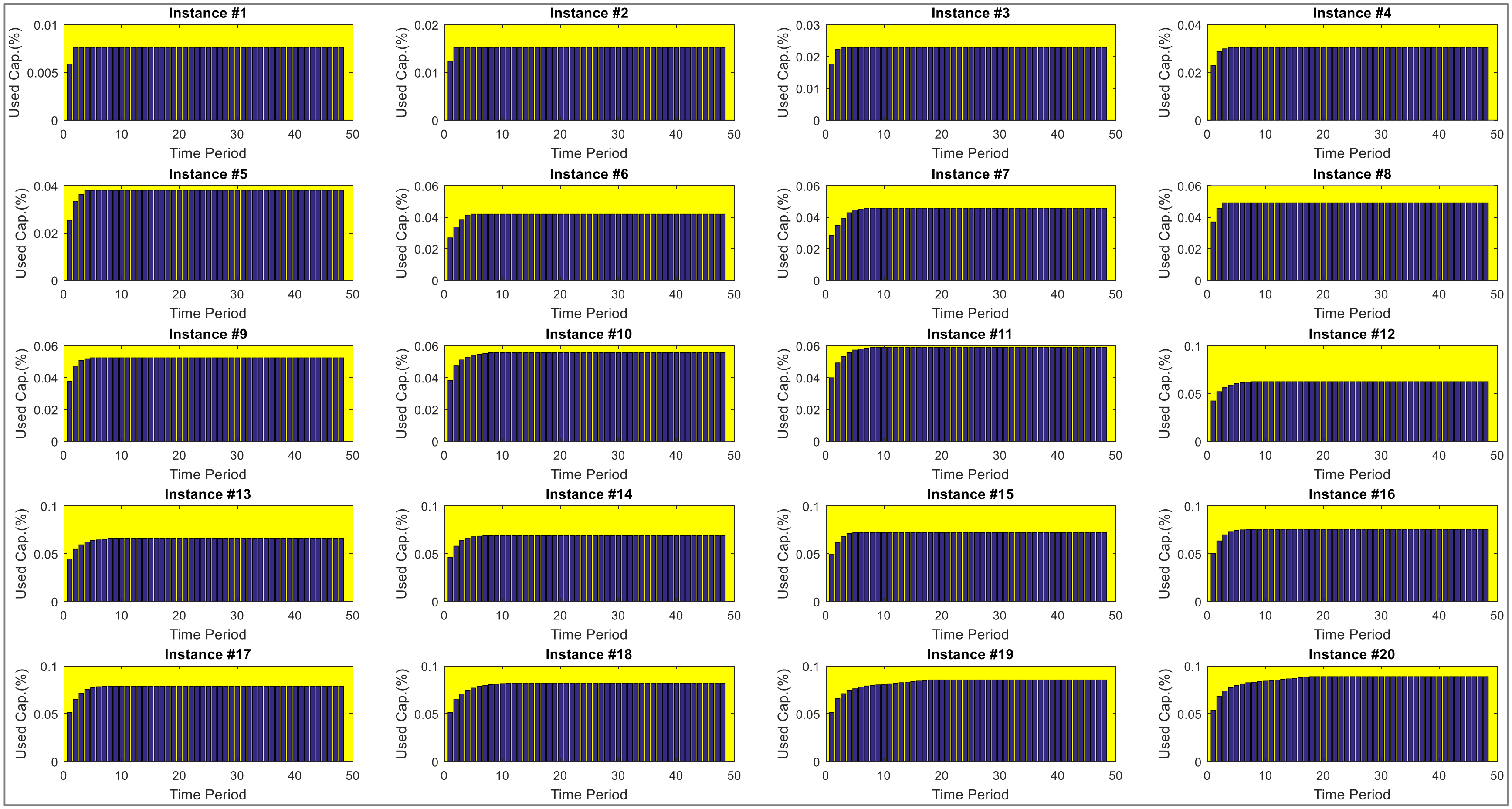

Figure 33 Total utilization of the available routes by time period throughout the evacuation process for large size problem instances (L-1 through L-20).

