International Journal of Disaster Risk Reduction 39 (2019) 101114

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

Exact and heuristic solution algorithms for efficient emergency evacuation in areas with vulnerable populations

Maxim A. Dulebenets[a,*], Junayed Pasha[b], Olumide F. Abioye[b], Masoud Kavoosi[b], Eren E. Ozguven[c], Ren Moses[d], Walter R. Boot[e], Thobias Sando[f]

[a] Department of Civil & Environmental Engineering, Florida A&M University-Florida State University, 2525 Pottsdamer Street, Building A, Suite A124, Tallahassee, FL, 32310-6046, USA
[b] Department of Civil & Environmental Engineering, Florida A&M University-Florida State University, 2525 Pottsdamer Street, Building B, Suite B339, Tallahassee, FL, 32310-6046, USA
[c] Department of Civil & Environmental Engineering, Florida A&M University-Florida State University, 2525 Pottsdamer Street, Building B, Suite B313, Tallahassee, FL, 32310-6046, USA
[d] Department of Civil & Environmental Engineering, Florida A&M University-Florida State University, 2525 Pottsdamer Street, Building A, Suite A129, Tallahassee, FL, 32310-6046, USA
[e] Department of Psychology, Florida State University, 1107 W Call St., Suite B432, Tallahassee, FL, 32306-4301, USA
[f] School of Engineering, University of North Florida, 1 UNF Drive, Building 50, Suite 2102, Jacksonville, FL, 32256, USA

ARTICLE INFO

Keywords:
Natural hazards
Emergency evacuation
Vulnerable populations
Optimization
Heuristics
Travel time

ABSTRACT

Proper emergency evacuation planning is a key to ensure safety and efficiency of transportation networks in the event of approaching natural hazards. A sound evacuation plan can save human lives and avoid congestion. In order to develop effective emergency evacuation plans, this study presents a mixed-integer programming model that assigns individuals, including vulnerable population groups, to emergency shelters through evacuation routes during the available time periods. The objective of the mathematical model is to minimize the total travel time of individuals leaving an evacuation zone. Unlike many emergency evacuation models presented in the literature, the proposed mathematical model directly accounts for the effects of socio-demographic characteristics of evacuees, evacuation route characteristics, driving conditions, and traffic characteristics on the travel time of evacuees. An exact optimization approach and a set of heuristic approaches are applied to yield solutions for the developed model. The numerical experiments are conducted for emergency evacuation of Broward County (Florida, United States). The results show that the exact optimization approach cannot tackle the large-size problem instances. On the other hand, the proposed heuristic algorithms are able to provide good-quality solutions within a reasonable computational time. Therefore, the developed mathematical model and heuristic algorithms can further assist the appropriate agencies with efficient and timely emergency evacuation planning.

1. Background

Various natural hazards, such as storms, hurricanes, floods, tsunamis, and others, have frequently thrashed the coastal areas across the United States (U.S.). Natural hazards may not only cause significant damages to the existing infrastructure but also pose a major threat to human life [1]. One of the recent hurricanes, Irma, which struck the U.S. coast in 2017, is regarded as one of the most severe natural hazards in the U.S. history. A category 4 hurricane Irma made a landfall in the Florida Keys and hit the southwestern part of Florida as a category 3 hurricane [2]. Seven direct deaths and 85 indirect deaths, in addition to hundreds of injuries, were reported in the U.S. Almost 6 million people from the coastal areas of Florida were evacuated [2]. Emergency evacuations of such magnitude are becoming a trend, especially in Florida, as Florida is very frequently struck by devastating natural hazards.

One of the most crucial challenges for a large-scale emergency evacuation is the limited number and capacity of evacuation routes, which may not be sufficient to serve the traffic demand exiting the evacuation zone [3]. Another challenge is the allocation of evacuees among the existing emergency shelters, considering the limited

* Corresponding author.
E-mail addresses: mdulebenets@eng.famu.fsu.edu (M.A. Dulebenets), jp17j@my.fsu.edu (J. Pasha), olumide1.abioye@famu.edu (O.F. Abioye), mk17@my.fsu.edu (M. Kavoosi), eozguven@eng.famu.fsu.edu (E.E. Ozguven), moses@eng.famu.fsu.edu (R. Moses), boot@psy.fsu.edu (W.R. Boot), t.sando@unf.edu (T. Sando).

https://doi.org/10.1016/j.ijdrr.2019.101114
Received 3 January 2019; Received in revised form 6 March 2019; Accepted 6 March 2019
Available online 12 March 2019
2212-4209/

capacity of the available shelters and the special needs of certain evacuee groups (e.g., individuals with disabilities have to be assigned to special-needs shelters). Construction of new roads and shelters to serve the additional surge is budget-sensitive and most likely infeasible from the practical standpoint due to shortage of time after the forecast of a natural hazard. So, proper planning of emergency evacuation is pivotal to save lives and minimize losses. A proper evacuation plan is even more important for aging adults, since many of them might require a significant amount of time to drive to the assigned emergency shelter. Such an increase in travel time for aging adults as compared to their younger counterparts can be explained by changes in vision, hearing, attention, speed of processing and responsiveness, presence of chronic diseases, and other factors associated with age [4–6]. Vulnerable population groups (e.g., aging adults, individuals with disabilities, individuals with medical condition) need special considerations during emergencies.

Nowadays, the design of efficient evacuation plans is one of the most urgent research paths. Recent studies on emergency evacuation are geared towards optimization [7–9]. Optimization models can improve utilization of evacuation routes, reduce congestion through the minimization of travel time during evacuation, and assist with allocation of evacuees among the available emergency shelters. Hence, decision makers should focus on design and deployment of advanced optimization-based tools and algorithms in order to develop efficient emergency evacuation plans. This study aims to facilitate natural hazard preparedness operations by developing an optimization model and solution algorithms for assigning evacuees to evacuation routes and emergency shelters. The objective of the proposed mixed-integer programming model is to minimize the total travel time of individuals, evacuating from a hazard zone. Unlike many emergency evacuation models presented in the contemporary literature, the developed mathematical model directly accounts for the effects of socio-demographic characteristics of evacuees, evacuation route characteristics, driving conditions, and traffic characteristics on the travel time of evacuees.

The remainder of this manuscript is organized as follows. The second section presents an up-to-date review of the relevant studies on emergency evacuation planning. The third section provides a detailed description of the emergency evacuation planning optimization problem studied herein. The fourth section describes a mixed-integer programming model, which was formulated for the emergency evacuation planning optimization problem. The fifth section discusses the adopted exact optimization approach and the heuristic approaches, which were developed to solve the proposed mathematical model. The sixth section presents a case study, which was conducted to evaluate performance of the developed solution approaches and demonstrate important managerial insights. The last section concludes this study and provides a set of future research extensions.

2. Review of the relevant studies

Numerous studies have been published to date concerning the emergency evacuation and planning decision problems. Some studies carried out a detailed review of the research efforts related to the emergency evacuation planning decision problems [10–13]. Analytical methods have been widely used in the emergency evacuation planning literature. For example, Cheng et al. [14] devised a time-dependent disaggregate destination choice model for evacuees leaving the emergency area due to approaching hurricanes. The destination choice model was inspired by the logit model. The structure of logit models was also adopted by Akbarzadeh and Wilmot [15] to determine the factors, which influence the route choice during hurricane evacuation. Route accessibility, route familiarity, roadway type, and availability of services (e.g., hotels) were found to be the critical factors. Abulhassan et al. [16] conducted statistical analyses using multiple linear regression models to assess the impacts of school grade level, evacuation scenario (depending on the emergency door used), and driver's assistance on evacuation times and flow rates in the event of school bus fire evacuation. Dulebenets et al. [6] performed a comprehensive pilot study using a driving simulator, where various factors influencing driving performance during emergency evacuation were identified based on a set of statistical models. It was found that the driving ability of individuals during emergency evacuation could be affected by 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), and traffic characteristics (space headway, time headway). A number of other studies also applied analytical methods, aiming to improve the efficiency of emergency evacuation [17–20].

Over the years, optimization and simulation modeling have been increasingly used for the emergency evacuation problems. Numerous heuristics, metaheuristics, and exact optimization algorithms have been presented over the past decades. Certain studies specifically used simulation-based approaches in order to emulate emergency evacuation and evaluate various methodologies for improving the efficiency of emergency evacuation. Among the reviewed studies, Han [21] was the oldest one, where the Transportation Evacuation System (TEVACS), a microcomputer-based decision support system, was proposed for emergency evacuation in Taiwan. A dynamic network simulation model was used to calculate the network clearance time. Kimms and Maassen [22] discussed vehicle routing through narrow street networks in urban areas during emergency evacuation. The study proposed a mathematical model, minimizing the weighted number of vehicles that used the street sections over time. The weights were introduced in the model to capture potential danger of street sections. An optimization-based simulation procedure was proposed to solve the model. The numerical experiments, conducted for one of the German neighborhoods, demonstrated applicability of the developed approach for the large-scale emergency evacuations.

Bi and Gelenbe [23] proposed a cloud-enabled emergency navigation framework for guiding evacuees from the emergency area in a coordinated manner. Cloud navigation was available through smartphones. An ad hoc Cognitive Packet Network (CPN) protocol was developed to prolong the lifetime of smartphones and search for the optimal communication routes. The conducted simulation experiments indicated that the proposed protocol could significantly reduce the number of drained smartphones. The cloud-enabled emergency navigation framework and the ad hoc CPN protocol were also adopted in the study, conducted by Gelenbe and Bi [24]. Bi and Gelenbe [25] classified evacuees into different groups based on their abilities to move and heath condition. A set of new CPN-based algorithms was presented to tailor various quality of service needs for different evacuee groups. The Distributed Building Evacuation Simulator was used to evaluate the candidate algorithms. It was found that the CPN with the shortest time metric generally yielded lower average evacuation time as compared to the CPN with shortest path metric and the Dijkstra's algorithm.

Akinwande et al. [26] proposed a routing algorithm, which captured age, mobility, and level of resistance to fatigue and hazard of the evacuating individuals. The algorithm also allowed the evacuees adjusting their actions depending on their physical condition and environment. The results from the performed simulation experiments showcased that consideration of the on-going mobility and health condition of the evacuating individuals within the presented algorithm increased the survival rates. Bi et al. [27] also presented a routing algorithm that explicitly accounted for the on-going health condition of evacuees. The CPN with random neural networks and reinforcement learning was applied in order to effectively tackle multiple metrics for the quality of service. Similar to the findings, revealed by Akinwande et al. [26], sensitivity of the navigation system to the on-going mobility and health condition of evacuees resulted in higher survival rates.

Bi and Gelenbe [28] developed a simulation-based evacuee routing algorithm, which optimized the evacuation process by taking the advantage of high computational power of cloud servers. Instead of guiding evacuees using the pre-determined routing algorithms, the proposed CPN-based algorithm was initially evaluated in a faster-than-real-time manner, and afterwards a variant of the Dijkstra's algorithm was applied to obtain paths for the cases where the simulated casualties were observed. A set of simulation experiments demonstrated efficiency of the proposed methodology. Pereira et al. [29] proposed a simulation model via cellular automata, taking into account the route change probabilities and the group fields in order to capture pedestrian dynamics in case of emergency evacuation. The computational simulations revealed that consideration of the latter aspects improved the accuracy of the modeled estimates.

