A Bi-Objective Optimization Approach for Emergency Evacuation Planning under Pandemic Settings

A Technical Report Submitted to the Rural Safe Efficient Advanced Transportation (R-SEAT) Center and United States Department of Transportation

FINAL REPORT

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METRIC CONVERSION CHART

When You Know	Multiply by	To Find
Length		
inches (in)	25.4	millimeters (mm)
feet (ft)	0.305	meters (m)
yards (yd)	0.914	meters (m)
miles (mi)	1.61	kilometers (km)
Volume		
fluid ounces (fl oz)	29.57	milliliters (mL)
gallons (gal)	3.785	liters (L)
cubic feet (ft^3)	0.028	meters cubed (m^3)
cubic yards (yd^3)	0.765	meters cubed (m^3)
Area		
square inches (in^2)	645.1	millimeters squared (mm^2)
square feet (ft^2)	0.093	meters squared (m^2)
square yards (yd^2)	0.836	meters squared (m^2)
acres	0.405	hectares (ha)
square miles (mi^2)	2.59	kilometers squared (km^2)

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16. Abstract

Different types of hazards occur quite often in different parts of the globe. These hazards may cause significant property damages, monetary losses, and human fatalities. For certain types of disasters, populations are expected to evacuate from locations that anticipate the greatest impact. Emergency evacuation is generally challenging. Lack of proper planning may result in negative externalities (e.g., congestion on evacuation routes, anxiety of evacuees). Emergency evacuation can be extremely challenging in rural areas that may not have emergency shelters with adequate capacity in their vicinity, and transportation infrastructure may not be able to handle a large number of evacuees. Furthermore, a frequent occurrence of pandemics makes emergency evacuation planning even more challenging. Rushing to the closest emergency shelter may not be the best choice because the closest shelters may operate at the capacity level. Overcrowded emergency shelters are expected to have a high risk of virus transmission under pandemic settings. Therefore, this project proposes a new bi-objective optimization model for emergency evacuation planning, aiming not only to minimize the total travel time of evacuees to the assigned emergency shelters but also to minimize the risk of virus transmission in the assigned emergency shelters as well. A custom multi-objective optimization algorithm is developed to solve the proposed bi-objective optimization model. Various case studies are conducted to demonstrate applicability of the proposed methodology for real-life emergency evacuation scenarios. The findings from this research can be used to better prepare rural populations for approaching natural hazards and ensure their safety throughout the evacuation process.

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EXECUTIVE SUMMARY

Emergency evacuations during natural disasters pose significant challenges, particularly when complicated by pandemic conditions. The present project addresses this critical intersection, developing innovative solutions to protect both urban and rural populations while maintaining public health safety measures. This project introduces a groundbreaking bi-objective optimization approach for the planning of emergency evacuations that addresses two fundamental challenges: minimizing evacuation time while reducing virus transmission risk in emergency shelters. A primary innovation of this research lies in the development of the Emergency Evacuation Planning under Pandemic Settings (EEPPS) optimization framework. Unlike traditional evacuation approaches that focus solely on evacuation speed, the proposed model considers both evacuation efficiency and public health safety. It is well known that rushing evacuees to the nearest shelters, while expedient, can lead to dangerous overcrowding—a particular concern during pandemics. Instead, the proposed approach strategically distributes evacuees across available sheltering facilities while optimizing travel times.

Another contribution of this research is a novel decomposition-based epsilon-constraint (DECON) algorithm that efficiently handles large-scale evacuation scenarios. Using Palm Beach County, Florida as a case study—a region frequently impacted by natural disasters—the research team developed and tested a comprehensive framework that could serve as a model for other communities nationwide. Experiments across 17 different scenarios, ranging from 1,000 to 9,000 evacuees, demonstrated remarkable improvements: a significant reduction in shelter crowding along with a simultaneous reduction in evacuation times compared to traditional methods. Importantly, this project pays special attention to diverse population groups, including elderly individuals and those with disabilities. Specific protocols were developed for special needs (SN) shelters, and family-unit evacuation strategies were created to keep households together while ensuring appropriate medical care access. In summary, the key achievements of this project include the following:

- Creation of a flexible optimization model adaptable to various pandemic severity levels
- Development of efficient evacuation grouping strategies that balance speed with safety
- Integration of evacuation routes and emergency shelters in a comprehensive network
- Successful testing with real-world geographic and demographic data
- Special considerations for unique evacuation challenges common for rural communities

This research provides emergency managers with practical tools for making informed decisions during crisis situations. The research findings suggest that a balanced approach—the one that considers both evacuation speed and public health measures—is not only possible but essential for effective emergency management during pandemics. This project, supported by the Rural Safe Efficient Advanced Transportation (R-SEAT) Center and the United States Department of Transportation, represents a significant step forward in emergency management planning. The presented methodologies offer a blueprint for communities nationwide, helping ensure safer evacuations for all populations during these challenging times when natural disasters and public health crises intersect. The tools and insights developed through this research are now ready for practical implementation, offering emergency managers new capabilities to protect their communities through more efficient, comprehensive, and health-conscious evacuation strategies.

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1. INTRODUCTION

This section provides essential background information and context for the present research project on planning emergency evacuations during pandemic settings. The section is organized as follows: (1) an overview of natural hazards and their increasing impacts on communities, with a particular focus on coastal regions; (2) specific challenges faced during emergency evacuations in rural areas; (3) additional complexities introduced by pandemic conditions in evacuation planning; (4) primary and secondary objectives of this research project; (5) relevance of this work to the Rural Safe Efficient Advanced Transportation (R-SEAT) themes and USDOT Strategic Plan; and (6) structure of this technical report.

1.1. Natural Hazards

Natural hazards are significant environmental events that result from natural processes, including atmospheric, geological, and hydrological phenomena (Huppert and Sparks, 2006; Gill and Malamud, 2014; Alexander, 2018). These events, occurring frequently across various regions globally, have led to considerable economic, social, and environmental impacts, especially in highly populated and infrastructure-dense areas (Lau et al., 2021; Lau et al., 2022; Liang et al., 2023). The United States (U.S.) is especially susceptible to a broad spectrum of natural hazards due to its diverse climate zones and geographic features.

The types of natural hazards common in the U.S. include wildfires, floods, hurricanes, severe storms, and snowstorms. Each type poses unique risks tied to the specific characteristics of the impacted region. FEMA (2021a) highlights the distribution of these hazards and their frequent impacts across the country. States along the U.S. East Coast, such as Georgia, Florida, Louisiana, Texas, North Carolina, and South Carolina, are often affected by hurricanes and tropical storms. Due to the warm waters of the Atlantic and Gulf, these regions frequently experience hurricanes that bring heavy rainfall, high winds, and storm surges, contributing to widespread flooding and infrastructure damage. For example, Hurricane Idalia in 2023, a category 4 hurricane, caused significant damage in Florida, resulting in 10 fatalities and over \$2.5 billion in economic losses (NOAA, 2023). Prior to that, Hurricane Ian (2022) caused even more extensive damage, with losses estimated at over \$50 billion and 148 fatalities, making it one of the costliest natural disasters in U.S. history (NOAA, 2023). Western states, including California, Arizona, and Washington, face a different set of hazards. The hot, dry climate attributes contribute to conditions favorable for wildfires, particularly in California. Additionally, seasonal rains can trigger flash floods in areas with inadequate drainage or dry soil, which can result in rapid, destructive flooding events.

Earthquakes are also prevalent in these areas due to tectonic activity along the Pacific Ring of Fire – see Figure 1. This regional distribution underscores the importance of geographic-specific disaster preparedness and mitigation efforts. By identifying regions at heightened risk for specific hazards, federal and local agencies can prioritize resource allocation, planning, and response strategies. Climate change has recently intensified the frequency and severity of various hazards, increasing the likelihood of extreme weather events, such as prolonged droughts, intense hurricanes, and severe wildfires (IPCC, 2021). This escalation has created challenges for disaster management and emergency services, which must now respond to more frequent and costly events across diverse geographical locations.

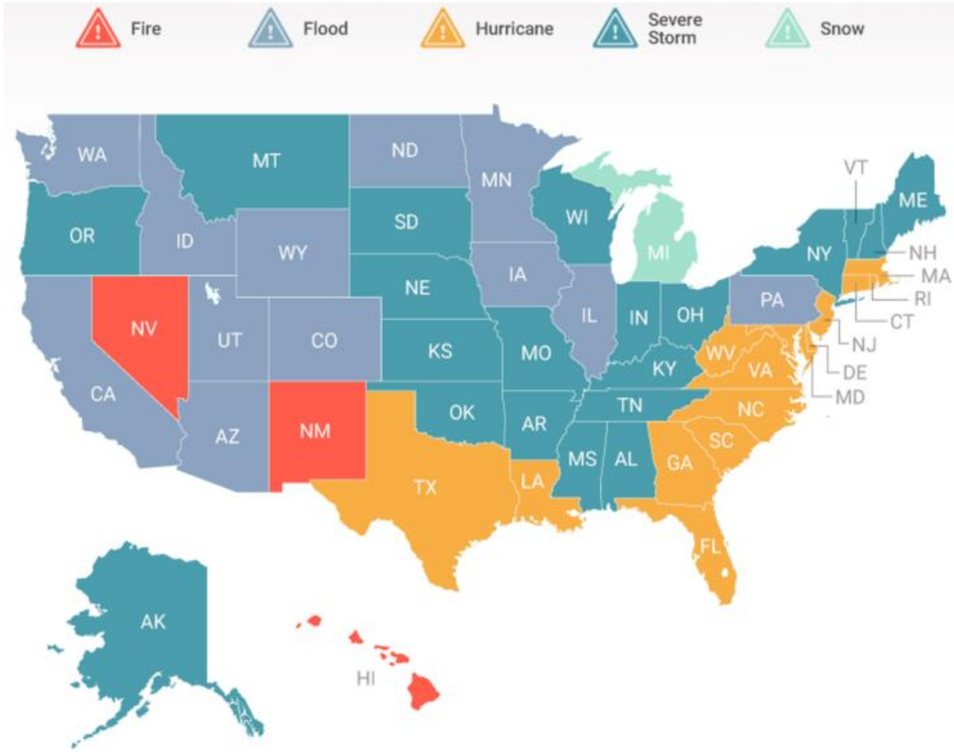


Figure 1 Natural hazards in the U.S. (FEMA, 2021a).