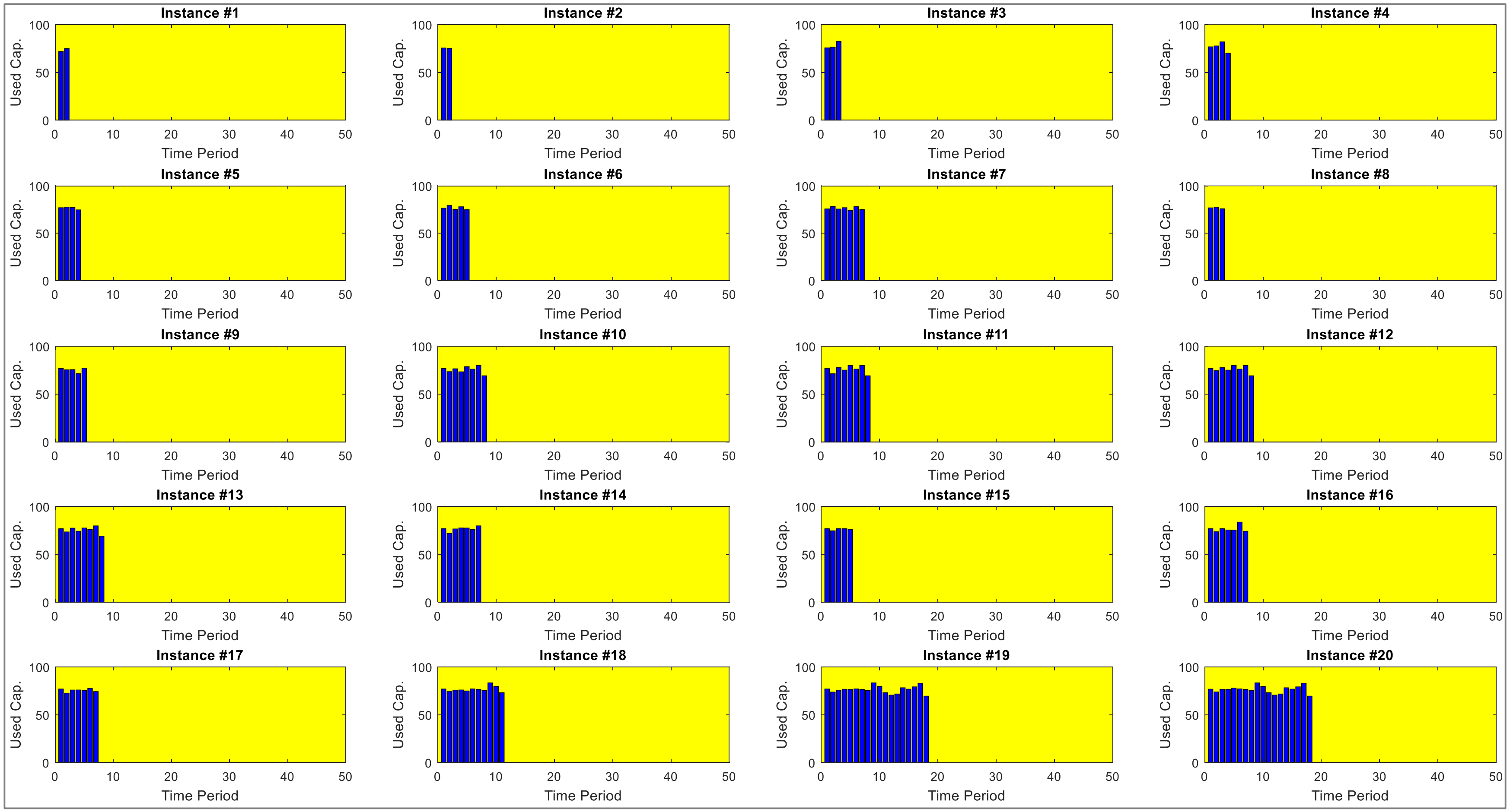

Figure 34 Average utilization of the assigned routes in each time period throughout the evacuation process for large size problem instances (L-1 through L-20).