A substantial number of studies used various heuristic-based algorithms for the emergency evacuation problems. For example, Bish [30] formulated a mathematical model for the bus-based evacuation problem, aiming to minimize the total evacuation time. The study focused on the differences between the traditional vehicle routing problem and the bus evacuation problem. Heuristic approaches were used to solve the models. It was found that the optimal solution, obtained for the vehicle routing problem, may have different properties as compared to the optimal solution, obtained for the bus evacuation problem. Abdelgawad and Abdulhai [10] proposed a mixed-integer nonlinear programming model for a large-scale evacuation through transit. A heuristic was applied to solve the problem. The solution algorithm was based on constraint programming and local search techniques. A case study was conducted for emergency evacuation of the City of Toronto (Canada). A heuristic algorithm was also presented by Apivatanagul et al. [31], who proposed a bi-level optimization model for emergency evacuation planning. The objective of the upper level problem was to minimize the total expected risk and the total travel time, while the lower-level objective aimed to solve the dynamic user equilibrium.

Ye et al. [32] proposed a heuristic, inspired by the Dijkstra's algorithm, for community-scale evacuation planning against an earthquake hazard. The computational experiments were performed for emergency evacuation of the residents along the Lujiazui Street (Shanghai, China). The proposed methodology was found to be promising for emergency evacuation planning. Bish et al. [33] presented a demand-based strategy, focusing on staging and routing of evacuees during hurricanes. A mixed-integer programming model was developed, where the objective minimized the network clearance time. The solution procedures were proposed based on the structure of the optimal strategies. The numerical experiments were performed using the Virginia Beach transportation network. Li and Ozbay [34] considered the impact of flow-related risks (e.g., vehicle incidents) in estimation of the evacuation time. A heuristic solution procedure, developed based on a sample average approximation, was used to solve the proposed mathematical model. The major features of the proposed methodology were discussed based the performed case study.

Trivedi and Singh [13] designed a hybrid multi-objective decision model based on the analytic hierarchy process, fuzzy set theory, and goal programming approach for emergency shelter location-relocation projects. The following objectives were optimized: weight function based on qualitative factors, total distance traversed by evacuees, total unmet demand, number of shelters to be set up, risk associated with sites, and degree of site ownership. Yi et al. [35] proposed a bi-level programming model in order to optimize the issuance of evacuation orders, taking into consideration highly uncertain evolution of the approaching storm and complexity of the behavioral reaction to evolving storm conditions. The proposed model was solved using a methodology, which was based on the progressive hedging algorithm. Li et al. [36] developed a set of heuristics for staged emergency evacuation to minimize the total clearance time and the travel time of each evacuee, aiming to avoid traffic congestion and balance the traffic loads among different exits. Shahabi and Wilson [37] proposed an iterative algorithm for scalable evacuation routing, considering unexpected roadway capacity changes during evacuation. The computational experiments, conducted for the case of wildfire evacuation in Southern California, showed that the developed algorithm produced efficient evacuation plans in a competitive computational time.

Along with heuristics, metaheuristic approaches have been also used to determine good-quality solutions for the emergency evacuation planning problems. Various metaheuristics can be found in the emergency evacuation planning literature, such as Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Evolutionary-based Algorithms (e.g., Genetic Algorithms – GAs), and others. For example, Apte et al. [38] applied ACO for evacuation of mobility-challenged people from the emergency areas before the occurrence of short-notice hazards. Dhingra and Roy [39] developed a model for emergency evacuation planning, considering time and resource constraints. A GA was developed in order to optimize the allocation of resources and achieve the target evacuation time. A case study was presented for the nuclear power plant emergency evacuation in Gujarat (India). It was found that the proposed methodology could serve as an effective emergency evacuation planning tool. Hu et al. [40] proposed a nonlinear integer programming model to plan bus bridging evacuations. The model objective was to minimize the maximum evacuation time over all the disrupted railway stations. The problem was solved with a customized GA that incorporated a custom mutation operator. Noh et al. [41] employed a simulation-based optimization approach, which relied on PSO, to minimize the average evacuation time of a heterogeneous population. Vahdani et al. [42] proposed a multi-objective multi-period multi-commodity model in order to locate distribution centers for effective distribution of relief, vehicle routing, and emergency roadway repair operations. Non-Dominated Sorting GA-II (NSGA-II) and multi-objective PSO (MOPSO) were adopted as the solution approaches. It was found that MOPSO generally had more solutions in the Pareto frontier and yielded greater population diversity.

Global optimality can be reached with the exact optimization solvers, such as CPLEX, BARON, CONOPT, LINGO, XPRESS, and others. A number of studies have applied these solvers for the emergency evacuation planning problems. Liu et al. [43] proposed a two-level integrated optimization system in order to generate the candidate set of optimal evacuation plans. The upper level aimed to maximize the total throughput, while the lower level minimized the total travel time and waiting time. LINGO was used to solve the upper- and lower-level problems. The results indicated that the proposed system could provide the optimal emergency evacuation plans. However, the difficulty in capturing all the operational constraints with analytical formulations was noticed. Horner and Widener [44] studied the effects of transportation network failure on hurricane hazard relief planning strategies. An integer programming model was formulated and solved with CPLEX. Findings demonstrated that moderate network failures might change the number and spatial configuration of relief facilities. Huang and Fan [45] studied the problem of allocating service resources during emergencies. The study used deterministic, stochastic, and robust optimization for modeling risk preferences in decision making. CPLEX was used as a solution approach. It was found that the stochastic models had improved reliability and robustness of the system performance.

CPLEX was also adopted by Tuydes-Yaman and Ziliaskopoulos [46] for demand management in case of emergencies. However, the CPLEX computational time issue was highlighted. It was indicated that heuristic algorithms would be more promising for the large-scale emergency evacuations in terms of the computational time. Bayram et al. [47] focused on the traffic assignment problem throughout emergency evacuation with shelter location decisions, where the viewpoints of the evacuation authority and the evacuees were taken into account. CPLEX was used to solve the mathematical formulation, which was based on the second order conic programming. Lim et al. [48] focused on evacuation route management with emphasis on re-routing due to potential accidents. A network preprocessing algorithm and a multi-commodity network flow optimization model were presented to minimize the delays caused by the accidents. The purpose of the network preprocessing algorithm was to update the transportation network after the accident occurrence and determine the locations of evacuees on the network. CPLEX was used to solve the proposed mathematical model. The computational experiments, conducted for the Greater Houston area transportation network, demonstrated that the proposed methodology could generate efficient re-routing paths.

After a detailed review of the collected studies, it was found that performance of the exact optimization approaches was not adequate for the large-size instances of emergency evacuation planning problems [46,49–52]. The exact optimization approaches might require a prohibitively large computational time for the large-size problems. The heuristic and metaheuristic approaches were found to be more practical in such cases [50]. Also, the literature review indicates that many studies disregard certain important aspects (e.g., socio-demographic characteristics of evacuees, evacuation route characteristics, driving conditions, traffic characteristics) throughout emergency evacuation modeling. This study aims to address the existing gaps in the state-of-the-art and proposes a mathematical model, which directly accounts for the effects of socio-demographic characteristics of evacuees, evacuation route characteristics, driving conditions, and traffic characteristics on the travel time of evacuees. Moreover, the exact optimization approach and a set of heuristic approaches are proposed and evaluated for the presented mathematical model.

3. Problem description

This section of the manuscript presents a detailed description of the emergency evacuation planning optimization problem studied herein. In case of an approaching natural hazard, the population, inhabiting the areas that would be affected by the hazard, is advised to evacuate. When the potential impact is expected to be devastating, state authorities announce a mandatory evacuation order. Let $I = \{1, \ldots, n^1\}$ denote a set of evacuating individuals. Throughout the evacuation process, some routes are designated as evacuation routes. Denote $R = \{1, \ldots, n^2\}$ as a set of available evacuation routes. Using the dedicated evacuation routes, evacuees can travel to one of the available emergency shelters $S = \{1, \ldots, n^3\}$. A set of available emergency shelters for the considered metropolitan area is illustrated in Fig. 1. 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 $P = \{1, \ldots, n^4\}$ 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 can be assessed based on communication with the appropriate state representatives, who are often involved throughout emergency evacuation (e.g., state troopers, emergency management personnel). 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 into two categories, including: (a) general-purpose (GP) shelters; and (b) special-needs (SN) shelters. Vulnerable population groups (e.g., individuals with disabilities) should be assigned to the SN shelters to ensure that these individuals will have adequate accommodations until the given metropolitan area is able to recuperate from the natural hazard effects and return to normal or close to normal operating conditions. However, other evacuees (i.e., the ones, who do not require special accommodations) can be assigned either to the GP shelters or to the SN 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 by 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 [6,11,14,53,54]. This study directly accounts for the potential effects of the aforementioned factors on the driving ability of individuals under emergency evacuation (more details are provided in section 4 of the manuscript). 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 from a given metropolitan area that expects an approaching natural hazard.

4. Model formulation

The emergency evacuation planning optimization problem (**EEPOP**) studied herein is formulated as a mixed-integer programming model. Table 1 presents the main components of the **EEPOP** mathematical model and their description.

Emergency Evacuation Planning Optimization Problem (EEPOP)

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

Subject to:

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

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

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

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

$$\sum_{i \in I} \boldsymbol{x}_{ipr} \le C^1_{pr} \quad \forall\, p \in P, r \in R \tag{6}$$

$$\sum_{i \in I} q_i \boldsymbol{z}_{is} \le C^2_s \quad \forall\, s \in S \tag{7}$$

$$\boldsymbol{t}_{ir} = f\,(J_i, K_r, D_{pr}, F_{pr}, \boldsymbol{x}_{ipr}) \quad \forall\, i \in I, p \in P, r \in R \tag{8}$$

$$\boldsymbol{x}_{ipr}, \boldsymbol{z}_{is}, y_{is}, w_{rs} \in \{0,1\} \quad \forall\, i \in I, p \in P, r \in R, s \in S \tag{9}$$

$$C^1_{pr}, C^2_s, q_i \in N \quad \forall\, i \in I, p \in P, r \in R, s \in S \tag{10}$$

$$\boldsymbol{t}_{ir} \in R^+ \quad \forall\, i \in I, r \in R \tag{11}$$

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 travel along 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