For certain types of natural hazards, particularly hurricanes, floods, and wildfires, evacuation is a critical response strategy to reduce the risk of loss of life (Simonovic and Ahmad, 2005; McCaffrey et al., 2014; Lim et al., 2016; McLennan et al., 2019). In the U.S., emergency evacuations have become a key component of disaster response plans in affected areas, with state and federal agencies collaborating to ensure timely and effective movement of people. However, the rapid nature of large-scale evacuations presents substantial logistical challenges. Effective evacuation requires sufficient planning, infrastructure, and coordination among agencies, especially in urban areas where many residents must be transported on a limited number of evacuation routes. Factors that can hinder evacuations include (Ohta et al., 2003; Lämmel et al., 2008; Gai et al., 2018; Belleville et al., 2021; Nagarajan and Shaw, 2021):

- **Congestion on evacuation routes**: High traffic volumes on limited routes often lead to significant delays. Traffic bottlenecks not only impede the timely evacuation of people but can also create uncomfortable situations for evacuees if they become trapped in areas close to the hazard.
- **Collisions and accidents on evacuation routes**: Traffic congestion, combined with the urgency of evacuation, increases the risk of traffic accidents, which can further block evacuation routes and delay the movement of evacuees.
- **Overcrowding of emergency shelters**: If evacuation planning is not efficient, emergency shelters may become overcrowded, reducing their effectiveness in providing safe, temporary housing. Overcrowded shelters may lack adequate resources, sanitation, or space, potentially exacerbating public health risks.

- **Failure to evacuate critical areas in time**: Populations in particularly high-risk zones, such as coastal areas prone to storm surge or flood zones, may face delays in evacuation, which can expose them to severe risk if evacuation is not completed before the hazard reaches its peak.
- **Psychological stress and anxiety among evacuees**: The need to evacuate one's home under uncertain and time-sensitive conditions can cause significant anxiety and stress for evacuees. This psychological impact can be long-lasting, especially for individuals repeatedly exposed to natural hazards.

Given the complex challenges posed by natural hazards, effective planning and preparedness are essential to protect lives and minimize losses (Paton et al., 2006; Paton et al., 2013; Fazeli et al., 2024).

1.2. Emergency Evacuation Challenges in Rural Areas

Emergency evacuation in rural areas presents a complex array of challenges that significantly differ from those encountered in urban environments. These challenges arise from a combination of geographical isolation, infrastructural limitations, economic factors, and inadequate resources—all of which can severely impede the effectiveness of evacuation efforts during emergencies, such as natural disasters or industrial accidents. One of the foremost challenges is the lack of nearby emergency shelters with adequate capacity. Many rural areas do not have sufficient funding for emergency preparedness activities, leading to a scarcity of well-equipped shelters and essential resources (Rural Health Information Hub, 2023). Agencies typically involved in emergency response, such as fire departments, emergency medical services, and rural public health agencies, often face shortages in equipment, staffing, training, and laboratory services (Rural Health Information Hub, 2023). This resource deficit hampers their ability to respond effectively when disasters strike.

Geography and transportation infrastructure further exacerbate the situation. Rural communities often cover large geographical areas, requiring residents to travel longer distances to reach healthcare centers, emergency shelters, and other critical establishments (Rural Health Information Hub, 2023). The limited accessibility and availability of evacuation routes mean that rural areas have fewer roads, which can lead to congestion and bottlenecks during mass evacuations. Research indicates that evacuation clearance times in rural regions can be significantly longer than in urban settings, sometimes exceeding the time it takes for a disaster, such as a flood, to reach certain communities (Cheng et al., 2011). This delay is compounded by the fact that rural populations may not have the same level of preparedness or experience with evacuations as urban populations, leading to slower response times (Li et al., 2013).

Economic dynamics and factors also play a pivotal role in hindering effective evacuation. Many residents lack access to personal vehicles, making independent evacuation challenging (Ozguven et al., 2016). This issue is particularly pronounced among certain population groups, such as individuals with disabilities and aging adults, who may require special accommodations or specialized transportation services (Rural Health Information Hub, 2023). The reliance on public transportation or community-organized evacuations creates logistical challenges, as these systems may not be adequately equipped to handle large-scale evacuations efficiently (Hess et al., 2013). Moreover, inadequate communications infrastructure imposes additional difficulties.

Certain rural areas do not have stable internet connections or reliable cell phone service, making it difficult for emergency managers and first responders to communicate effectively with residents before and after an emergency (Rural Health Information Hub, 2023). Important messages and evacuation orders may not reach these communities in a timely manner, leading to confusion and delays. Psychological factors compound this issue, and studies have shown that individuals in rural areas may exhibit a “wait and see” attitude, relying less on social cues compared to urban populations. This behavior can delay their decision to evacuate, further jeopardizing their safety (McCaffrey et al., 2018).

The geographical isolation of rural communities also poses significant challenges for emergency services. Response times for first responders can be longer due to the distances they must travel, which hinders timely evacuations and assistance (Jewer et al., 2018). Additionally, the lack of specialized medical facilities complicates the evacuation of those requiring urgent medical care, worsening the potential impacts on these populations during emergencies (Nishikawa et al., 2018). Despite these challenges, rural areas are often the most impacted by natural hazards. For instance, Hurricane Idalia in 2023 devastated some of the poorest rural areas in North Florida, underscoring the urgent need to address these issues (see Figure 2). The multifaceted nature of the challenges—logistical, psychological, infrastructural, and economic—necessitates comprehensive planning tailored to the unique characteristics of rural populations and their environments.

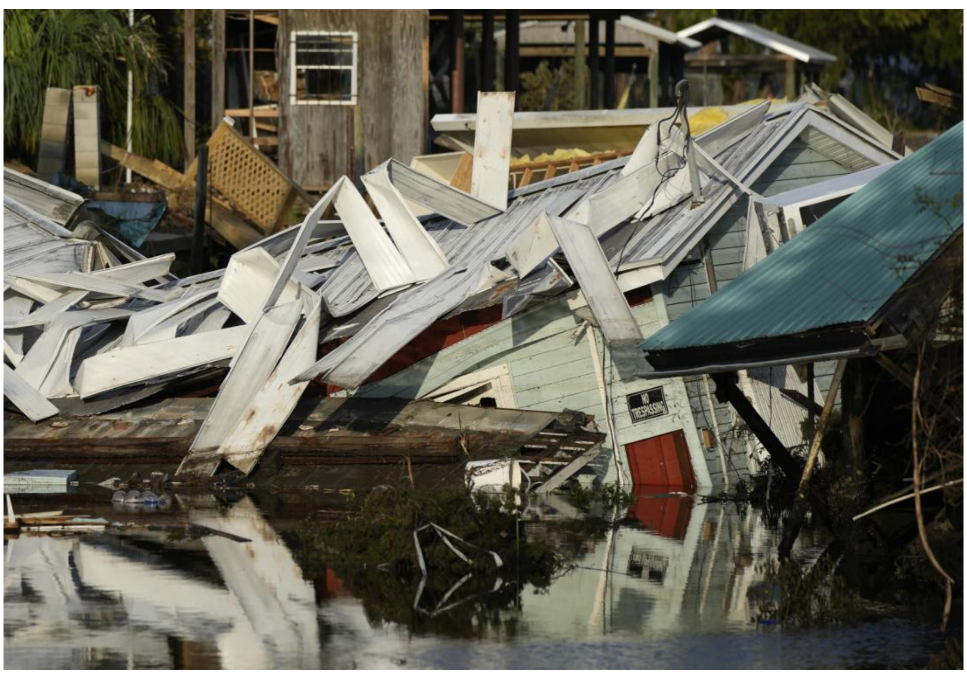


Figure 2 Destruction in North Florida due to Hurricane Idalia (Hudson, 2023).

Addressing these challenges requires a multifaceted approach. Improving transportation options, such as increasing the availability of evacuation routes and providing specialized transportation services for populations requiring special accommodations, is crucial (Ozguven et al., 2016). Enhancing communication systems to ensure timely and effective dissemination of emergency information can mitigate delays in evacuation decisions (Archibald & McNeil, 2012).

Conducting community preparedness training can empower residents with the knowledge and resources needed to respond promptly during emergencies (McCaffrey et al., 2018).

1.3. Emergency Evacuation under Pandemic Settings

The frequent occurrence of infectious disease outbreaks, epidemics, and pandemics in recent years has added significant complexity to emergency evacuation planning. Events, such as the Zika virus epidemic (2015–2016), the Angola yellow fever outbreak (2016), the Yemen cholera outbreak (2016–present), the Nigeria Lassa fever epidemic (2017), the Kivu Ebola epidemic (2018–2020), and most notably, the ongoing COVID-19 pandemic, have underscored the critical need to integrate public health considerations into evacuation strategies (World Health Organization [WHO], 2021). Traditional evacuation protocols prioritize the rapid relocation of populations to the nearest emergency shelters. However, during a pandemic, this approach can inadvertently facilitate the transmission of infectious diseases due to overcrowding in shelters operating at or near capacity (Centers for Disease Control and Prevention [CDC], 2020a). Overcrowded shelters increase the risk of virus spread and pose significant challenges for implementing infection prevention and control measures (CDC, 2020a). The COVID-19 pandemic has particularly highlighted these challenges, as social distancing and minimizing close contacts are essential to prevent the spread of the virus (Cheshmehzangi et al., 2023).

Populations evacuating from hazardous rural locations face additional difficulties. Emergency shelters are often located closer to urban areas and large cities, meaning rural evacuees may arrive at shelters already nearing capacity (Federal Emergency Management Agency [FEMA], 2009). This situation not only exacerbates the potential for disease transmission but also raises concerns about sufficient access to safe sheltering options. Certain population groups, such as individuals without personal vehicles or those requiring special accommodations, may experience increased hardship during evacuations under pandemic conditions (CDC, 2020b). A limited number of studies and guidelines have addressed the need to account for social distancing when assigning evacuees to emergency shelters. The CDC (2020a) provides interim guidance for general population disaster shelters during the COVID-19 pandemic, emphasizing the importance of maintaining physical distancing, enhancing cleaning and disinfection practices, and implementing health screening protocols. Similarly, FEMA (2021b) highlights the necessity of adapting evacuation and sheltering plans to reduce the risk of COVID-19 transmission, including the use of non-congregate shelters like hotels and dormitories to allow for better spacing of evacuees.

Overcrowded emergency shelters are expected to have a high risk of virus transmission under pandemic settings. In the meantime, populations evacuating from hazardous rural locations are likely to arrive to the closest shelters when they are close to their capacity level (since emergency shelters are often located closer to urban areas and large cities and farther away from rural areas). A few studies discuss the need to account for social distancing when assigning evacuees to emergency shelters (Nakai et al., 2021; Tripathy et al., 2021). While these studies represent significant advancements in integrating health considerations into evacuation planning, there remains a lack of holistic multi-objective optimization techniques that explicitly capture the conflicting objectives throughout the entire evacuation process under pandemic settings. The challenges lie in simultaneously optimizing for quick evacuation to minimize exposure to immediate hazards, reducing the risk of infectious disease transmission by preventing overcrowding, and efficiently allocating limited resources and shelter capacities. Developing comprehensive models that address these conflicting objectives is crucial for enhancing the effectiveness and safety of emergency evacuations during pandemics. Designing advanced optimization models that incorporate epidemiological factors is essential for enhancing the effectiveness and resilience of evacuation strategies. Such models need to consider a variety of essential variables, including shelter capacities adjusted for social distancing, transportation logistics procedures that minimize contact among evacuees, and prioritization protocols for populations requiring special accommodations.