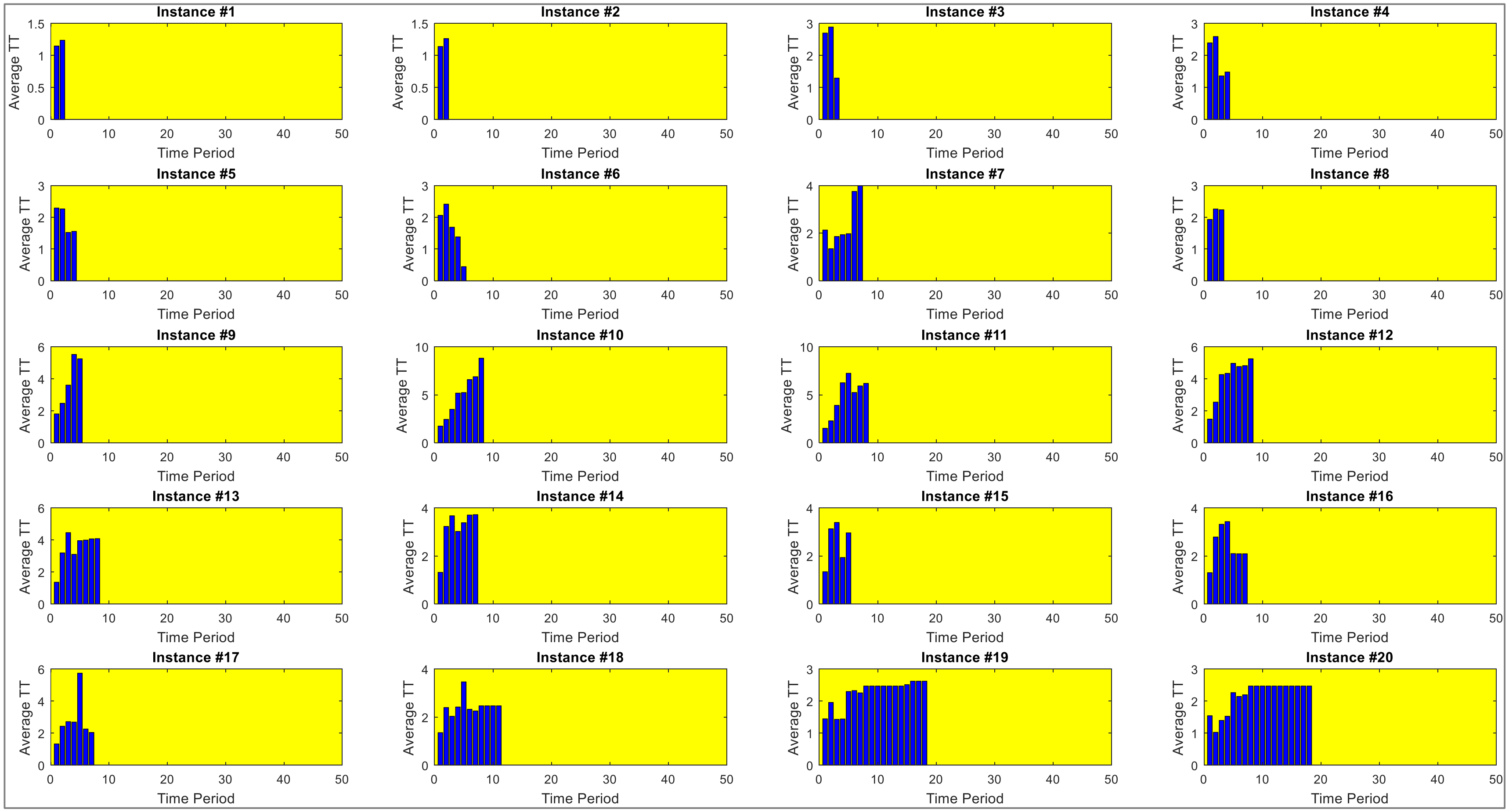

Figure 35 Average travel time (TT) of evacuees (in hours) for each time period throughout the evacuation process for large size problem instances (L-1 through L-20).