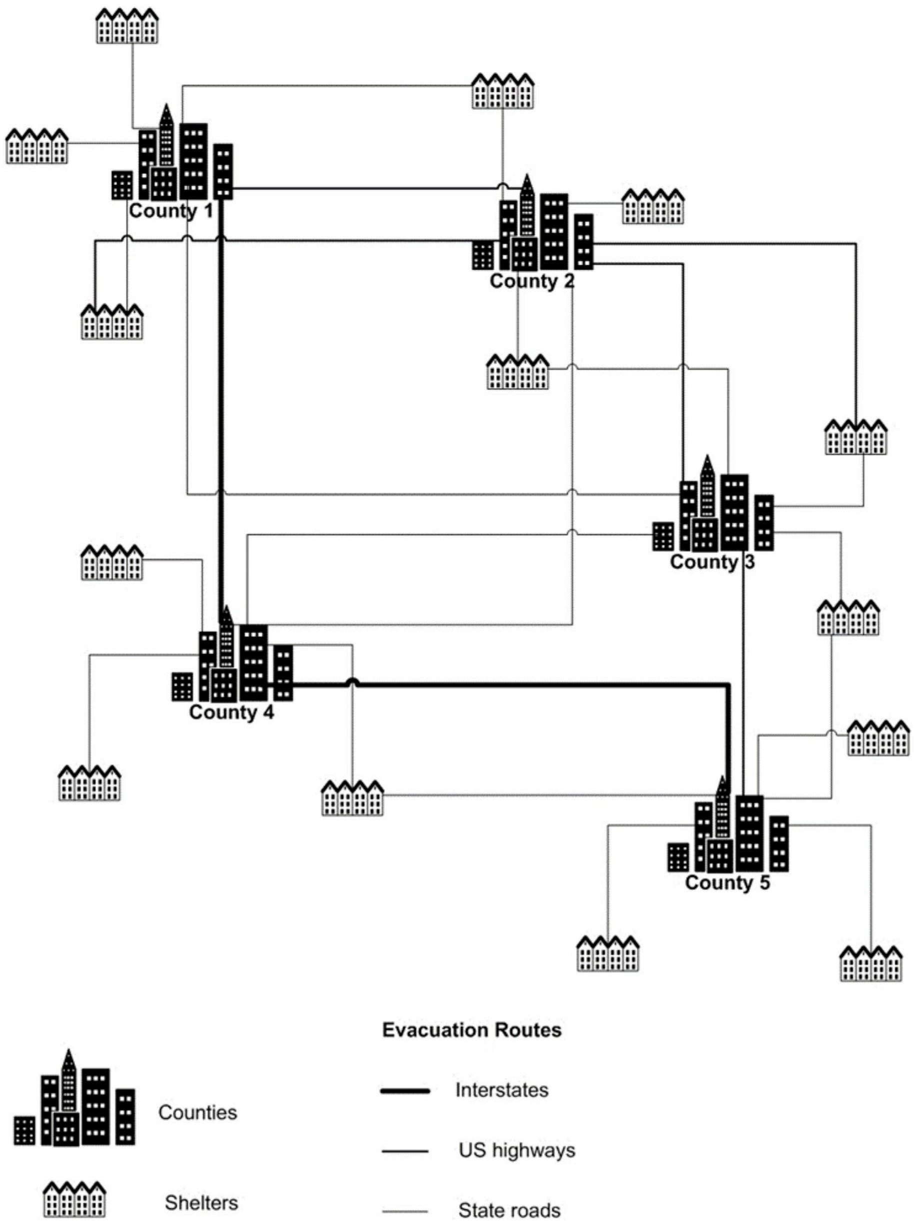

Fig. 1. The emergency evacuation planning problem.

will be assigned to the specific shelter based on the individual's needs (e.g., vulnerable population groups may require additional accommodations, and, therefore, should be assigned to the SN shelters; on the other hand, general population groups can be assigned either to the GP shelters or to the SN 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 the term $q_i, i \in I$ to account for the other passengers, who will be traveling with a given individual to the assigned emergency shelter (e.g., the whole family will be evacuating the emergency area in 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's 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 the function for estimating the travel time of individuals (i.e. $f(J_i, K_r, D_{pr}, F_{pr}, \boldsymbol{x}_{ipr})$) will determine complexity of the **EEPOP** mathematical model (e.g., mixed-integer linear programming model vs. mixed-integer nonlinear programming model). Based on a comprehensive driving simulator study, conducted by Dulebenets et al. [6], the most influential predictors of travel time under emergency evacuation settings (among other socio-demographic characteristics of evacuees, evacuation route characteristics, driving conditions, and traffic characteristics) are: age, driving frequency (*Dr_Freq*), distance driven per week (*Dist_Dr*), difficulty evacuating (*Diff_Ev*), ability to make quick decisions (*Ab_QDec*), driving simulator experience (*Sim_Exp*), and average space headway (*Avg_SpHead*). Let l_r, $r \in R$ be the length of emergency evacuation route r (measured in miles). Taking into consideration findings from the study, previously conducted by Dulebenets et al. [6], the original **EEPOP** mathematical model can be reformulated as a mixed-integer linear programming model as follows:

Table 1
The nomenclature adopted for the **EEPOP** mathematical model.

Model Component		Description
Type	Nomenclature	
Sets	$I = \{1, \ldots, n^1\}$	set of evacuees (evacuees)
	$R = \{1, \ldots, n^2\}$	set of available evacuation routes (evacuation routes)
	$S = \{1, \ldots, n^3\}$	set of available shelters (shelters)
	$P = \{1, \ldots, n^4\}$	set of time periods (time periods)
	$J_i = \{1, \ldots, a_i\},\ i \in I$	set of socio-demographic characteristics for individual i (socio-demographic characteristics)
	$K_r = \{1, \ldots, b_r\},\ r \in R$	set of characteristics for route r (routes characteristics)
	$D_{pr} = \{1, \ldots, c_{pr}\},\ p \in P,\ r \in R$	set of driving conditions on route r during time period p (driving conditions)
	$F_{pr} = \{1, \ldots, h_{pr}\},\ p \in P,\ r \in R$	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 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)

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

Similar to the **EEPOP** mathematical model, the objective function (12) of 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 for each individual (and other passengers carpooling with that individual) along the selected evacuation route based on the major factors, which could influence the travel time during emergency evacuation, including age, driving frequency, distance driven per week, difficulty evacuating, ability to make quick decisions, driving simulator experience, and average space headway. Note that the 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 in the previously conducted driving simulator study [6]. This study assumes that the travel time of evacuees will be increasing proportionally to the evacuation route length.

5. Solution algorithms

The **EEPOP-L** mathematical model is a mixed-integer linear programming model, which can be solved to the global optimality using the exact optimization methods. CPLEX has been widely used in operations research as the exact solution approach for large-scale mixed-integer linear programming models [55]. Furthermore, CPLEX has been adopted as the exact solution approach in many studies dealing specifically with the emergency evacuation and planning decision problems [44–48]. This study will also use CPLEX in order to solve the **EEPOP-L** mathematical model to the global optimality. CPLEX will be executed via the General Algebraic Modeling System (GAMS) environment [56]. However, finding the optimal solution, given the number of decision variables and constraints, may require a significant computational time for the large-size problem instances (e.g., when 100,000 individuals are expected to evacuate from the area that expects a devastating natural hazard). Therefore, along with using the exact optimization approach, a number of heuristic algorithms will be developed in this study as well. The heuristic algorithms are expected to obtain good-quality solutions and reduce the computational time significantly. The latter aspect can be considered as critical, taking into account that all the emergency evacuation decisions have to be made in a timely manner in case of an approaching devastating natural hazard.

A total of four heuristic algorithms were developed under this study: (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. 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 vulnerable population groups, which require greater evacuation time as compared to general population groups). The developed heuristic algorithms are described in the following sections of the manuscript.

5.1. The Most Urgent Evacuee First (MUEF) 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 priority and evacuate the emergency area first. Note that the expected travel time of evacuees can be assessed based on the socio-demographic characteristics of evacuees, evacuation route characteristics, driving conditions, and traffic characteristics (which can be obtained from the publicly available socio-demographic databases and other relevant sources) using equation (13) – see section 4 of the manuscript. The main steps of the MUEF heuristic are outlined in Pseudocode 1.

Pseudocode 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 the individuals in a given vehicle) as follows: $priority_i = min_{r \in R}(q_i \boldsymbol{t}_{ir})$, where $priority_i$ – is the priority of evacuee i. 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 (i.e., certain evacuees may have to be assigned to the SN shelters). In step 4, the MUEF heuristic determines "the shortest route" (i.e., the route that endures the least travel time), 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 during 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 the 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 the 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. The Most Urgent Evacuee Last (MUEL) 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 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 SN shelters, and the remaining capacity of the SN shelters may not be sufficient for all the individuals, who require special accommodations. In order to avoid the latter shortcoming, the MUEL heuristic will reassign the individuals, who do not require special accommodations, to the GP shelters in order to create a sufficient capacity of the SN shelters for all the individuals, who require special accommodations.

5.3. The Most Urgent Evacuee Group First (MUEGF) 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 higher priority and evacuate the emergency area first. However, unlike the MUEF heuristic, the MUEGF heuristic does not assign evacuees one by one to the evacuation routes, emergency shelters, 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 $G = \{1, ..., n^5\}$ as a set of evacuee groups. Let $\tilde{\boldsymbol{x}}_{ig}$, $i \in I$, $g \in G$ 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 Pseudocode 2.

Pseudocode 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: $C_{pr}^1 = C_{pr}^1 - \sum_{i \in I} \tilde{\boldsymbol{x}}_{ig}$. Update capacity of shelter s: $C_s^2 = C_s^2 - \sum_{i \in I} q_i \tilde{\boldsymbol{x}}_{ig}$.
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 evacuee groups G is initialized. 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 SN 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 the evacuees within the considered group 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 during 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 the 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 the 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 large-size problem instances with a significant number of evacuating individuals (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 (especially, for the cases with large group sizes), as at the optimal/near-optimal solution, two individuals of the same group can be assigned to different evacuation routes and emergency shelters. Selection of the appropriate group size and evaluation of the “grouping effect” within the MUEGF heuristic will be performed throughout the numerical experiments.

5.4. The Most Urgent Evacuee Group Last (MUEGL) heuristic

The main steps of the Most Urgent Evacuee Group Last (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. That is, 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 SN shelters, and the remaining capacity of the SN shelters may not be sufficient for all the 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 GP shelters in order to create a sufficient capacity of the SN shelters for all the individuals, who require special accommodations.

6. Case study

All the coastal areas of the U.S., including the East Coast, the West Coast, and the Gulf of Mexico, are characterized by frequent occurrences of natural hazards (such as hurricanes, severe storms, tropical storms, straight-line winds, severe thunderstorms, etc.). Especially, South Florida is often struck by natural hazards and subject to emergency evacuation. The numerical experiments in this study were conducted for Broward County, a county in South Florida with a population of 1,935,878 in 2017 [57], which often experiences natural hazards.

6.1. Input data

In order to conduct the numerical experiments, a set of input parameters is required for the **EEPOP-L** mathematical model and the solution algorithms. This study primarily relied on the data available through public databases. The ArcGIS software (ArcMap 10.3.1) [58] was used in preparing all the geographic maps throughout this study. This section of the manuscript provides detailed information regarding the following aspects: (1) emergency shelters; (2) evacuation routes; (3) evacuation time periods; and (4) evacuee age sampling (based on the socio-demographic data available for the Broward County population).

6.1.1. Emergency shelters

According to the Florida Division of Emergency Management [59], there are 1,422 GP shelters in Florida with a total capacity of 1,039,468 shelter spaces. On the other hand, there are 111 SN shelters in Florida with a total capacity of 36,648 shelter spaces [59]. Throughout emergency evacuation planning for the population residing in Broward County, both GP and SN shelter types in Florida were considered. The input data for the **EEPOP-L** mathematical model were generated in such way that the available capacity of the GP and SN shelters was sufficient to accommodate all the individuals, evacuating from Broward County. A map, depicting the GP and SN shelters that were considered throughout the numerical experiments in this study, is presented in Fig. 2.