1.4. Project Objectives

Considering an increasing occurrence of natural hazards along the U.S. coastal areas, substantial property damages and an increasing number of human fatalities as a result of these natural hazards, challenges experienced by rural populations during emergency evacuation, and increasing frequency of pandemics, this project aims to develop a new bi-objective optimization model for emergency evacuation planning, striving not only at minimizing the overall travel time of evacuees to the assigned emergency shelters but also minimizing the virus transmission risk in the assigned emergency shelters as well. The outcomes of this project are expected to assist with achieving the following objectives:

Primary Objectives:

1) Develop a new bi-objective optimization model for emergency evacuation planning, seeking not only to minimize the overall travel time of evacuees to the assigned emergency shelters but also to minimize the risk of potential virus transmission in the assigned emergency shelters;
2) Deploy more accurate travel time functions specifically calibrated for emergency evacuation conditions, taking into account representative characteristics of evacuees, evacuation route characteristics, driving conditions, and traffic characteristics;
3) Explicitly capture potential virus transmission in overcrowded emergency shelters;
4) Develop a custom multi-objective optimization algorithm to solve the proposed bi-objective optimization model and assist with decision making in a timely manner;
5) Apply the proposed methodology for real-life evacuation scenarios to showcase its efficiency and draw important managerial insights that can be useful to the relevant stakeholders for planning emergency evacuations not only in urban areas but in rural areas as well;
6) Develop a decision support system that can be used to better prepare rural populations for approaching natural hazards and ensure their safety throughout the evacuation process.

Secondary Objectives:

7) Disseminate the findings from this project to academicians, policymakers, and practitioners at the major national and international conferences and forums;
8) Enhance the existing FAMU-FSU educational STEM (science, technology, engineering, and mathematics) program by adding another dimension to the program with a specific focus on natural hazards and emergency evacuation of various population groups (including rural populations with their special needs);

9) Involve FAMU-FSU students throughout the project activities, improve their theoretical background, so they will be able to assist with the development of advanced optimization models and solution algorithms for efficient emergency evacuation.

1.5. Project Relevance to the REAT Themes and USDOT Strategic Plan

The proposed project fits very well the broad themes of the REAT Center and explicitly contributes to the following thrust areas:

Access and Transportation Efficiency: Emergency evacuation can be extremely challenging in rural areas that may not have emergency shelters with adequate capacity in their vicinity, and transportation infrastructure may not be able to handle a large number of evacuees in a short span of time. The bi-objective mathematical model developed as a part of this project for planning emergency evacuations will assist with an effective selection of emergency shelters and evacuation routes for rural populations, aiming not only to minimize their travel time to emergency shelters in case of approaching hazards but also to minimize the potential virus transmission risk in the assigned emergency shelters as well under pandemic settings.

Safety of Users: The existing studies on planning emergency evacuations generally ignore representative characteristics of drivers. However, representative characteristics of individuals directly influence their driving ability not only under normal driving conditions but under emergency evacuation conditions as well. This project will use comprehensive travel time functions that were calibrated for emergency evacuation conditions using the driving simulator and capture a large variety of factors, including representative characteristics of evacuees, evacuation route characteristics, driving conditions, and traffic characteristics. Consideration of representative characteristics of drivers throughout the emergency evacuation process is expected to improve the accuracy of the proposed bi-objective optimization model. Furthermore, such a methodological approach will allow accommodating diverse population groups residing in rural areas, including individuals with impaired vision, individuals with other disabilities, and individuals with chronic diseases.

Resilience: The proposed bi-objective optimization approach is expected to improve resilience of rural populations not only to approaching natural hazards but also to the ongoing and future pandemics. The outcomes of this research will be critical for many states across the U.S. and especially for Florida, as Florida (including its rural areas) is one of the states that often experience different types of natural hazards every year and significantly suffered from the ongoing COVID-19 pandemic.

Furthermore, the proposed project is expected to assist with meeting some of the major goals outlined in the USDOT 2022-2026 strategic plan, including the following: (1) improve safety of transportation systems and their users; (2) facilitate transportation efficiency across transportation systems and the communities they affect; (3) develop purpose-driven innovative decision support systems that can serve transportation users today and in the years to come; and (4) establish new policies and procedures (mainly focusing on emergency evacuation planning) to satisfy the critical needs of communities.

1.6. Structure of This Report

This report is organized to guide the readers through the major activities associated with the development of a bi-objective mathematical model for planning emergency evacuations in pandemic settings. More specifically, the main sections of the present report were organized as follows. Section 1 sets the project background. The project examines how natural disasters affect communities, especially in rural America, and how COVID-19 imposes additional challenges. Furthermore, the relevance of the present project to the goals of the Rural Safe Efficient Advanced Transportation (R-SEAT) Center and U.S. Department of Transportation are clearly highlighted as well. Section 2 reviews the previous efforts related to the theme of this project. Different approaches to evacuation planning are discussed from simple single-objective models to more complex multi-objective ones. Important gaps in the state of the art are determined. In section 3, a bi-objective mathematical model for planning emergency evacuations in pandemic settings is developed. The model focuses on timely evacuations with a reduced virus transmission risk in emergency shelters. Section 4 covers the proposed solution algorithm, which can efficiently handle complex trade-offs during planning emergency evacuations in pandemic settings. Section 5 uses the actual evacuation data to perform comprehensive computational experiments. The experiments aim to achieve the following two objectives: (1) evaluate the proposed solution approach; and (2) showcase some valuable managerial implications that can be obtained with the proposed modeling framework. Section 6 provides the main concluding remarks and summarizes the main outcomes of this project.

2. LITERATURE REVIEW

In this section, the project focuses on a comprehensive review of existing research related to emergency evacuation planning. First, single-objective optimization models, which focus on a singular goal (e.g., minimizing evacuation time), are explored in detail. Multi-objective optimization models that consider multiple goals simultaneously (e.g., balancing evacuation time with resource allocation) are investigated after that. Hierarchical optimization models are also discussed, highlighting how they structure complex decision-making processes into different levels. This review helps identifying gaps in the current methodologies, particularly the need for models that can handle conflicting objectives during pandemics.

2.1. Single-Objective Optimization Models for Emergency Evacuation Planning

One critical aspect of urban planning is effective planning of emergency evacuations, particularly in the face of increasing natural disasters and emergencies. Single-objective optimization models have traditionally played a key role in improving evacuation efficiency by targeting specific goals, such as minimizing the overall evacuation duration, maximizing the overall number of evacuees transported, or reducing risk exposure. Recent advancements have introduced innovative methodologies and computational techniques that significantly improve evacuation strategies.

One of the foundational studies in this area was conducted by Chiu et al. (2007). Integrating destination, route, and departure time choices became a focus of the study by Chiu et al. (2007), who unified these elements through a network transformation technique. Their approach aimed to minimize the total system travel time for more efficient evacuation outcomes by integrating evacuation modeling within a System Optimal Dynamic Traffic Assignment (SODTA) framework. This holistic approach provided valuable insights into the interdependencies of evacuation decisions and set the stage for more integrated models. Advancements continued with Kalafatas and Peeta (2009), who systematically investigated large-scale zone-based evacuation planning. They evaluated the benefits and limitations of strategies like contraflows and additional traffic lanes, offering practical insights for implementation. Their efficient formulation for the Evacuation Network Design Problem enabled timely evaluation for multiple scenarios, which is crucial for effective planning in emergency situations.

The unique challenges of bus-based evacuations were addressed by Bish (2011), who developed a model tailored specifically for this mode of transportation. Recognizing that traditional vehicle routing problems did not account for capacitated shelters and the objective of minimizing evacuation duration, the study provided heuristic algorithms capable of quickly generating feasible solutions. These algorithms proved effective in large-scale scenarios where exact optimization methods were impractical due to computational constraints. Lim et al. (2012) presented an optimization approach for the capacitated network flow decision problem in response to the need for rapid solutions in short-notice evacuations. Their Evacuation Scheduling Algorithm (ESA) utilized the Dijkstra algorithm and a greedy heuristic to efficiently determine the maximum flow for every path, balancing computational efficiency with solution quality. Numerical experiments validated the ESA performance across various cases, demonstrating its practicality for emergency management agencies.

The integration of optimization and traffic simulation was explored by Gan et al. (2016), who aimed to provide individuals in disaster-prone areas with efficient evacuation times and exit routes. Their mixed-integer linear program minimized the average evacuation time and the additional arc capacity penalty. When combined with a traffic simulator accounting for dynamic factors like driver behavior and traffic flow, they demonstrated significant improvements over ad-hoc evacuations. Their case studies in Victoria (Australia) underscored the importance of context-specific applications and the benefits of coupling optimization with simulation. Addressing risk and safety considerations, Ndiaye et al. (2017) developed a discrete macroscopic model using a pseudopolynomial method to address earliest arrival and quickest flow challenges. Taking into account safety as one of the key criteria, they achieved optimal solutions for evacuation time and approximate solutions concerning safety. Their innovative approach managed challenging instances more efficiently, contributing to a broader understanding of evacuation dynamics and the trade-offs involved.

Recognizing the importance of multimodal transportation, Yang et al. (2018) introduced a macroscopic multimodal network evacuation model. By considering the interactions between autos, buses, and subways, and aiming to minimize the total system evacuation time, they highlighted the significant impact of multimodal coordination on evacuation performance. Their iterative solution algorithm, validated through a case study in Lower Manhattan (New York), showcased the potential of such integrated models to improve evacuation efficiency in densely populated urban areas. Uncertainty in evacuation scenarios became a focal point in the study by Bayram and Yaman (2018), who proposed a stochastic optimization model. Their two-stage stochastic mixed-integer nonlinear programming model minimized the total evacuation time across various scenarios, making the evacuation plan robust to uncertainties in parameters like demand and network conditions. This approach addressed the inherent unpredictability of emergencies, enhancing the resilience of evacuation strategies and providing a more reliable framework for decision-makers.

Further emphasizing the role of timely evacuations, Dulebenets et al. (2019a) developed a mixed-integer programming model that minimized the total travel time while considering representative characteristics of drivers, route characteristics, driving conditions, and traffic. Due to computational limitations with the application of exact methods, they introduced heuristic algorithms that provided high-quality solutions more suitable for large-scale problems, particularly focusing on diverse population groups. Their work highlighted the importance of accounting for diverse evacuee needs in planning efforts. Advancements in bus evacuation models continued with Zhao et al. (2020), who proposed a round-trip bus evacuation model with unfixed routes. By optimizing bus scheduling and routing simultaneously, they significantly reduced the total evacuee time costs and network clearance times. Their case studies demonstrated the importance of flexibility and efficiency in evacuation operations, particularly in urban settings where time and resource constraints are critical.