9. CONCLUSIONS AND FUTURE RESEARCH

The coastal areas across the U.S. are subject to natural hazards, including severe storms, straight-line winds, severe thunderstorms, tornadoes, flooding, hurricanes, severe freezes, and others. Natural hazards may not only cause significant damages to the existing infrastructure, but also pose a major threat to human lives. In case of approaching natural hazards, the population, inhabiting areas where the potential impact of a hazard is expected to be devastating, is advised to evacuate. The population is required to evacuate the emergency area in a timely manner. However, evacuees are generally not advised to use a specific evacuation route and are not assigned to a specific emergency shelter. The latter causes congestion at some of the emergency routes and inefficient utilization of the available emergency shelters. Specifically, in many cases evacuees are trying to use the same evacuation route (usually the shortest route to a shelter), which may further cause the route congestion due to limited capacity of the evacuation route and significantly delay the evacuation process. Emergency evacuation is even more challenging for vulnerable population groups may require additional time in order to evacuate the emergency areas as a result of approaching natural disaster.

To address the aforementioned challenges associated with emergency evacuation and facilitate the evacuation process, this study focused on the development of a mathematical model and solution algorithms for the emergency evacuation planning optimization problem. The objective of the proposed mixed integer mathematical model aimed to assign individuals to evacuate the emergency area using one of the available emergency evacuation routes to one of the emergency shelters during a specific time period, by minimizing the total travel time of evacuees and considering the following factors: (1) limited capacity of the available emergency evacuation routes and shelters; (2) potential carpooling of individuals (e.g., the whole family is evacuating); (3) shelter requirements for vulnerable population groups (e.g., assignment of individuals with special needs shelters to ensure that these individuals will have the adequate accommodations); (4) major socio-demographic characteristics of drivers, evacuation route characteristics, driving conditions, and traffic characteristics, which may affect the driving ability of individuals under emergency evacuation; and others. Two groups of algorithms were developed to solve the proposed mathematical formulation for the emergency evacuation planning optimization problem, including: (a) exact optimization algorithm (CPLEX); and (2) heuristic algorithms approaches, including the following: 1) Most Urgent Evacuee First (MUEF); 2) Most Urgent Evacuee Last (MUEL); 3) Most Urgent Evacuee Group First (MUEGF); and 4) Most Urgent Evacuee Group Last (MUEGL)).

In order to assess performance of the proposed solution approaches, the formulated mathematical model and the developed solution algorithms were applied for evacuation of Broward County, Florida, a coastal area of the U.S., which is often impacted by tropical storms. The data (including potential evacuation routes and evacuation route capacity, emergency shelters and shelter capacity, demographic characteristics of the population, etc.), required to conduct the computational experiments, were collected and a set of numerical experiments were conducted to assess the performance of the proposed algorithms in terms of in terms of both solution quality and the computational time for small and realistic size problem instances. Findings from this research provide a lot of insights regarding emergency evacuation route and shelter utilization as well as the average travel time of evacuees throughout the evacuation process. The proposed mathematical model and solution algorithm may be used as an efficient practical tool by State and local authorities (e.g., FEMA, Department of Homeland Security, and others) in improving the utilization of emergency evacuation routes and emergency shelters, reducing or eliminating traffic congestion on roadways during emergency evacuation, and reducing the travel time of evacuees during emergency evacuation. Moreover, the developed decision support tools are expected to improve the overall effectiveness of emergency evacuation process, and ensure safety of evacuees, including vulnerable population groups.

The scope of future research for this study includes the following:

1) Implement the developed **EEPOP** optimization model for other types of natural and man-made hazards (such as wildfire, tsunami, terrorist attack, nuclear plant radiation, earthquake, etc.);
2) Apply the developed **EEPOP** mathematical model to evacuate multiple counties (e.g. evacuation of all counties along Florida's costal area);
3) Explore alternative optimization algorithms (e.g., metaheuristic algorithms);
4) Account for the effects of other factors that were not considered (including weather and contraflow of traffic) on the emergency evacuation process;
5) Conduct a comprehensive analysis to account for the effects of shadow evacuation on the proposed **EEPOP** mathematical model.

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