6.1.2. Emergency evacuation routes

During emergency evacuation, an additional demand (representing the evacuating individuals) is generated for the roadways, along with the other vehicles traveling on these roadways. This evacuation demand is assigned to the available evacuation routes. In this study, four types of roadways were considered for evacuation routes: (1) interstates, (2) U.S. roadways, (3) state roadways, and (4) local roadways in Florida. The total number of modeled evacuation routes, connecting the centroid of Broward County, and the available emergency shelters comprised 1,314 evacuation routes. The Highway Capacity Manual [60] was adopted for estimating capacities of the roadways. Level of Service (LOS) D was selected while determining capacities of the roadways, since the traffic characteristics at LOS D emulate the traffic conditions that are similar to emergency evacuation (especially, at earlier stages of emergency evacuation; while more severe congestion can be observed at later stages of emergency evacuation [6]). Capturing congestion effects at later stages of emergency evacuation will be one of the future research extensions for this study. Two to five evacuation routes were considered to travel from Broward County to each emergency shelter.

Candidate evacuation routes have multiple segments, which may comprise of freeways, multilane highways, and/or two-lane highways. Although the range of flow (i.e., additional demand that can be accommodated throughout emergency evacuation during a given time period for the considered level of service) was estimated for all the roadway types of each evacuation route, the capacity of a given evacuation route was assumed to be the lower available capacity value, which corresponds to a range of flows on the two-lane highway segments (550 vehicles/hour). Such conservative assumption was made based on the fact that traffic demand during emergency evacuation is always significant. Also, a large number of potential evacuation routes are expected to have two-lane highway segments (that may further lead to freeways or multilane highways).

6.1.3. Evacuation time periods

In order to reduce congestion along the evacuation routes, this study

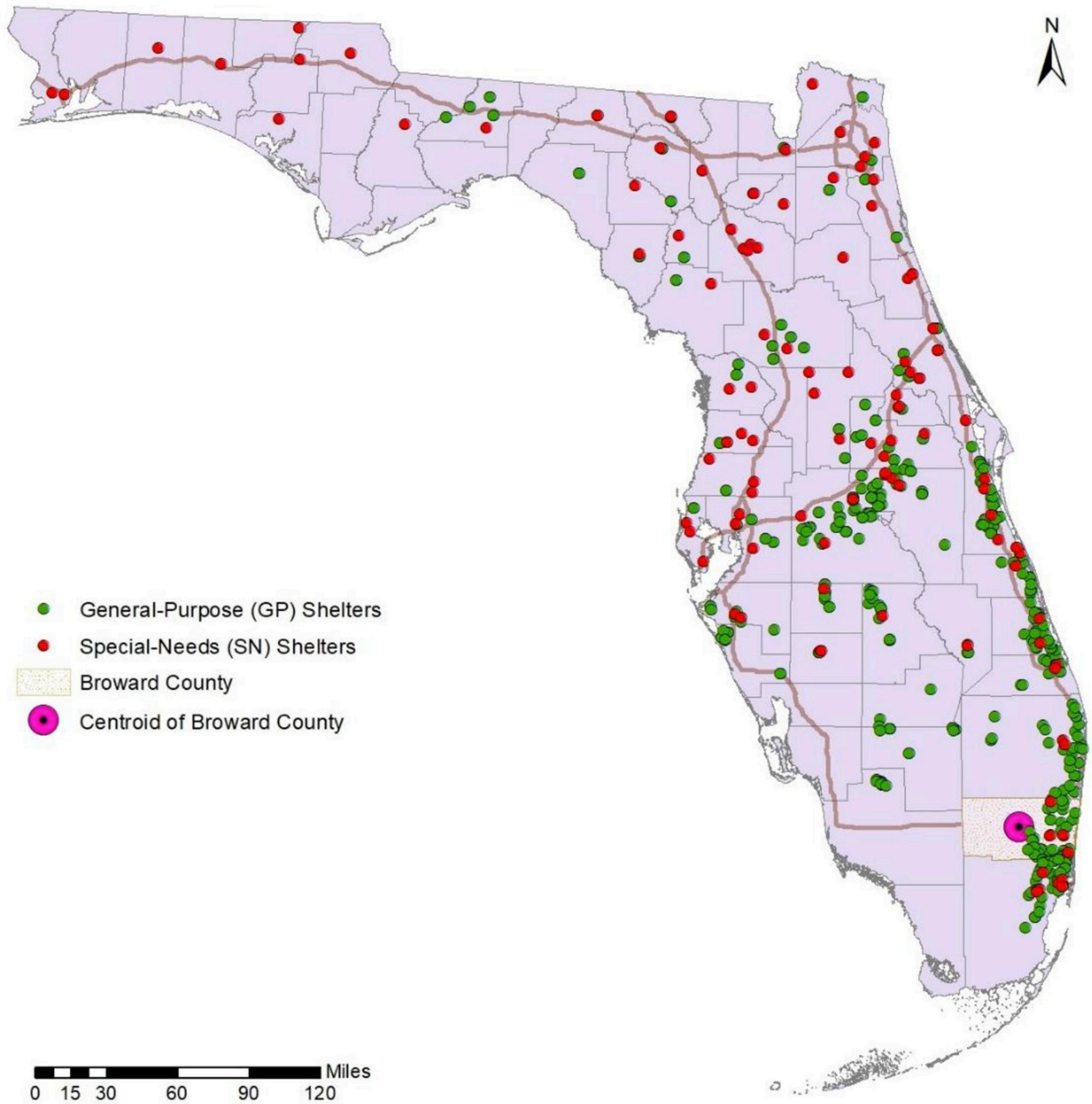

Fig. 2. Shelters considered for emergency evacuation of Broward County (Florida).

proposes a time period-based (or staged) emergency evacuation throughout the considered planning horizon. Furthermore, evacuation by time periods facilitates adequate planning in terms of utilized capacity of the evacuation routes, which is estimated per hour. For the numerical experiments, a sufficiently large number of time periods were considered to evacuate all the individuals from the emergency area.

6.1.4. Evacuee age sampling

The age of population, residing in Broward County, was extracted from the publicly available socio-demographic database – U.S. Census Bureau [57]. MATLAB was used to randomly generate the age of evacuee(s) in each evacuating vehicle for each household, following the age probability distribution developed based on the data available through the U.S. Census Bureau. If a vehicle was 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 approach was adopted to ensure that there was at least one experienced (and eligible) driver in the vehicles with only young individuals. The worst case values were assumed for the remainder of travel time predictors (i.e., driving frequency, distance driven per week, difficulty evacuating, ability to make quick decisions, driving simulator experience, and average space headway – see equation (13) in section 4 of the manuscript) based on the ranges that were adopted in the previously conducted driving simulator study [6], as the information regarding these predictors was not provided in the publicly available socio-demographic database. The latter approach would yield more conservative values of travel time, estimated for the evacuating individuals.

6.2. Major assumptions

A number of assumptions were made in order to solve the **EEPOP-L** mathematical model. The assumptions were critical to prepare the input data for the **EEPOP-L** mathematical model; so, the developed solution algorithms, described in section 5 of the manuscript, can be applied to assign evacuating individuals to the available evacuation routes, emergency shelters, and time periods. The list of the adopted assumptions includes the following:

- The evacuation demand (i.e., the number of individuals who need to travel to the assigned shelters) was assumed to be originating from

Table 2
The analysis results for the small-size problem instances: average objective function and computational time values, obtained by the candidate 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

the centroid of Broward County (see Fig. 2).

- After receiving an evacuation order, the individuals, living in Broward County, evacuate based on time periods (each time period is equal to 1 hour). An evacuee must evacuate within the time period assigned. The emergency evacuation order compliance issues have not been explicitly modeled as a part of this study and will be one of the future research directions.
- Each household drives 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.
- The total number of individuals, traveling in a vehicle to the assigned emergency shelter, was set using uniformly distributed pseudorandom numbers, varying from 1 individual to 4 individuals.
- Only American Red Cross-approved shelters were considered throughout the numerical experiments. Locally-recognized shelters were ignored.
- All the emergency shelters are opened immediately after 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 that shelter.
- Vulnerable population groups (e.g., aging adults, individuals with disabilities and/or chronic diseases) have to be assigned to the SN shelters.
- If a family is evacuating in one vehicle and one of the family members is an aging adult, the whole family would be assigned to the SN shelter (to make sure that the aging adult will have access to adequate accommodations).

Note that, without loss of generality, the proposed **EEPOP-L** mathematical model and the developed solution algorithms will be applicable even if some of the aforementioned assumptions are relaxed or modified. For example, the proposed methodology still can be implemented for emergency evacuation planning if coordinates of the households are available for evacuating individuals. The latter will allow more accurate estimation of the total travel time of evacuees as compared to the case when all the individuals are assumed to start evacuating from the centroid of Broward County. Furthermore, this study assumes that all the individuals use their own vehicles to evacuate. However, the proposed methodology can be implemented for emergency evacuation using public transport as well with an appropriate adjustment of the values for the parameters of the **EEPOP-L** mathematical model (e.g., the number of evacuating individuals in a given transport unit [q_i, $i \in I$] will have to be altered accordingly, since public transport is generally able to transfer more individuals at a time as compared to private vehicles).

6.3. Numerical experiments

Throughout this study, the numerical experiments have been performed on a CPU with Dell Intel(R) Core™ i7 Processor, 32 GB of RAM, and Operating System Windows 10. A total of 40 problem instances were developed for evaluation of the candidate solution algorithms (i.e., CPLEX and the MUEF, MUEL, MUEGF, and MUEGL heuristic algorithms). The developed problem instances can be divided into the following two groups:

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 S-1 to S-20); 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 L-1 to L-20).

Note that the values for the remaining parameters of the **EEPOP-L** 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 problem 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., the available memory was not sufficient for solving the problem instances with more than 400 evacuees). It was determined that CPLEX returned the memory error for the problem instances with more than 400 evacuees due to the fact that the memory size, required to store parameters and variables of the **EEPOP-L** mathematical model (e.g., the number of evacuees, the number of available evacuation routes, the number of available shelters, the number of available time periods, capacity values for the available evacuation routes and shelters, the evacuee to evacuation route and time period assignment variable, the evacuee to emergency shelter assignment variable, etc.), exceeded the random-access memory (RAM) of the available CPU, which was used in this study (32 GB of RAM). However, evaluation of the developed heuristic algorithms against CPLEX for the small-size problem instances was important, since such analysis allowed comparing the solutions, returned by the proposed heuristic algorithms, with the global optimal solutions, returned by CPLEX.

The MUEGF and MUEGL heuristics have an additional parameter, representing the group size. Selection of the appropriate values for the algorithmic parameters is critical, as it may directly affect the algorithmic performance [61–65]. A set of preliminary experiments was conducted to select the appropriate group size values for the small-size and large-size problem instances. A total of 20 scenarios were analyzed, where the group size was changed from 20 to 400 with an increment of 20 evacuees. The appropriate group size was identified based on a tradeoff between the solution quality obtained and the computational time required. Based on analysis of the results, obtained for the small-size problem instances, the group size value was set to 300 evacuees for both MUEGF and MUEGL heuristics. On the other hand, the group size value of 380 evacuees was found to be the most appropriate for both MUEGF and MUEGL heuristics for the large-size problem instances.