Combining simulation and optimization techniques, Yazdani et al. (2020) developed a hybrid approach for emergency evacuation during extreme weather events. Their model maximized the number of evacuees transported using limited buses, considering route-specific risk profiles due to potential infrastructure disruptions. By introducing a novel Differential Evolution algorithm with opposition-based learning strategies, they addressed the complexities of evacuation under extreme weather events, offering a flexible and efficient tool for emergency managers. Lu et al. (2021) proposed an optimization model for pedestrian-bus route and pickup location planning during emergency evacuations. The main purpose was to determine the optimal pick-up nodes within a given transportation network and then allocate the available buses among the evacuees, so that they can be delivered to emergency shelters. The objective function of the developed optimization model aimed to minimize the total evacuation duration. The model was solved to optimality using the GAMS optimization suite. Through numerical examples with a realistic transportation network, they demonstrated the model effectiveness in enhancing evacuation efficiency by coordinating pedestrian and bus transportation modes, highlighting the importance of integrating multimodal strategies in evacuation planning.

Dynamic evacuation demands were considered in Zeng et al. (2021), who proposed a model integrating a bidirectional multilane conflict-eliminating cell transmission model with the split delivery vehicle routing problem. Their genetic algorithm-based solution managed the complexities of routing buses and cars, committed to minimizing the total evacuation time and effectively handling conflicts at intersections. This approach improved the accuracy of outflows in different movements, contributing to more realistic and efficient evacuation planning. Focusing on specific populations requiring mobility assistance, Alam et al. (2022) combined optimization and traffic microsimulation to optimize emergency vehicle allocation. Their study on evacuating individuals from hospitals and nursing homes highlighted the benefits of dedicated evacuation routes and provided practical methods for planning such operations. By addressing the specific needs of those with mobility challenges, they emphasized the importance of comprehensive evacuation strategies that ensure the safety of all community members.

The study by Ham et al. (2022) discussed traffic management strategies for large-scale evacuations using public transportation, which is crucial for minimizing congestion and ensuring efficient movement of evacuees. The research was motivated by the fact that the International Atomic Energy Agency updated the recommended maximum range of the emergency planning zone to 30 km, which prompted the Kori Nuclear Power Plant (Korea) to increase the emergency planning zone to 30 km. Such an increase could impose additional challenges during evacuations. The research underscored the importance of integrating transportation logistics (i.e., consideration of public transportation with basic passenger vehicles) into evacuation planning to enhance the overall effectiveness. Aiming to address the critical need for robust evacuation plans during nuclear emergencies, Zhou et al. (2023) introduced a vehicle evacuation model utilizing a fuzzy improved genetic algorithm. By dynamically adjusting the algorithm parameters and incorporating fuzzy credibility theory to handle uncertainty in evacuee numbers, they aimed to reduce radiation exposure and optimize vehicle capacity utilization. The proposed approach demonstrated significant improvements over alternative solution approaches, offering a valuable tool for managing evacuations in high-stake environments.

The study by Ren et al. (2024) presented an integrated solution for effective evacuation path planning specifically for nuclear power plants, utilizing atmospheric dispersion and dose models to enhance decision-making during emergencies. An improved Dijkstra algorithm was developed and implemented for evacuation path identification. A set of computational experiments were conducted to assess the proposed methodology. It was found that the proposed approach could decrease the effective dose by more than 60% compared to the shortest evacuation route approach. This study emphasized the importance of optimizing evacuation routes in high-risk environments, which is critical for ensuring the safety of large populations.

These studies collectively illustrate the evolution and advancements in single-objective optimization models for planning emergency evacuations over the past few decades. From foundational models optimizing evacuation paths to sophisticated algorithms accounting for uncertainty and multimodal transportation during large-scale evacuations, the field has significantly progressed. As emergencies and natural disasters continue to pose significant threats, ongoing research in this domain remains essential for enhancing community resilience and ensuring the safety of populations during evacuations.

2.2. Multi-Objective Optimization Models for Emergency Evacuation Planning

The process of planning emergency evacuations is a fairly challenging task that often involves multiple conflicting objectives which include minimizing evacuation time, reducing risk exposure, and optimizing resource allocation. Multi-objective optimization models have emerged as vital tools to address these complexities, allowing planners to consider and balance various factors simultaneously.

One prominent approach in this domain is the integration of multimodal transportation systems, which combines vehicular traffic and mass transit to optimize evacuation routes. Abdelgawad et al. (2010) presented a multi-objective optimization framework that focuses on minimizing at-origin waiting time, in-vehicle travel time, and fleet costs for mass transit evacuations. This framework highlighted the necessity of considering multiple transportation modes to enhance evacuation efficiency, especially in urban settings where traffic congestion can severely hinder evacuation efforts. The integration of Geographic Information Systems (GIS) with multi-objective optimization marked a significant advancement in the field. Coutinho-Rodrigues et al. (2012) harnessed the power of GIS to design evacuation plans that not only optimized routes but also identified optimal shelter locations. Their approach considered a variety of objectives, such as minimizing the total travel distance, evacuation risk, evacuation time to hospitals, and the number of shelters required. Applying their model to the historic city center of Coimbra, Portugal—a location characterized by narrow streets and old buildings—they demonstrated how such integration could effectively handle geographical constraints and complex urban environments.

The importance of data granularity and aggregation in evacuation modeling was highlighted by Goerigk et al. (2014). They presented an integrated macroscopic multi-criteria optimization model that simultaneously addressed shelter location, routing for both buses and individual vehicles, and risk assessment of chosen routes. By employing a custom evolutionary algorithm inspired by NSGA-II, a well-known evolutionary algorithm for multi-objective optimization, they solved complex evacuation problems in real-world scenarios in Nice (France) and Kaiserslautern (Germany). Their research demonstrated how different levels of data aggregation could significantly impact the quality of solutions and computation times, providing valuable guidance for future modeling efforts. In urban areas susceptible to natural disasters, efficient evacuation planning is crucial. Liu et al. (2016) proposed a quantum ant colony algorithm for planning emergency evacuations with the objectives of minimizing the overall evacuation time and total evacuation route density. Numerical experiments were conducted for evaluation of the computational efficiency of the suggested solution approach against the traditional ant colony optimization algorithm. It was found that the quantum ant colony algorithm was able to identify superior solutions as the number of algorithmic iterations increased.

Gai et al. (2017) explored the optimization of evacuation routes with multiple objectives in the context of toxic cloud releases. Their study introduced a model intended to decrease both the total time required for evacuation and the risk of hazardous substance exposure. By considering the dynamic dispersion of toxic clouds, the model integrated the spread of contaminants into the evacuation planning process. Two heuristic approaches were proposed to solve the developed optimization model, and their computational effectiveness was assessed during the computational experiments. Niyomubyeyi et al. (2019) introduced a modified multi-objective artificial bee colony (MOABC) algorithm to optimize evacuation routes and shelter assignments. Aimed at minimizing the total travel distance and reducing shelter overload, their algorithm incorporated innovative neighborhood search methods. When applied to realistic data collected for Kigali (Rwanda), their approach outperformed traditional algorithms in both computational time and solution quality, demonstrating its practicality for real-world emergency evacuation scenarios and challenges.

Transportation logistics play a pivotal role in evacuation efficiency. Recognizing this, Gao et al. (2019) developed a robust two-stage evacuation framework utilizing public transit. The first stage focused on selecting pick-up points to minimize the walking distance for evacuees. The first stage decision problem was solved using a hybrid genetic algorithm. The second stage focused on optimizing vehicle routing and scheduling to minimize the total time of evacuation and the required number of vehicles. A custom heuristic was developed to address the second stage decision problem. Their model coordinated logistics between evacuees and transit fleets, enhancing the overall efficiency of the evacuation process. Ma et al. (2019) tackled the emergency shelter location-allocation problem in the Beijing central area through a multi-objective optimization model. They aimed to minimize evacuation distances while ensuring balanced shelter utilization and accounting for resource limitations. The model incorporated uncertainties in the temporal dynamics of population distribution. Through a scenario-based approach and particle swarm algorithm implementation, their study demonstrated how to create efficient, resilient evacuation plans that could effectively respond to various disaster situations.

As urban populations grow denser, innovative solutions for sheltering evacuees become necessary. Jin et al. (2021) explored underground space utilization, such as parking lots and metro stations, as emergency shelters in densely populated urban communities. They developed a mathematical optimization framework combined with a customized network flow algorithm employed to identify the most effective shelter locations and pedestrian evacuation pathways. Their case study in Shanghai (China) demonstrated that leveraging underground spaces could significantly enhance evacuation capacity while minimizing the total evacuation distance. Ebrahimnejad and Harifi (2022) developed an innovative evacuation model focusing on disability-related compatibility constraints. They introduced the Giza Pyramids Construction (GPC) metaheuristic algorithm, inspired by ancient Egyptian construction methods, to optimize evacuation planning. Their multi-objective model aimed to minimize evacuation time and costs while maximizing compatibility between disabled evacuees and available resources. Through the GPC metaheuristic's efficient solution space exploration, their work demonstrated how to create comprehensive and cost-effective evacuation plans that specifically address the needs of populations requiring special accommodations.

The allocation of evacuees to shelters while considering safe routes and minimizing risks was the focus of Sicuaio et al. (2022). They developed a multi-objective optimization model, aiming to minimize the overall travel distance, reduce evacuation risks, and decrease the potential shelter overload. Utilizing a discrete multi-objective cuckoo search (DMOCS) algorithm, they achieved superior performance over standard algorithms. Their work provided practical decision support tools for emergency managers, particularly valuable for disaster-prone regions requiring efficient and safe evacuation strategies. Li et al. (2023) addressed the location-allocation of fixed shelters for elderly evacuees in Hefei (China) through a multi-objective optimization model. Their approach focused on minimizing evacuation distances while maximizing shelter suitability based on age-specific criteria, including accessibility features and proximity to medical facilities. A metaheuristic algorithm inspired by the features of genetic algorithms and simulated annealing was adopted as a solution approach. Using GIS for spatial analysis, their approach developed tailored evacuation strategies that considered shelter capacity constraints while prioritizing elderly needs. The study demonstrated how emergency planning can be effectively adapted to serve diverse demographic groups.

Another significant contribution is from Yin et al. (2023) who developed an emergency shelter allocation planning methodology based on a quantum genetic algorithm. Their model addressed the challenges posed by large-scale evacuations, considering the total evacuation distance and capacity constraints of evacuation sites. Numerical experiments confirmed the effectiveness of the proposed solution algorithm for realistic emergency evacuation scenarios simulated for the Wuhan metropolitan area (China). This research highlighted the need for efficient resource allocation strategies that can adapt to the dynamic nature of emergency situations. Tang and Osaragi (2024) presented a multi-objective evacuation planning model, particularly in the context of post-earthquake fire spread, specifically focusing on a case study in Tokyo (Japan). This study emphasized the need for evacuation plans that not only minimize distance or cost but also consider risk factors associated with potential hazards during the evacuation process. The proposed risk reduction model aimed to enhance the safety and efficiency of evacuation processes in disaster-prone areas. AUGMECON was applied to solve the developed optimization model, and important insights were demonstrated during the experiments.

Collectively, these studies highlight the evolution and diversification of multi-objective optimization models in emergency evacuation planning. The integration of advanced algorithms, consideration of human factors, and incorporation of uncertainties has made these models more robust and applicable. The progression of this field reflects a deeper understanding of the multifaceted nature of evacuations. Modern models not only strive for efficiency but also prioritize safety, psychological well-being, and accessibility. By balancing multiple objectives, planners can develop evacuation strategies that are not only effective in terms of logistics but also responsive to the needs of affected populations.