6.3.1. Analysis of the small-size problem instances

The first step of the numerical experiments focused on a detailed comparative analysis of the developed heuristic algorithms (i.e., the MUEF, MUEL, MUEGF, and MUEGL algorithms) against the exact solution algorithm (CPLEX) for the small-size problem instances. CPLEX and the developed heuristic 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 2, 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., the 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.

Findings from the conducted analysis indicate that the CPLEX computational time is significantly affected with the problem size. Specifically, the CPLEX computational time increases exponentially 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 CPLEX, MUEF, MUEL, MUEGF, and MUEGL, respectively. The "grouping effect" (i.e., assignment of evacuees in groups to the evacuation routes, emergency shelters, and time periods) allowed the MUEGF and MUEGL heuristics to solve the **EEPOP-L** mathematical model significantly faster as compared to the MUEF and MUEL heuristics.

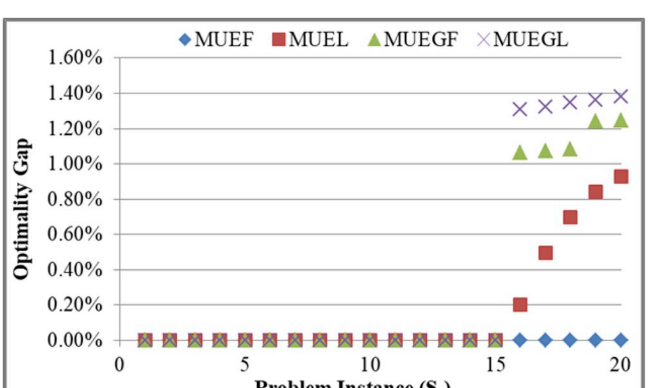

Fig. 3. The optimality gap values for the developed solution algorithms.

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 Fig. 3. Note that the optimality gap for algorithm *alg* ($\boldsymbol{Gap}_{alg}$) was estimated as follows: $\boldsymbol{Gap}_{alg} = \frac{\boldsymbol{TTT}_{alg} - \boldsymbol{TTT}_{CPLEX}}{\boldsymbol{TTT}_{CPLEX}}$, 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 evacuation routes, emergency shelters, and time periods. On the other hand, the "grouping effect", adopted within the MUEGF and MUEGL heuristics, negatively affected the solution quality, as two individuals of the same group can be assigned to different evacuation routes and emergency shelters at the optimal/near-optimal solution. 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% over the generated small-size problem instances.

6.3.2. Analysis of the large-size problem instances

The second 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 discussed earlier, CPLEX was not able to solve the problem instances with more than 400 evacuees, as the available memory was not sufficient to load the input data. Therefore, the optimality gaps of the proposed heuristic algorithms could not be estimated for the large-size problem instances. However, the optimality gaps did not exceed 1.38% over the generated small-size problem instances, which can be considered as acceptable. Hence, the developed heuristic algorithms can be used for analysis of the large-size problem instances. 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 3, 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., the total travel time of evacuees – $\boldsymbol{TTT}$) for each heuristic algorithm; and (4) average computational time (CPU time) values over 5 replications for each heuristic algorithm.

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. The MUEGF heuristic outperformed the MUEL and MUEGL heuristics 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).

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 large-size problem instances for the MUEF, MUEL,

Table 3
The analysis results for the large-size problem instances: average objective function and computational time values, obtained by the candidate solution algorithms.

Instance	$\sum_{i \in I} q_i$	MUEF		MUEL		MUEGF		MUEGL	
		TTT, hours	CPU time, sec	TTT, hours	CPU time, sec	TTT, hours	CPU time, sec	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

MUEGF, and MUEGL algorithms, respectively. The “grouping effect” allowed the MUEGF and MUEGL heuristics to solve the **EEPOP-L** mathematical model significantly faster as compared to the MUEF and MUEL heuristics for the large-size problem instances. It can be observed that the computational time savings of the MUEGF and MUEGL heuristics over the MUEF and MUEL heuristics increase with increasing problem size. The latter finding highlights the importance of the “grouping effect”, considering the fact that all the emergency evacuation decisions have to be made in a timely manner in case of an approaching devastating natural hazard. Although MUEF outperformed the other algorithms in terms of the objective function, its CPU time was considerably larger as compared to MUEGF and MUEGL. MUEGF, on the contrary, exhibited the lowest CPU times and competitive objective function values. Therefore, the MUEGF heuristic will be further used for analysis of the managerial insights.

Note that the capacity of evacuation routes may change due to deteriorating roadway conditions and/or interaction between various roadways. Throughput the numerical experiments, it was found that the MUEGF heuristic was able to solve the large-size problem instances of the **EEPOP-L** mathematical model fairly quickly (e.g., problem instance L-20 with 100,000 evacuees was solved within ≈ 21.05 min – see Table 3). Therefore, the MUEGF heuristic can be applied in online/real-time settings, where the information regarding the capacity of evacuation routes is updated dynamically (i.e., once the capacity of evacuation routes changes due to deteriorating roadway conditions and/or interaction between various roadways, the MUEGF heuristic can be terminated and then executed again for the remaining number of evacuees, who have not been assigned to the available evacuation routes and emergency shelters, considering the updated capacity of evacuation routes). The accurate information regarding the evacuation route capacity can be obtained from the appropriate representatives, who are directly involved in the emergency evacuation process and monitor traffic conditions on evacuation routes throughout emergency evacuation (e.g., state troopers, emergency management personnel).

Moreover, the developed heuristic algorithms were executed for the large-size problem instances with up to 100,000 evacuees. As for the problem instances with more than 100,000 evacuees, the heuristic algorithms can be applied recursively. For example, if a total of 200,000 individuals have to be evacuated, the developed heuristic algorithms can be executed twice (during the first algorithmic run the first 100,000 evacuees will be assigned to the available evacuation routes and emergency shelters, while the remaining evacuees will be assigned during the second algorithmic run). A recursive execution of the heuristic algorithms is expected to be more promising in terms of the computational time rather than executing the heuristics to assign more than 100,000 evacuees at a time (i.e., it may be faster to solve two problem instances with 100,000 evacuees per instance rather than solving one problem instance with 200,000 evacuees at a time).

6.4. Managerial insights

This section discusses the managerial insights that were revealed using the developed mathematical model and heuristics based on the conducted numerical experiments. Although all the developed heuristics (including MUEF, MUEL, MUEGF, and MUEGL) were applied to solve the **EEPOP-L** mathematical model, the managerial insights will be analyzed using the MUEGF heuristic only, because the results from the numerical experiments indicated that it is superior to the other heuristics.

6.4.1. Total utilization of shelters

The total utilization of the available shelters over the considered time periods throughout the evacuation process is presented in Fig. 4 for all the generated large-size problem instances. For example, the outmost top left chart shows the total utilization of the available shelters for problem instance L-1. Based on the conducted numerical experiments, the MUEGF heuristic assigned 5,000 evacuees to 11 shelters for problem instance L-1. The top five shelters with the 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 School (ID number 485); (4) South Mainland (Micco) (ID number 521); and (5) John Hopkins Middle School (ID number 506). Furthermore, the total utilization of the available shelters for problem instance L-20 is illustrated in the outmost bottom right chart of Fig. 4. The MUEGF heuristic assigned 100,000 evacuees to 99 shelters for problem instance L-20. 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 the GP shelters, while shelters 477 through 587 are the SN shelters. The GP shelters and the SN shelters were listed in an increasing order of their distance from the centroid of Broward County; hence, the closest shelters are listed first for both shelter types.

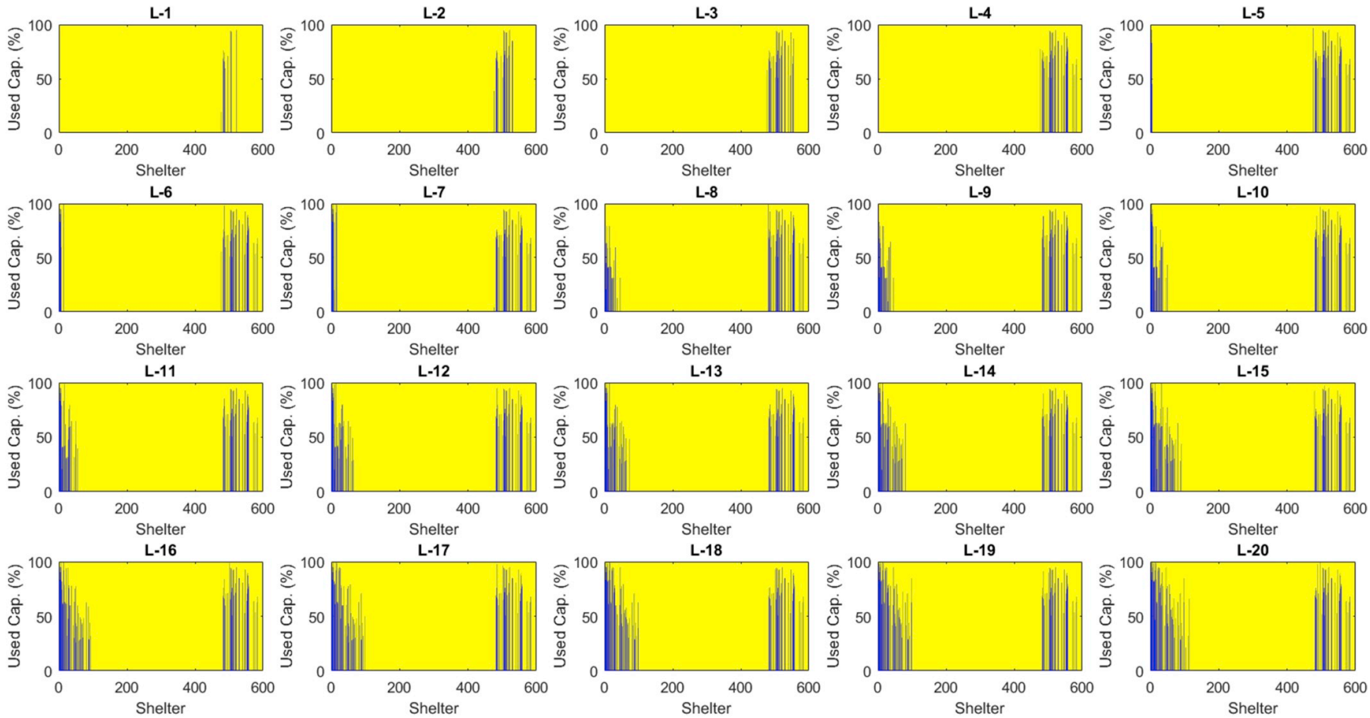

Fig. 4. The total utilization of the available shelters over the considered time periods throughout the evacuation process.

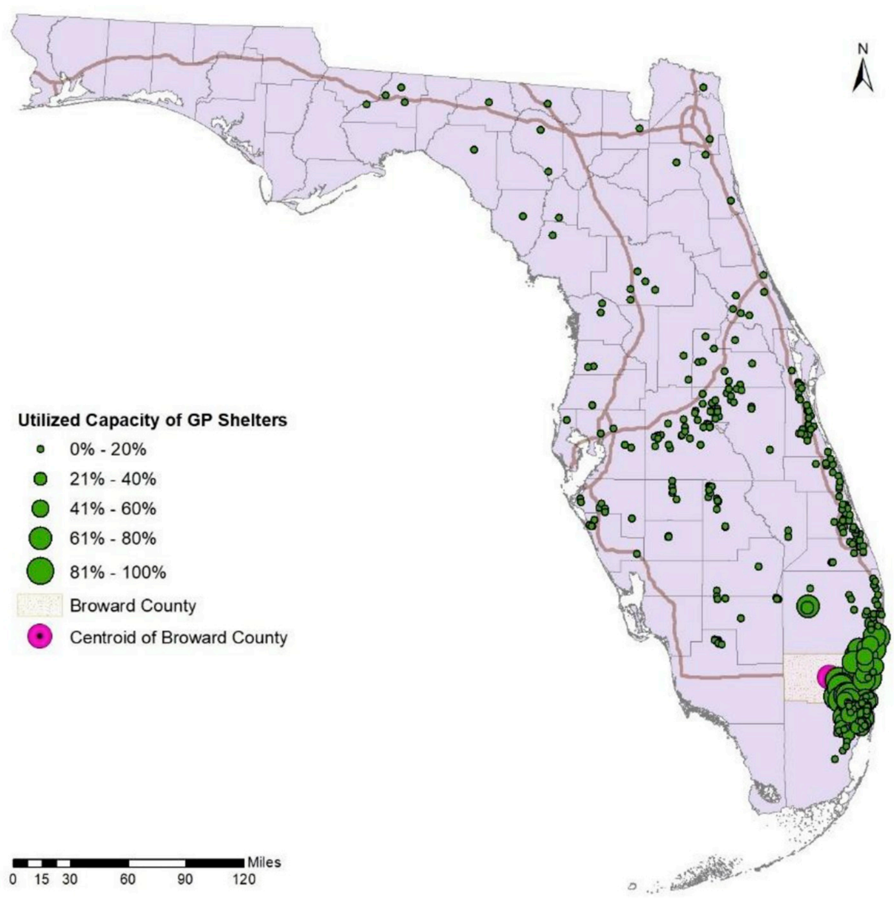

Fig. 5. The total utilization of GP shelter capacity for problem instance L-20.

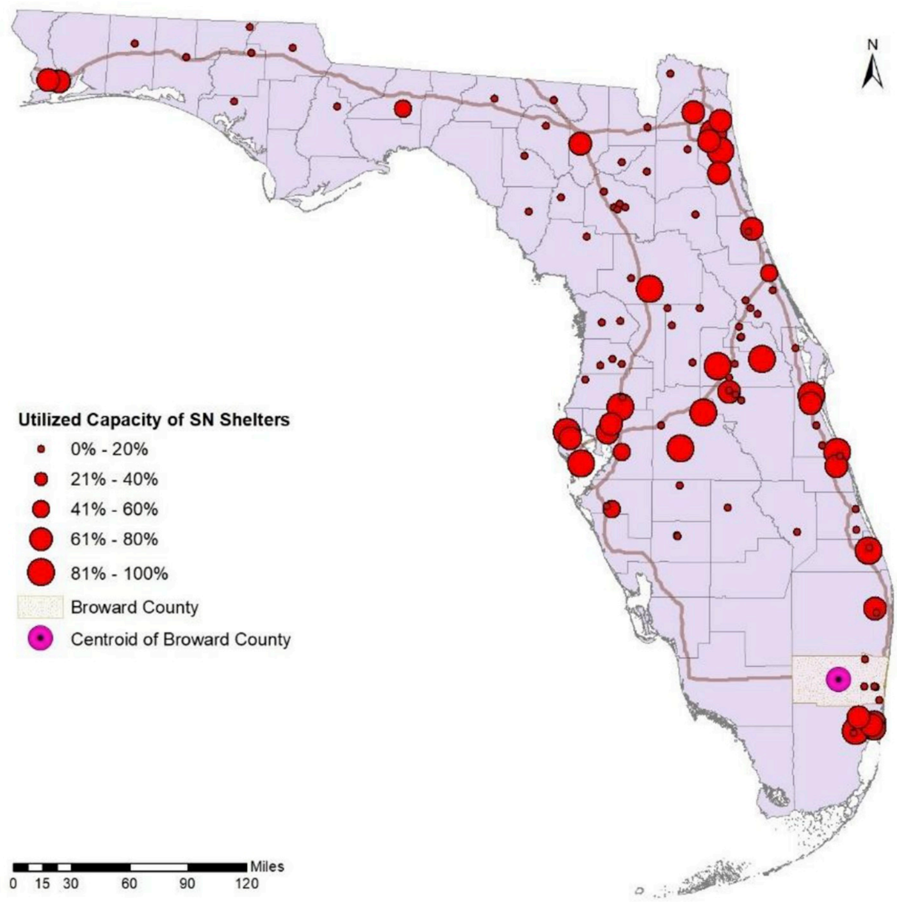

Fig. 6. The total utilization of SN shelter capacity for problem instance L-20.

The charts, presented in Fig. 4 for the 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 the GP shelters and the SN shelters for problem instance L-20, are presented in Fig. 5 and Fig. 6, respectively. From Figs. 5 and 6, it can be observed that certain shelters, which are closer to Broward County, were not fully utilized, while the shelters farther from the centroid of Broward County were fully or close to fully utilized. The latter finding can 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.

6.4.2. Utilization of assigned shelters by time period

Fig. 7 illustrates the utilization of assigned shelters by time period throughout the evacuation process for all the generated large-size problem instances. For example, the outmost top left chart shows the utilization of assigned shelters by time period for 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 problem 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 the computational experiments indicate 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 affected population to the available shelters in the shortest possible time. The results, obtained for large-size problem instances L-1 through L-20, demonstrated that the MUEGF heuristic utilized most of the available shelter capacity within the first time periods (see Fig. 7); thus, the majority of evacuees were evacuated within the first time periods.

6.4.3. Average utilization of evacuation routes

The average utilization of the available evacuation routes over the considered time periods throughout the evacuation process is shown in Fig. 8 for all the generated large-size problem instances. For example, the outmost top left chart shows the average utilization of the available evacuation routes for 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 the SN shelters, for problem instance L-1. The latter finding can be supported by the fact that there was at least one evacuee in each group, created for problem instance L-1, who needed to be assigned to one of the SN shelters. Note that based on the input data prepared for the numerical experiments, the first 904 evacuation routes lead to the GP shelters, while evacuation routes 905 through 1,314 lead to the SN shelters. Also, the evacuation routes, leading to the GP shelters and the SN shelters, were listed in an increasing order of the route lengths from the centroid of Broward County; thus, the shortest evacuation routes were listed first for both shelter types. As the problem size increased, the MUEGF heuristic assigned evacuees to the shortest evacuation routes, which led to both GP shelters and SN shelters. Furthermore, the average utilization of all the evacuation routes did not exceed 80% throughout the evacuation process.

6.4.4. Average travel time of evacuees

Fig. 9 presents the average travel time of evacuees for each time

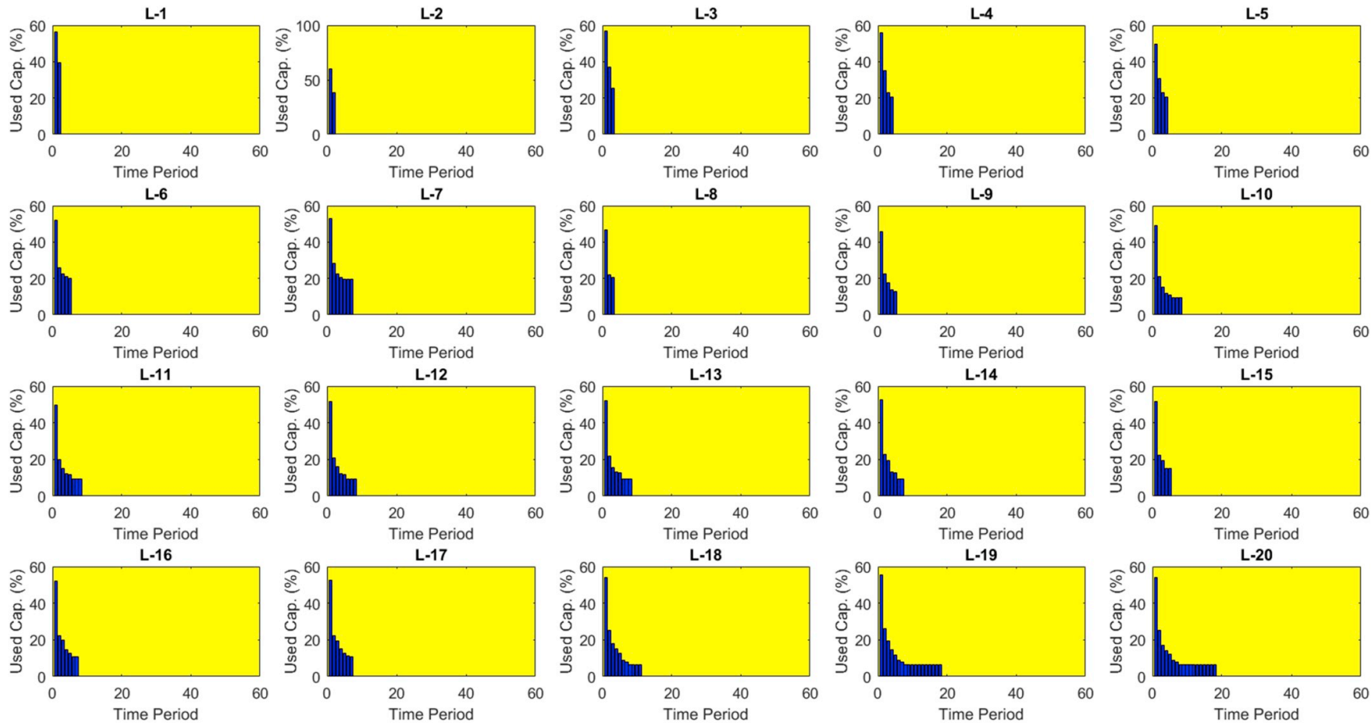

Fig. 7. The utilization of assigned shelters by time period throughout the evacuation process.

period throughout the evacuation process for all the generated large-size problem instances. Note that the term "travel time" denotes the total time required by a given evacuee to travel from the emergency area to the assigned emergency shelter. For example, the outmost bottom right chart shows the average travel time of evacuees, leaving the emergency area during one of the time periods, for problem instance L-20, where 100,000 evacuees were assigned using the MUEGF heuristic. The results, presented in Fig. 9, indicate that the average travel time of evacuees may vary from one evacuation time period to another for all the large-size problem instances considered (L-1 through L-20). The latter finding can be explained by the fact that the travel time function, encoded in the MUEGF heuristic, is dependent on various socio-demographic characteristics of drivers (which vary among individuals) as well as the length of evacuation routes.