2.3. Hierarchical Optimization Models for Emergency Evacuation Planning

Planning emergency evacuations involves complex decision-making processes that must account for multiple stakeholders with differing objectives and priorities. Hierarchical optimization models, such as bilevel and multilevel programming, have been developed to address these complexities by structuring problems into different decision-making levels. Over the years, significant studies have advanced hierarchical optimization models in emergency evacuation planning. This section narratively explores essential works highlighting both foundational contributions and recent developments.

Kongsomsaksakul et al. (2005) introduced a hierarchical optimization approach for flood evacuation planning by developing a shelter location-allocation model. The model consisted of two levels: the upper level determined optimal shelter locations to minimize the total travel time, while the lower level allocated evacuees to shelters based on the shortest travel time. This hierarchical structure allowed for a coordinated evacuation strategy that balanced efficiency and safety. An evolutionary algorithm was presented as a solution approach. Apivatanagul et al. (2011) introduced an innovative bilevel optimization framework tailored for risk-informed regional hurricane evacuation planning. Their approach was designed to simultaneously reduce both the associated risks and the required travel time by evaluating multiple scenarios and alternative strategies, including sheltering-in-place and phased evacuation processes. Unlike traditional models that typically specify in advance who should evacuate, their methodology aimed to determine who should remain, who should evacuate, the optimal timing for departures, and the appropriate destinations as the hurricane approaches. The upper level was responsible for creating the evacuation strategy, while the lower level utilized a dynamic user equilibrium traffic assignment model to assess the proposed plan across various hurricane scenarios. This groundbreaking model incorporated scenario-based analysis to address the inherent uncertainties in hurricane forecasting, thereby offering a more flexible and responsive approach to evacuation planning.

Advancing hierarchical optimization in evacuation planning, Li et al. (2011) extended the hierarchical optimization framework by proposing a bilevel model that integrated shelter location analysis with transportation planning for hurricane events. The upper level focused on strategic decisions regarding shelter placement and capacity to minimize the unmet demand and travel times spent by evacuees traveling to shelters and other destinations, while the lower level dealt with the stochastic user equilibrium to determine the travel times across the transportation network. This integrated approach allowed for adaptive evacuation strategies responsive to evolving hurricane scenarios. A similar bilevel framework was explored in the study by Li et al. (2012). The conducted experiments showed that the consideration of various scenarios was found to be important for planning emergency evacuations and sheltering decisions. Ren et al. (2013) tackled the optimization of evacuation routes and traffic signal timing amid uncertainties in the background demand (i.e., regular traffic that can be present along with evacuees) by implementing a hierarchical modeling approach. The top tier of their model focused on reducing the overall evacuation time and enhancing the performance of the transportation network through the optimization of evacuation flows and traffic signals. In contrast, the lower tier accounted for the most challenging background traffic scenarios within a certain probability region. Utilizing robust optimization techniques alongside the Non-dominated Sorting Genetic Algorithm II (NSGA-II), the study successfully identified Pareto-optimal solutions. The proposed methodology proved to be both effective and applicable to urban networks, such as the Sioux Falls network and the Jianye network surrounding the Nanjing Olympics Sports Center.

Zhao et al. (2016) developed an evacuation network optimization model that incorporated lane-based reversals and routing strategies. The upper-level problem aimed to minimize the total evacuation time by optimizing lane reversals and assigning evacuation routes. The lower-level problem dealt with evacuee route choices and intersection crossing conflict elimination. A tabu search algorithm was implemented at the upper level, whereas the lower-level problem was solved with simulated annealing. The proposed model incorporated lane-based traffic management strategies, such as contraflow operations, to enhance road capacity during evacuations. The study demonstrated that lane-based reversal strategies could significantly improve evacuation efficiency. Yi et al. (2017) investigated the optimization of issuing evacuation orders under the uncertain and evolving conditions of hurricanes. Acknowledging that the timing of evacuation orders is critical and involves significant trade-offs, they developed a stochastic dynamic programming model to assist in decision-making. The model aims to minimize the total travel time, total time away from home, total risk associated with evacuation, and total risk associated with staying at home at the upper level. The lower level model focused on dynamic traffic assignment, considering the total travel time and time away from home. By integrating real-time hurricane forecast updates and accounting for uncertainties in the hurricane path and intensity, their approach allows emergency managers to make more informed and timely decisions. The study enhances planning of emergency evacuations by providing a quantitative framework that optimizes the timing of evacuation orders, balancing the risks and costs associated with hurricanes whose conditions evolve over time.

Addressing uncertainties in earthquake emergency shelter allocation, Xu et al. (2018) proposed a scenario-based hybrid bilevel model using a Stackelberg game mechanism. The upper level (manager's objective) minimized the total evacuation distance, while the lower level (evacuees' objective) minimized the maximum individual evacuation distance. By applying a modified particle swarm optimization algorithm, they improved computation efficiency and solution quality compared to conventional models, particularly in complex, high-dimensional scenarios. Hammad (2019) introduced a bilevel multi-objective optimization model addressing evacuation location-allocation considering phases before and after a disaster. The upper-level model representing urban planners aimed to minimize the shelter construction costs and total system travel time, while the lower level focused on evacuees minimizing their individual travel times under user-equilibrium conditions. By transforming the bilevel model into a mixed-integer linear programming model, the study showed that the solutions were significantly less expensive in terms of construction costs and total system travel time compared to alternative methods. This work highlighted the effectiveness of bilevel optimization in achieving cost-efficient and comprehensive evacuation strategies.

More recently, He and Xie (2022) emphasized the importance of efficient planning and layout of urban emergency shelters through a bilevel multi-objective location-allocation model called the Accessibility, Economy, and Efficiency (AEE) model. The upper-level model sought to minimize investment costs associated with constructing and maintaining shelters, considering budget constraints and long-term economic sustainability. The lower level aimed to minimize comprehensive evacuation time, enhancing the efficiency of evacuations by optimizing shelter assignments and evacuation routes. By incorporating sequential decision-making and the gravity model to simulate evacuee behavior—reflecting factors like distance attractiveness and shelter capacity—the AEE model balanced economic sustainability and social utility. Their approach presented a more realistic representation of evacuee demands and behaviors.

Hierarchical optimization models have significantly advanced the planning of emergency evacuations by accommodating complex interactions between decision-makers and objectives. From early models focusing on building evacuations to sophisticated frameworks addressing uncertainties, human behavior, and dynamic conditions, these studies have enhanced the effectiveness of evacuation strategies. Structuring problems into hierarchical levels allows for more effective, realistic, and comprehensive evacuation plans adaptable to changing scenarios and stakeholder needs. The inclusion of multimodal transportation strategies, dynamic traffic management, and real-time data integration underscores the necessity of considering various factors to optimize resource allocation during emergencies. The ongoing evolution of hierarchical optimization models promises to further improve emergency response and resilience in the face of natural disasters and other emergencies.

2.4. Literature Summary

This comprehensive review of single-objective, multi-objective, and hierarchical optimization models for planning emergency evacuations illustrates the growing complexity of emergency evacuation planning tools. By balancing evacuation time, safety, shelter capacity, and economic efficiency, these models address the multifaceted nature of evacuation, offering tailored solutions that are increasingly resilient, comprehensive, and adaptive to dynamic, high-risk scenarios (see Table 1). Despite the advancements in emergency evacuation planning, **none of these studies explicitly address optimization under pandemic conditions**, where unique challenges, such as social distancing, additional restrictions on the use of shelter capacities, and health safety protocols, critically impact evacuation strategies. This gap highlights the necessity for developing new models that integrate pandemic-specific requirements into emergency evacuation planning. The present project can be viewed as one of the pioneering efforts that comprehensively consider these health and logistical constraints to ensure safe, efficient evacuations during public health crises, ultimately improving resilience in pandemic scenarios.

Table 1 Overview of analyzed research on emergency evacuation planning.

Single-Objective Optimization Models for Emergency Evacuation Planning					
a/a	**Authors**	**Solution Approaches**	**Objective**	**Case Study/Simulation**	**Notes/Important Considerations**
1	Chiu et al. (2007)	Exact optimization	Minimize total evacuation time	Test network with 8 nodes	Network transformation converts a transportation network into a single-destination evacuation model with a hot zone and super-safe node
2	Kalafatas and Peeta (2009)	Exact optimization	Minimize network clearance time	Hypothetical urban network	Contraflow and additional lanes with efficient formulation for multiple scenarios
3	Bish (2011)	Heuristic algorithms	Minimize network clearance time	Hypothetical urban network	Models for bus-based evacuations considering shelter capacity that have distinctive features from the traditional vehicle routing problem

4	Lim et al. (2012)	Heuristic	Maximize the total number of evacuees	Greater Houston Area network (USA)	Balanced computational efficiency with solution quality for rapid response
5	Gan et al. (2016)	Simulation + optimization	Minimize the average evacuation time and the additional arc capacity penalty	Victoria (Australia)	Performance depends heavily on population density and road network topology
6	Ndiaye et al. (2017)	Exact optimization	Minimize total evacuation time Minimize risk	Nice (France)	Innovative approach handling both duration and safety objectives
7	Yang et al. (2018)	Heuristic	Minimize total system evacuation time	Lower Manhattan, New York (USA)	First approach to model multimodal evacuation with modal interactions
8	Bayram and Yaman (2018)	Exact optimization	Minimize total evacuation time	Istanbul Metropolitan Municipality	Utilizing branch-and-bound approaches combined with cutting-plane methods
9	Dulebenets et al. (2019a)	Exact and heuristic methods	Minimize total travel time considering representative characteristics of drivers	Broward County, Florida (USA)	First to incorporate comprehensive considerations for representative characteristics of drivers
10	Zhao et al. (2020)	Heuristic	Minimize total evacuee time cost	Sioux Falls network; Ningbo (China) network	Novel approach to flexible bus routing in evacuations
11	Yazdani et al. (2020)	Simheuristic	Maximize the number of evacuees	Hypothetical transportation network	Method accounts for uncertainties in travel times and route disruptions
12	Lu et al. (2021)	Exact optimization	Minimize total evacuation duration	Sioux Falls network	The model jointly optimized pedestrian routes, pickup nodes, and bus allocations under constraints of bus capacity and availability
13	Zeng et al. (2021)	Metaheuristic	Minimize total evacuation time	Sioux Falls network	Advanced handling of intersection conflicts
14	Alam et al. (2022)	Simulation + optimization	Minimize total evacuation time	Halifax network (Canada)	Specialized focus on populations with mobility needs
15	Ham et al. (2022)	Simulation	Minimize total evacuation time	Ulsan Metropolitan City (South Korea)	Pure car evacuation takes 435 min; even a 20% bus share could reduce the total evacuation time by more than 50%