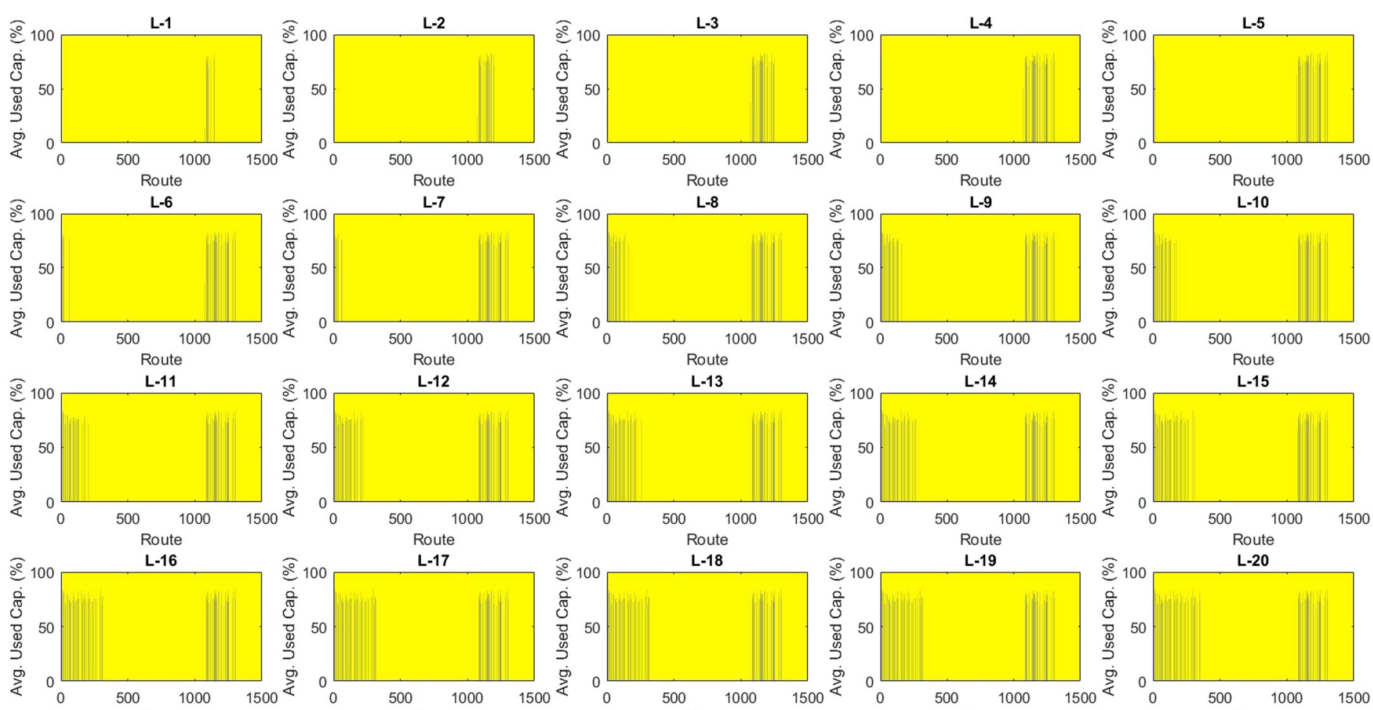

Fig. 8. The average utilization of the available evacuation routes over the considered time periods throughout the evacuation process.

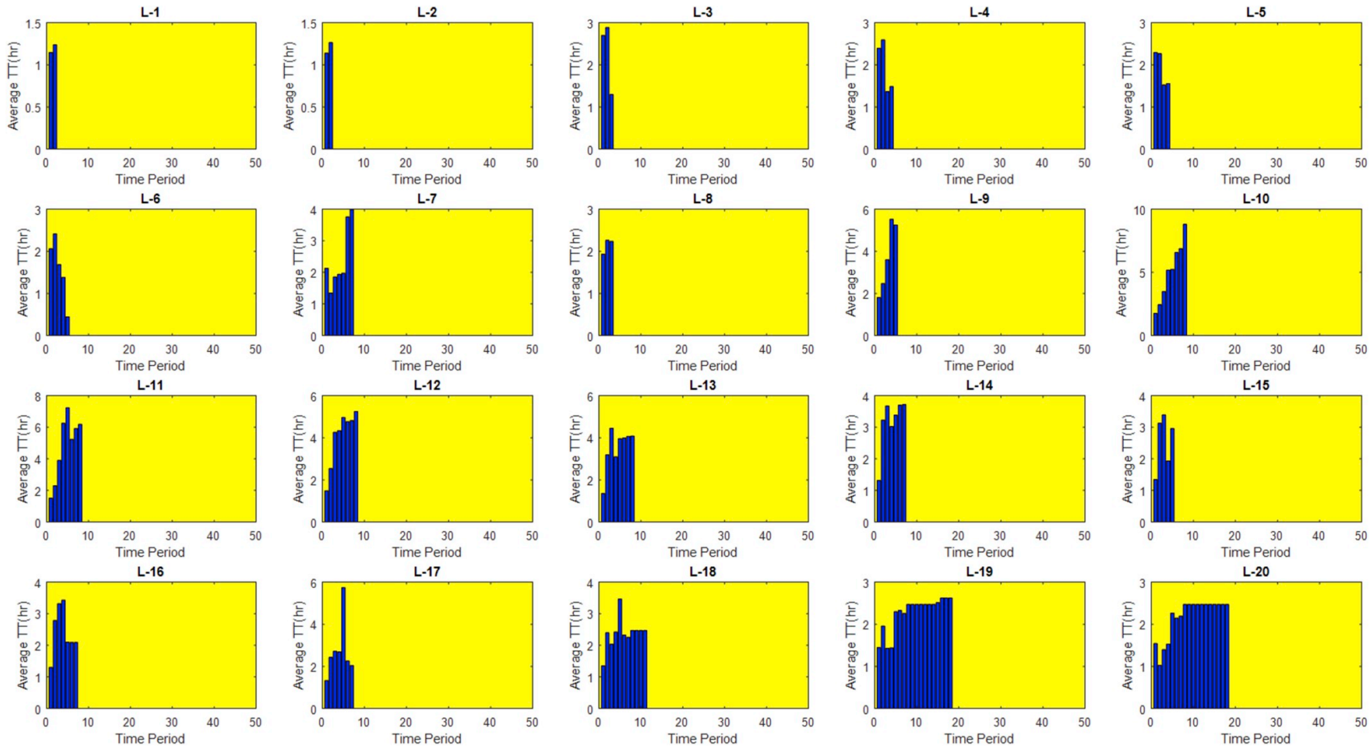

Fig. 9. The average travel time (TT) of evacuees (in hours) for each time period throughout the evacuation process.

7. Conclusions and future research

The coastal areas across the United States are prone to natural hazards. In case of approaching natural hazards, the population, inhabiting the 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 on some of the evacuation routes and inefficient utilization of the available emergency shelters. Specifically, in many cases, evacuees tend to use the same evacuation route, which may further cause route congestion due to limited capacity of the evacuation routes and significantly delay the evacuation process. Emergency evacuation is even more challenging for vulnerable population groups, who may require additional time in order to evacuate the hazard zone as a result of an approaching natural hazard.

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 problem. The objective of the proposed mixed-integer mathematical model aimed to assign individuals to evacuate the emergency area via the available emergency evacuation routes to the available emergency shelters during a specific time period by minimizing the total travel time of evacuees and considering the 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. Two groups of algorithms were applied to solve the proposed mathematical formulation for the emergency evacuation planning optimization problem, including: (a) exact optimization algorithm (CPLEX); and (b) heuristic algorithms. The heuristic algorithms included 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, United States). A set of numerical experiments was conducted to evaluate the proposed algorithms in terms of both solution quality and computational time for the generated problem instances. The heuristic algorithms were found to be more promising than CPLEX for the large-size problem instances. Furthermore, the MUEGF heuristic demonstrated a good tradeoff between the solution quality and the computational time. Findings from this research provide a number 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 heuristic algorithms can be used as efficient practical tools by federal, state, and local authorities (e.g., Federal Emergency Management Agency, Department of Homeland Security) 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 extensions:

- Implement the developed **EEPOP-L** optimization model for other types of natural and man-made hazards (such as wildfire, tsunami, terrorist attack, nuclear plant radiation, earthquake, etc.);
- Apply the developed **EEPOP-L** mathematical model to evacuate multiple counties (e.g., evacuation of all the counties along Florida's costal area);
- Explore alternative optimization algorithms (e.g., metaheuristic algorithms such as Tabu Search, Variable Neighborhood Search, Simulated Annealing, Evolutionary Algorithms, and others);
- Account for the effects of other factors that were not considered throughout the emergency evacuation process (e.g., weather, traffic

contraflow, etc.);

- Conduct a comprehensive analysis to account for the effects of shadow evacuation on emergency evacuation planning;
- Assess the most critical factors that may influence compliance of a given population to the emergency evacuation orders;
- Consideration of congestion effects at later stages of emergency evacuation;
- Embedding the developed heuristic algorithms within traffic simulation software packages (e.g., PARAMICS, VISSIM, CUBE) and comprehensive evaluation of the algorithmic performance via extensive simulation experiments, emulating emergency evacuation.

Acknowledgment

This study was supported by United States Department of Transportation grant DTRT13-G-UTC42, and administered by the Center for Accessibility and Safety for an Aging Population (ASAP) at the Florida State University (FSU), Florida A&M University (FAMU), and University of North Florida (UNF). The opinions, results, and findings expressed in this study are those of the authors and do not necessarily represent the views of the United States Department of Transportation, the Center for Accessibility and Safety for an Aging Population, the Florida State University, the Florida A&M University, or the University of North Florida.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2019.101114.