16	Zhou et al. (2023)	Metaheuristic	Minimize radiation exposure	Nuclear facility areas	Application of fuzzy credibility theory to model uncertain evacuee demand
17	Ren et al. (2024)	Heuristic	Minimize radiation dose	Nuclear power plant in China	The proposed approach reduced the effective radiation dose by up to 67.3% compared to the shortest distance path method
			Multi-Objective Optimization Models for Emergency Evacuation Planning		
18	Abdelgawad et al. (2010)	Metaheuristic + heuristic	Minimizing in-vehicle travel time Minimizing at-origin waiting time Minimizing fleet costs	Downtown Toronto (Canada)	Including waiting time and travel time in objectives reduced network clearance time by 40% compared to including travel time only
19	Coutinho-Rodrigues et al. (2012)	Exact + heuristic approaches	Minimize total travel distance to reach evacuation shelters Minimize total risk of primary evacuation paths Minimize total travel distance of backup paths Minimize total risk at shelter locations Minimize total time to transfer people from shelters to hospitals Minimize total number of shelters	Historical center, Portugal	Focus on nighttime planning due to higher fire risks between 8 pm and 8 am
20	Goerigk et al. (2014)	Metaheuristic	Minimize total evacuation time Minimize risk exposure for evacuees Minimize number of shelters in use	Nice (France), Kaiserslautern (Germany)	Merging the aspects of location, routing, and risk, which are usually considered separately in evacuation planning
21	Liu et al. (2016)	Metaheuristic	Minimize total evacuation time for all evacuees Balance the load of evacuation network	Hypothetical network	The proposed quantum ant colony optimization algorithm provides efficient evacuation paths
22	Gai et al. (2017)	Heuristics	Minimize total travel time along the evacuation path Minimize individual evacuation risk along the evacuation path	Hypothetical network	Integration of risk assessment into evacuation routing and consideration of time-varying travel conditions
23	Niyomubyeyi et al. (2019)	Metaheuristic	Minimize total evacuation distance Minimize total shelter capacity overload	Kigali (Rwanda)	The proposed approach outperformed alternative methods, making it suitable for evacuation planning with time constraints
24	Gao et al. (2019)	Metaheuristic + heuristic	Minimize total walking time of evacuees to pick-up points Minimize total transit-based evacuation time Minimize the number of vehicles while satisfying time window constraints	Hypothetical network	The model addresses time windows and resource limitations, optimizing both pick-up points and vehicle schedules

25	Ma et al. (2019)	Metaheuristic	Minimize total shelter area Minimize total evacuation distance	Beijing (China)	A supplemental model that prioritizes designated shelters, addressing spatiotemporal variations in evacuee distribution and accommodating uncertainty in earthquake scenarios
26	Jin et al. (2021)	Heuristic	Maximize satisfied evacuation demand Minimize total evacuation distance	East Nanjing Road area in Shanghai	Sidewalks were identified as the main bottleneck due to their limited capacity
27	Ebrahimnejad and Harifi (2022)	Metaheuristic	Minimize total distance traveled by vehicles Minimize maximum distance of a tour Minimize the hybrid weighted combination of both objectives	Hypothetical network	Focuses on compatibility constraints for people with disabilities, heterogeneous vehicles, and the time required for transporting disabled individuals
28	Sicuaio et al. (2022)	Metaheuristic	Minimize total travel distance from evacuation zones to shelters Minimize risk on evacuation routes Minimize shelter overload	Maputo City (Mozambique)	Provided multiple effective solutions for decision-makers based on different priorities (risk, distance, and shelter capacity)
29	Li et al. (2023)	Metaheuristic	Minimize total evacuation distance Maximize the number of successful evacuees	Hefei (China)	The model incorporates unique needs of the elderly for shorter evacuation distances and indoor sheltering options
30	Yin et al. (2023)	Metaheuristic	Minimize total evacuation distance Minimize congestion Minimize the occurrence of unreasonable starting points	Wuhan metropolitan area (China)	Novel quantum computing approach to emergency shelter allocation
31	Tang and Osaragi (2024)	Exact optimization	Minimize total evacuation distance Minimize risk in lower-level shelters Minimize risk along evacuation paths Maximize the pass ratio of paths	Ogu Area, Tokyo (Japan)	Integration of multi-hazard risks during emergency evacuation planning
			Hierarchical Optimization Models for Emergency Evacuation Planning		
32	Kongsomsaksakul et al. (2005)	Metaheuristic	Minimize total evacuation time (authority: shelter locations) Minimize individual travel times (evacuees: shelter assignment)	Utah (USA)	The model treats the planning authority as the leader and evacuees as followers, capturing realistic behavior by allowing evacuees to decide shelter destinations and routes
33	Apivatanagul et al. (2011)	Heuristic	Minimize expected risk (at home, en route, at destinations) Minimize total travel time Minimize risk beyond critical threshold Minimize early departure penalties User equilibrium	North Carolina (USA)	Considering storm track uncertainty; an iterative optimization algorithm for the bilevel model

34	Li et al. (2011)	Heuristic	Minimize expected unmet shelter demand Minimize expected total network travel time User equilibrium	North Carolina (USA)	The proposed approach could yield significant benefits by jointly optimizing sheltering and transportation strategies
35	Li et al. (2012)	Heuristic	Minimize expected unmet shelter demand Minimize expected total network travel time User equilibrium	North Carolina (USA)	Consideration of various scenarios was found to be important for planning emergency evacuations and sheltering decisions
36	Ren et al. (2013)	Metaheuristic	Minimize total travel time of evacuation flows Minimize network performance index Maximize the background traffic impact degree	Sioux Falls network; Nanjing Olympics Sports Center (China)	Accounts for uncertain background traffic demands using robust optimization
37	Zhao et al. (2016)	Metaheuristics	Minimize total evacuation time Integrate lane-based reversal design and routing with intersection crossing conflict elimination	Nanjing Olympics Sports Center (China)	The model accounts for both lane reversal and routing simultaneously
38	Yi et al. (2017)	Heuristic	Minimize total travel time Minimize total time away from home Minimize total evacuation risk Minimize total risk staying at home User equilibrium	North Carolina (USA)	Explicitly accounts for uncertainty in hurricane evolution
39	Xu et al. (2018)	Metaheuristic	Minimize total evacuation distance Minimize the maximum individual evacuation distance	Beijing (China)	The model captures population movement patterns and earthquake damage situations, underscoring the varying evacuation needs for daytime and nighttime
40	Hammad (2019)	Exact optimization	Minimize shelter construction costs Minimize total system travel time User equilibrium	Hypothetical network	Integrates both pre-disaster (shelter location) and post-disaster (evacuation routing) planning
41	He and Xie (2022)	Metaheuristic	Minimize investment in shelter construction Minimize evacuation time	Urban development zone in China	Integrates the gravity model to reflect evacuees' shelter preferences based on distance and shelter scale

3. OPTIMIZATION MODEL DEVELOPMENT

This section of the report focuses on the development of a mathematical formulation for the bi-objective mathematical model for planning emergency evacuations under pandemic settings. First, the main notations to be used in the model are defined. Then, a concise problem description is provided. Third, the bi-objective optimization model is formulated.

3.1. Notations

The optimization model known as the bi-objective optimization model for Emergency Evacuation Planning under Pandemic Settings (EEPPS) is structured around multiple components, including the key sets, decision variables, and parameters. These essential elements of the model are systematically presented in Table 2 to provide a comprehensive overview and facilitate easier understanding.

Table 2 Adopted notations.

Sets	**Description of Sets**
$E = \{1, \dots, n^1\}$	set of evacuating individuals considered in a specific time horizon (evacuees)
$R = \{1, \dots, n^2\}$	set of routes that can be used by evacuees to depart from the evacuation zone (routes)
$S = \{1, \dots, n^3\}$	set of emergency sheltering facilities that can be used for evacuees (shelters)
$P = \{1, \dots, n^4\}$	set of time intervals that can be modeled for a specific time horizon (time intervals)
Variables	**Description of Variables**
$\boldsymbol{x}_{erp} \in \mathbb{B}, e \in E, r \in R, p \in P$	=1 if evacuating individual e is expected to evacuate the dangerous zone using evacuation route r during time interval p (else = 0)
$\boldsymbol{z}_{es} \in \mathbb{B}, e \in E, s \in S$	=1 if evacuating individual e is expected to stay at emergency sheltering facility s (else = 0)
$\boldsymbol{t}_{er} \in \mathbb{R}^+, e \in E, r \in R$	travel time of evacuating individual e using evacuation route r (hours)
$\boldsymbol{U}_s \in \mathbb{R}^+, s \in S$	overall utilization of emergency sheltering facility s (%)
$\Delta\boldsymbol{U}_s \in \mathbb{R}^+, s \in S$	deviation from the average utilization for emergency sheltering facility s compared to other sheltering facilities used for accommodating the evacuating individuals (%)
Parameters	**Description of Parameters**
$y_{es} \in \mathbb{B}, e \in E, s \in S$	=1 if evacuating individual e can be potentially assigned to sheltering facility s (else = 0)
$w_{rs} \in \mathbb{B}, r \in R, s \in S$	=1 if evacuation route r has a connection to sheltering facility s (else = 0)
$q_e \in \mathbb{R}^+, e \in E$	total number of evacuating individuals who carpool with evacuating individual e (evacuating individuals)
$C_{rp}^{route} \in \mathbb{R}^+, r \in R, p \in P$	total capacity of evacuation route r for time interval p (vehicles)
$C_s^{shelter} \in \mathbb{R}^+, s \in S$	total capacity of sheltering facility s (evacuees)
$U_s^{max} \in \mathbb{R}^+, s \in S$	upper bound on the utilization of sheltering facility s (%)
$\sigma_s \in \mathbb{R}^+, s \in S$	weight value of shelter s linked with the risk of virus transmission (%)

3.2. Description of the Decision Problem

The coordination of evacuation timing presents significant challenges. Research indicates that while quick action is essential, an excessive emphasis on rapid evacuation can have negative consequences. Specifically, when shelters become too crowded, it creates substantial problems, particularly during pandemic situations where maintaining social distance and reducing close contact is vital. This demonstrates the importance of implementing a measured approach to evacuation planning that considers both efficiency and safety protocols. Contemporary evacuation strategies frequently fail to adequately address the requirements of at-risk populations, including elderly individuals and those with medical conditions, who typically need more specialized evacuation approaches to ensure appropriate care and assistance.

The management of shelters and evacuation pathways must be handled carefully due to their inherent capacity constraints. The primary objective is to facilitate swift and secure evacuation for all individuals while preventing shelter overcrowding and traffic congestion along evacuation routes. The process extends beyond merely relocating people quickly; it encompasses protecting their well-being, especially during pandemic conditions. The core challenge lies in achieving equilibrium between these competing objectives to ensure evacuations remain efficient while minimizing health-related risks. The Emergency Evacuation Planning under Pandemic Settings (EEPPS) model has been developed to address these multifaceted challenges, offering a structured approach for safely and effectively moving populations from areas threatened by disasters, even amid the COVID-19 pandemic. As predictions suggest the possibility of severe events, government authorities must make crucial decisions regarding population movement, ranging from voluntary evacuation recommendations to mandatory evacuation orders based on the projected intensity of approaching disasters.