References

[1] M.H. Crawford, K. Crowley, S.H. Potter, W.S.A. Saunders, D.M. Johnston, Risk modelling as a tool to support natural hazard risk management in New Zealand local government, Int. J. Disaster Risk Reduct. 28 (2018) 610–619.
[2] NOAA, National Hurricane Center: Hurricane Irma: August 30 – September 12, 2017. Tropical Cyclone Report, National Weather Service, 2018, https://www.nhc.noaa.gov/data/tcr/AL112017_Irma.pdf , Accessed date: 22 March 2018.
[3] L. Han, F. Yuan, T. Urbanik II, What is an effective evacuation operation? J. Urban Plan. Dev. 133 (2007) 3–8.
[4] M. Bédard, E. Leonard, J. McAuliffe, B. Weaver, C. Gibbons, S. Dubois, Visual attention and older drivers: the contribution of inhibition of return to safe driving, Exp. Aging Res. 32 (2006) 119–135.
[5] A. Kocatepe, E.E. Ozguven, M. Horner, H. Ozel, Pet-and special needs-friendly shelter planning in South Florida: a spatial capacitated p-median-based approach, Int. J. Disaster Risk Reduct. 31 (2018) 1207–1222.
[6] M.A. Dulebenets, O.F. Abioye, E.E. Ozguven, R. Moses, W.R. Boot, T. Sando, Development of statistical models for improving efficiency of emergency evacuation in areas with vulnerable population, Reliab. Eng. Syst. Saf. 182 (2019) 233–249.
[7] A. Pel, M. Bliemer, S. Hoogendoorn, A review on travel behaviour modelling in dynamic traffic simulation models for evacuations, Transportation 39 (2012) 97–123.
[8] O. Alisan, H. Tuydes-Yaman, A. Kocatepe, E.E. Ozguven, Developing performance measures to evaluate impact of cross-county collaboration for populations with access and functional needs, Int. J. Disaster Risk Reduct. 31 (2018) 873–885.
[9] M.A. Dulebenets, E.E. Ozguven, R. Moses, W.R. Boot, O.F. Abioye, M. Kavoosi, J. Pasha, Development of efficient algorithms to facilitate emergency evacuation in areas with vulnerable population groups, A Final Report Prepared for U.S. Department of Transportation and Center for Accessibility and Safety for an Aging Population, 2018.
[10] H. Abdelgawad, B. Abdulhai, Large-scale evacuation using subway and bus transit: approach and application in city of Toronto, J. Transport. Eng. 138 (2012) 1215–1232.
[11] Z. Xu, X. Yang, X. Zhao, L. Li, Differences in driving characteristics between normal and emergency situations and model of car-following behavior, J. Transport. Eng. 138 (2012) 1303–1313.
[12] S. Liu, P. Murray-Tuite, L. Schweitzer, Incorporating household gathering and mode decisions in large-scale no-notice evacuation modeling, Comput. Aided Civ. Infrastruct. Eng. 29 (2) (2014) 107–122.
[13] A. Trivedi, A. Singh, A hybrid multi-objective decision model for emergency shelter location-relocation projects using fuzzy analytic hierarchy process and goal programming approach, Int. J. Proj. Manag. 35 (5) (2017) 827–840.
[14] G. Cheng, C. Wilmot, E. Baker, Development of a time-dependent disaggregate hurricane evacuation destination choice model, Nat. Hazards Rev. 14 (2013) 163–174.
[15] M. Akbarzadeh, C. Wilmot, Time-dependent route choice in hurricane evacuation, Nat. Hazards Rev. 16 (2015) 04014021.
[16] Y. Abulhassan, J. Davis, R. Sesek, S. Gallagher, M. Schall, Establishing school bus baseline emergency evacuation times for elementary school students, Saf. Sci. 89 (2016) 249–255.
[17] F. Ozel, Time pressure and stress as a factor during emergency egress, Saf. Sci. 38 (2) (2001) 95–107.
[18] J.D. Sime, An occupant response shelter escape time (ORSET) model, Saf. Sci. 38 (2) (2001) 109–125.
[19] S. Liu, P. Murray-Tuite, L. Schweitzer, Uniting multi-adult households during emergency evacuation planning, Disasters 38 (3) (2014) 587–609.
[20] J. Wang, J. Sun, S. Lo, Randomness in the evacuation route selection of large-scale crowds under emergencies, Appl. Math. Model. 39 (18) (2015) 5693–5706.
[21] A. Han, TEVACS: decision support system for evacuation planning in Taiwan, J. Transport. Eng. 116 (1990) 821–830.
[22] A. Kimms, K. Maassen, Optimization and simulation of traffic flows in the case of evacuating urban areas, Spectrum 33 (2011) 571–593.
[23] H. Bi, E. Gelenbe, A Cooperative Emergency Navigation Framework Using Mobile Cloud Computing. Information Sciences and Systems, Springer, 2014, pp. 41–48.
[24] E. Gelenbe, H. Bi, Emergency navigation without an infrastructure, Sensors 14 (8) (2014) 15142–15162.
[25] H. Bi, E. Gelenbe, Routing diverse evacuees with cognitive packets, The Fourth International Workshop on Pervasive Networks for Emergency Management, IEEE, 2014, pp. 291–296.
[26] O.J. Akinwande, H. Bi, E. Gelenbe, Managing crowds in hazards with dynamic grouping, IEEE Access 3 (2015) 1060–1070.
[27] H. Bi, O.J. Akinwande, E. Gelenbe, Emergency navigation in confined spaces using dynamic grouping, 9th International Conference on Next Generation Mobile Applications, Services and Technologies, IEEE, 2015, pp. 120–125.
[28] H. Bi, E. Gelenbe, Cloud enabled emergency navigation using faster-than-real-time simulation, The Fifth International Workshop on Pervasive Networks for Emergency Management, IEEE, 2015, pp. 475–480.
[29] L. Pereira, D. Burgarelli, L. Duczmal, F. Cruz, Emergency evacuation models based on cellular automata with route changes and group fields, Phys. Stat. Mech. Appl. 473 (2017) 97–110.
[30] D. Bish, Planning for a bus-based evacuation, Spectrum 33 (2011) 629–654.
[31] P. Apivatanagul, R. Davidson, L. Nozick, Bi-level optimization for risk-based regional hurricane evacuation planning, Nat. Hazards 60 (2012) 567–588.
[32] M. Ye, J. Wang, J. Huang, S. Xu, Z. Chen, Methodology and its application for community-scale evacuation planning against earthquake disaster, Nat. Hazards 61 (2012) 881–892.
[33] D. Bish, H. Sherali, A. Hobeika, Optimal evacuation planning using staging and routing, J. Oper. Res. Soc. 65 (2014) 124–140.
[34] J. Li, K. Ozbay, Evacuation planning with endogenous transportation network degradations: a stochastic cell-based model and solution procedure, Network. Spatial Econ. 15 (2015) 677–696.
[35] W. Yi, L. Nozick, R. Davidson, B. Blanton, B. Colle, Optimization of the issuance of evacuation orders under evolving hurricane conditions, Transp. Res. Part B Methodol. 95 (2017) 285–304.
[36] X. Li, Q. Li, C. Claramunt, A time-extended network model for staged evacuation planning, Saf. Sci. 108 (2018) 225–236.
[37] K. Shahabi, J. Wilson, Scalable evacuation routing in a dynamic environment, Comput. Environ. Urban Syst. 67 (2018) 29–40.
[38] A. Apte, S. Heath, A. Pico, Y. Tan, Evacuating people with mobility-challenges in a short-notice disaster, Decis. Sci. J. 46 (4) (2015) 731–754.
[39] V. Dhingra, D. Roy, Modeling emergency evacuation with time and resource constraints: a case study from Gujarat, Soc. Econ. Plann. Sci. 51 (2015) 23–33.
[40] H. Hu, Y. Gao, J. Yu, Z. Liu, X. Li, Planning bus bridging evacuation during rail transit operation disruption, J. Urban Plan. Dev. 142 (2016) 04016015.
[41] D. Noh, J. Koo, B. Kim, An efficient partially dedicated strategy for evacuation of a heterogeneous population, Simulat. Model. Pract. Theor. 62 (2016) 157–165.
[42] B. Vahdani, D. Veysmoradi, N. Shekari, S. Mousavi, Multi-objective, multi-period location-routing model to distribute relief after earthquake by considering emergency roadway repair, Neural Comput. Appl. 30 (3) (2018) 835–854.
[43] Y. Liu, X. Lai, G. Chang, Two-level integrated optimization system for planning of emergency evacuation, J. Transport. Eng. 132 (2006) 800–807.
[44] M. Horner, M. Widener, The effects of transportation network failure on people's accessibility to hurricane disaster relief goods: a modeling approach and application to a Florida case study, Nat. Hazards 59 (2011) 1619–1634.
[45] Y. Huang, Y. Fan, Modeling uncertainties in emergency service resource allocation, J. Infrastruct. Syst. 17 (2011) 35–41.
[46] H. Tuydes-Yaman, A. Ziliaskopoulos, Modeling demand management strategies for evacuations, Ann. Oper. Res. 217 (2014) 491–512.
[47] V. Bayram, B. Tansel, H. Yaman, Compromising system and user interests in shelter location and evacuation planning, Transp. Res. Part B Methodol. 72 (2015) 146–163.
[48] G. Lim, M. Baharnemati, S. Kim, An optimization approach for real time evacuation reroute planning, Ann. Oper. Res. 238 (2016) 375–388.
[49] A. Kimms, K. Maassen, A fast heuristic approach for large-scale cell--transmission-based evacuation route planning, Networks 60 (3) (2012) 179–193.
[50] M. Heydar, J. Yu, Y. Liu, M. Petering, Strategic evacuation planning with pedestrian guidance and bus routing: a mixed integer programming model and heuristic solution Mojtaba, J. Adv. Transp. 50 (2016) 1314–1335.
[51] C. Boonmee, M. Arimura, T. Asada, Facility location optimization model for emergency humanitarian logistics, Int. J. Disaster Risk Reduct. 24 (2017) 485–498.
[52] S. Shahparvari, B. Abbasi, P. Chhetri, Possibilistic scheduling routing for short-notice bushfire emergency evacuation under uncertainties: an Australian case

study, Omega 72 (2017) 96–117.
[53] C. Wilmot, B. Mei, Comparison of alternative trip generation models for hurricane evacuation, Nat. Hazards Rev. 5 (4) (2004) 170–178.
[54] A. Sadri, S. Ukkusuri, P. Murray-Tuite, H. Gladwin, How to evacuate: model for understanding the routing strategies during hurricane evacuation, J. Transport. Eng. 140 (2014) 61–69.
[55] IBM, CPLEX Optimizer, (2019) https://www.ibm.com/analytics/cplex-optimizer , Accessed date: 2 February 2019.
[56] GAMS, Cutting Edge Modeling, (2019) https://www.gams.com/ , Accessed date: 3 January 2019.
[57] U.S. Census Bureau, https://www.census.gov/geo/maps-data/data/tiger.html, (2018) , Accessed date: 22 March 2018.
[58] ArcGIS, ArcMap. ArcGIS Desktop, (2018) http://desktop.arcgis.com/en/arcmap/ , Accessed date: 7 April 2018.
[59] FDEM, Division of Emergency Management: Statewide Emergency Shelter Plan, (2018) https://www.floridadisaster.org/globalassets/dem/response/sesp/2018/2018-sesp-entire-document.pdf , Accessed date: 7 April 2018.
[60] HCM, Highway Capacity Manual, (2010) http://hcm.trb.org/?qr=1 , Accessed date: 7 April 2018.
[61] M.A. Dulebenets, A novel memetic algorithm with a deterministic parameter control for efficient berth scheduling at marine container terminals, Maritime Business Review 2 (4) (2017) 302–330.
[62] M.A. Dulebenets, Application of evolutionary computation for berth scheduling at marine container terminals: parameter tuning versus parameter control, IEEE Trans. Intell. Transp. Syst. 19 (1) (2018) 25–37.
[63] M.A. Dulebenets, A comprehensive multi-objective optimization model for the vessel scheduling problem in liner shipping, Int. J. Prod. Econ. 196 (2018) 293–318.
[64] M.A. Dulebenets, M. Kavoosi, O.F. Abioye, J. Pasha, A self-adaptive evolutionary algorithm for the berth scheduling problem: towards efficient parameter control, Algorithms 11 (7) (2018) 1–35.
[65] E.B. De Lima, G.L. Pappa, J.M. De Almeida, M.A. Goncalves, W.M. Junior, Tuning Genetic Programming parameters with factorial designs, IEEE Congress on Evolutionary Computation, IEEE, 2010, pp. 1–8.