The EEPPS model represents evacuating individuals through set $E = \{1, \dots, n^1\}$, while designated evacuation routes are denoted by set $R = \{1, \dots, n^2\}$. These routes may incorporate multiple roadway segments, chosen strategically to enable efficient population movement. Emergency shelters, represented by set $S = \{1, \dots, n^3\}$, are established to accommodate evacuees. The model distinguishes between two shelter categories: general purpose (GP) and special needs (SN) facilities. During emergencies, individuals requiring specific support, such as those with medical conditions, disabilities, or advanced age, are directed to SN shelters designed for populations with special accommodation requirements. Other evacuees may utilize either GP or SN shelters. Each shelter location s maintains a specific capacity, indicated by $C_s^{shelter}, s \in S$, defining the maximum number of evacuees it can support.

The EEPPS model recognizes that evacuation typically occurs in groups rather than individually. This accounts for scenarios where family units are evacuating together or individuals sharing transportation to expedite their departure from danger zones. The model incorporates a parameter $q_e, e \in E$ to represent the number of occupants in each evacuating transport vehicle driven by a specific evacuee. To minimize viral transmission risks during pandemic conditions, an upper limit can be established for $q_e, e \in E$, restricting vehicle occupancy. State authorities, particularly state troopers, determine and communicate the capacity of evacuation routes during different time periods. The model uses set $P = \{1, \dots, n^4\}$ to represent available evacuation time intervals (or periods), with $C_{rp}^{route}, r \in R, p \in P$ indicating the capacity of route r for time interval p. Evacuees receive instructions to depart when their assigned routes have adequate capacity. These capacities are determined by considering multiple factors, including evacuation demand patterns, speed restrictions, road characteristics, and traffic flow adjustments.

Previous research frequently employed the BPR formula to estimate congested travel times during emergency evacuations (Dulebenets et al., 2020; Tang et al., 2022). However, this approach primarily considered evacuation routes and traffic conditions while overlooking crucial representative characteristics of evacuees. Factors, such as age, gender, educational background, regular and congested driving experience, and previous evacuation participation, can significantly impact the overall evacuation duration. The EEPPS model advances beyond earlier emergency evacuation studies by incorporating these representative characteristics of drivers alongside traditional route and traffic considerations. Similar to previous research, this model emphasizes timely evacuation and aims to minimize the total evacuation duration as its primary objective.

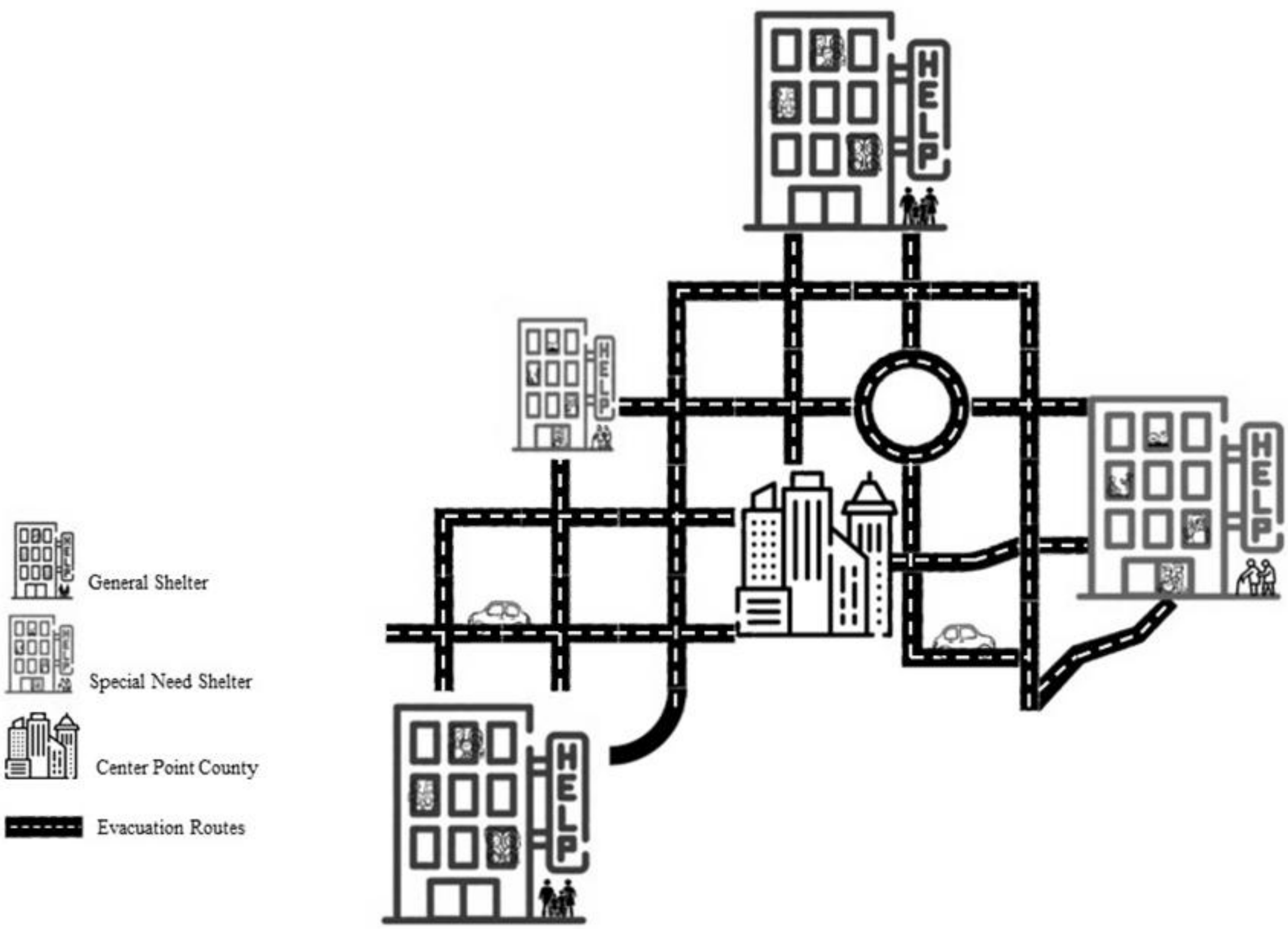


Figure 3 A decision framework for planning emergency evacuations.

Given pandemic conditions, rapidly directing evacuees to their nearest emergency shelters may not represent the optimal strategy, as this approach could lead to overcrowding and increased viral transmission risk in nearby facilities. Consequently, the EEPPS model incorporates a secondary objective of reducing viral transmission risk by promoting an even distribution of evacuees across all the available shelters, specifically by minimizing variations in average shelter utilization. The model introduces parameter $\sigma_s, s \in S$ to account for location-specific viral transmission risk associated with each emergency shelter s. Additionally, the optimization framework implements maximum utilization limits ($U_s^{max}, s \in S$) for each shelter. This comprehensive approach prioritizes maintaining social distancing measures and minimizing viral transmission potential within emergency shelters during pandemic-related evacuations.

3.3. Optimization Model Formulation

The proposed bi-objective optimization framework directly captures the total evacuation time minimization objective, which is one of the most common objectives in the existing emergency evacuation optimization literature (Dulebenets et al., 2017, 2019a, 2019b; Abioye et al., 2020) and can be mathematically presented as follows.

$$min\, \boldsymbol{F}_1 = \sum_{e \in E} \sum_{r \in R} q_e \cdot \boldsymbol{t}_{er} \tag{1}$$

In case of an approaching hazard, individuals are generally trying to evacuate the hazardous locations in a timely manner and travel to the nearest emergency shelters. Although this strategy can be helpful to minimize the total evacuation time, it may not be the best option under pandemic settings, as the closest shelters may be operating close to the capacity level or at the capacity level. <u>It will be challenging for evacuees to maintain social distancing and hygiene in overcrowded shelters, which increases the risk of virus transmission</u>. Therefore, it would be a reasonable approach for state authorities to evenly distribute evacuees among the available emergency shelters, considering shelter capacity and virus transmission risk. The second objective function ($\boldsymbol{F}_2$), minimizing the total deviation in the average shelter utilization, can be formulated as follows.

$$min\, \boldsymbol{F}_2 = \sum_{s \in S} \sigma_s \cdot \Delta \boldsymbol{U}_s \tag{2}$$

Note that objective function $\boldsymbol{F}_2$ includes the weight associated with virus transmission ($\sigma_s, s \in S$), which can be used to assign higher penalties for deviations from the average shelter utilization in the areas that are impacted by the virus the most. The deviation (positive of negative) in the average shelter utilization for each emergency shelter available for evacuees can be estimated as follows.

$$\boldsymbol{U}_s = \sum_{e \in E} \left(\frac{q_e \cdot \boldsymbol{z}_{es}}{C_s^{shelter}} \right) \forall s \in S \tag{3}$$

$$\Delta \boldsymbol{U}_{\overline{s}} \geq \boldsymbol{U}_{\overline{s}} - [\left(\sum_{\underline{s} \in S: \underline{s} \neq \overline{s}} \boldsymbol{U}_{\underline{s}} \right) / (n^3 - 1)] \; \forall \overline{s} \in S \tag{4}$$

$$\Delta \boldsymbol{U}_{\overline{s}} \geq [\left(\sum_{\underline{s} \in S: \underline{s} \neq \overline{s}} \boldsymbol{U}_{\underline{s}} \right) / (n^3 - 1)] - \boldsymbol{U}_{\overline{s}} \; \forall \overline{s} \in S \tag{5}$$

Furthermore, depending on the virus transmission rates, state authorities can impose a limit ($U_s^{max}, s \in S$) on capacity utilization for each emergency shelter to ensure that adequate social distancing can be maintained. Such a requirement can be expressed as follows.

$$\boldsymbol{U}_s \leq U_s^{max} \; \forall s \in S \tag{6}$$

To better demonstrate the conflicting nature of objective functions $\boldsymbol{F}_1$ and $\boldsymbol{F}_2$, consider an illustrative example of partial Broward County evacuation (see Figure 4). Although Broward County is mainly surrounded by urban areas, there are some rural areas in the vicinity of Broward County as well (e.g., Hendry County). The populations from rural counties may have to eventually seek a shelter in the vicinity of Broward County. Assume that 7,200 individuals have to evacuate during the first hour, and a total of 4 emergency shelters are available to accommodate these evacuees, including the following (see Figure 5): (a) shelter #1 with capacity $C_1^{shelter} = 4{,}000$ evacuees; (b) shelter #2 with capacity $C_2^{shelter} = 6{,}000$ evacuees; (c) shelter #3 with capacity $C_3^{shelter} = 2{,}000$ evacuees; and (d) shelter #4 with capacity $C_4^{shelter} = 6{,}000$ evacuees. Thus, the total capacity of shelters is $4{,}000 + 6{,}000 + 2{,}000 + 6{,}000 = 18{,}000$ evacuees. Assume that all the available shelters are located in the areas with the same risk of virus transmission (i.e., the weight associated with virus transmission can be set as $\sigma_1 = \sigma_2 = \sigma_3 = \sigma_4 = 1$ for the available shelters). In order to minimize $\boldsymbol{F}_1$, the evacuees can be distributed among the shelters proportionally to the capacity of shelters with the average shelter utilization of $[7{,}200/18{,}000] = 40\%$. Hence, $4{,}000 \cdot 40\% = 1{,}600$ evacuees will be assigned to shelter #1, and the assignments for other shelters will be performed in a similar way – see Figure 5 (left).

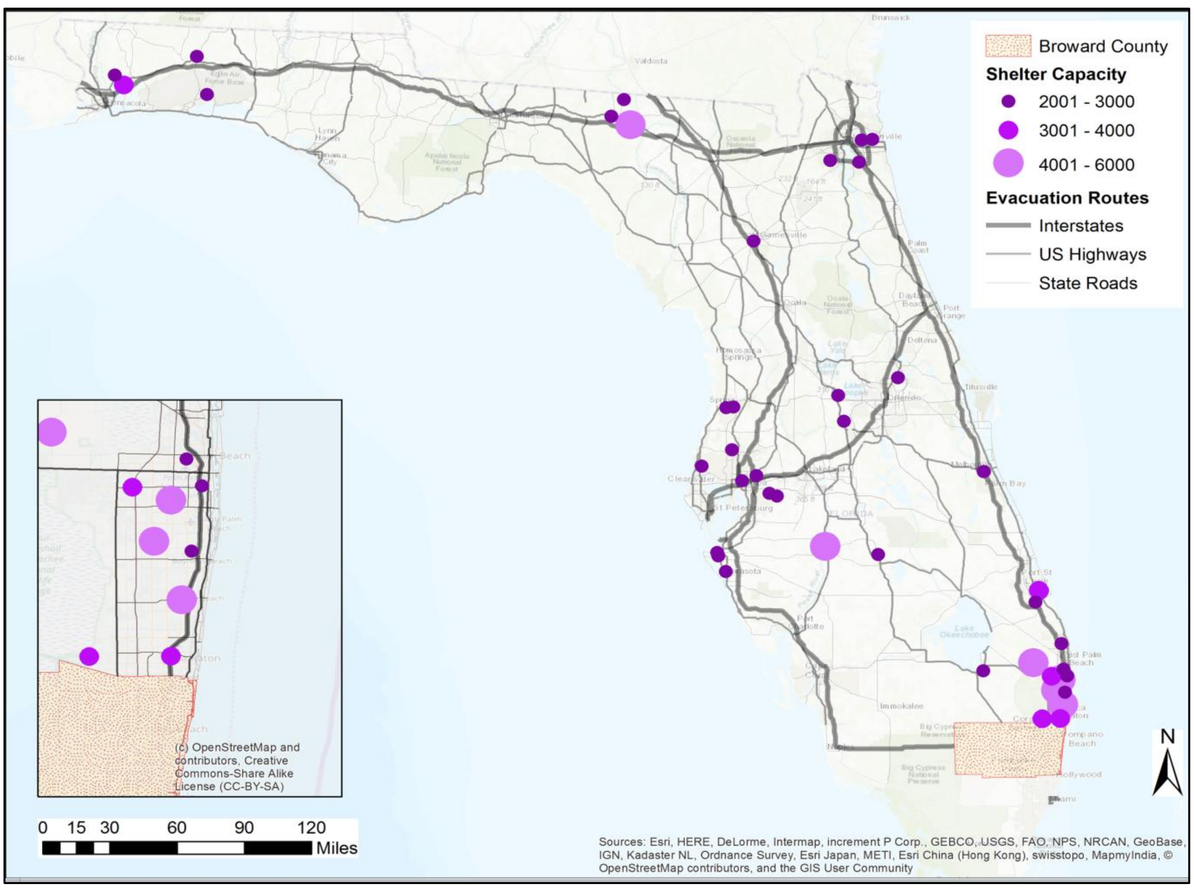


Figure 4 Broward County evacuation example.

However, when the objective is to minimize the total evacuation time ($\boldsymbol{F}_2$), all the evacuees will be assigned to the closest emergency shelters. In the considered example, a total of 4,000 evacuees will be assigned to shelter #1, and the remaining 3,200 evacuees will be assigned shelter #2 – see Figure 5 (right). Although the minimum total evacuation time will be achieved by such an assignment of evacuees to emergency shelters, shelter #1 will be operating at the capacity level and will have a high risk of virus transmission. Therefore, assignments of evacuees to evacuation routes and emergency routes can be quite different depending on the objective function selected.

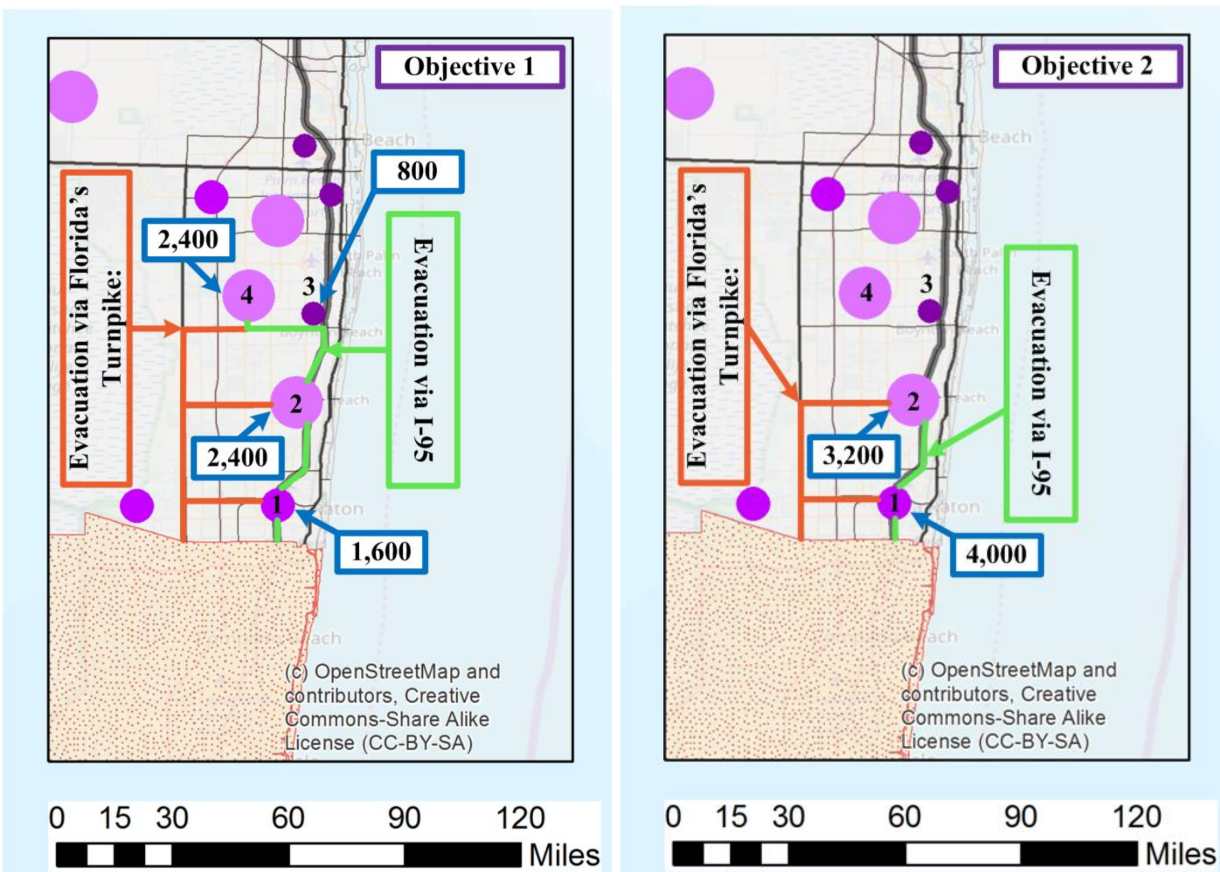


Figure 5 Assignment of evacuees based on conflicting objectives.

Along with constraint sets (3)-(6) that are directly related to objective function $\boldsymbol{F}_2$, there are some other practical constraints that are captured within the proposed bi-objective optimization framework. These constraints include the following.

$$\sum_{r \in R} \sum_{p \in P} \boldsymbol{x}_{erp} = 1 \ \forall e \in E \tag{7}$$

$$\sum_{s \in S} \boldsymbol{z}_{es} = 1 \ \forall e \in E \tag{8}$$

$$\boldsymbol{z}_{es} \leq y_{es} \ \forall e \in E, s \in S \tag{9}$$

$$\boldsymbol{x}_{erp} \leq \sum_{s \in S} w_{rs} \cdot \boldsymbol{z}_{es} \ \ \forall e \in E, r \in R, p \in P \tag{10}$$

$$\sum_{e \in E} \boldsymbol{x}_{erp} \leq C_{rp}^{route} \ \forall r \in R, p \in P \tag{11}$$

$$\sum_{e \in E} q_e \cdot \boldsymbol{z}_{es} \leq C_s^{shelter} \ \forall s \in S \tag{12}$$

Constraint set (7) ensures that each evacuee is assigned to one of the available evacuation routes to travel during one of the time periods in the considered planning horizon. Constraint set (8) indicates that each evacuee should be assigned to one of the available emergency shelters. Constraint set (9) takes into consideration the feasibility of assigning certain evacuees to specific shelters. As an example, certain population groups evacuating from rural areas may require special accommodations and have to be assigned to special need shelters (i.e., they cannot be assigned to general purpose shelters that do not have the appropriate accommodations). Constraint set (10) ensures that the selected evacuation route leads to the assigned emergency shelter (i.e., there is a roadway connection between the evacuating location and the destination shelter). Constraint set (11) indicates that the number of evacuating vehicles cannot exceed the capacity of each evacuation route during each time period in the considered planning horizon. Constraint set (12) guarantees that the total number of assigned evacuees does not exceed the capacity of the corresponding emergency shelter. The term $q_e, e \in E$ considers not only the individuals driving the evacuating vehicles but also the individuals who are carpooling with the drivers. Furthermore, constraint set (6) can be used to control the utilization of shelters based on the virus transmission risk in the areas where these shelters are located.

The optimization models used for transportation planning generally rely on the Bureau of Public Roads formula (or BPR formula), which estimates the congested travel time for a given highway section based on certain standard components, including the free-flow travel time, observed travel volume, capacity of the highway section, and calibrated coefficients that are related to the highway section characteristics (Ortúzar and Willumsen, 2011). The BPR formula has been widely used by the studies on emergency evacuations planning for travel time estimations as well (Kongsomsaksakul et al., 2005; Li et al., 2011; Apivatanagul et al., 2012; Li et al., 2012; Hammad, 2019). However, this formula does have its limitations, as it does not capture representative characteristics of drivers (e.g., age, gender, education, presence of chronic diseases, driving experience under normal conditions, driving experience under emergency evacuation conditions, etc.). Representative characteristics of individuals directly influence their driving ability not only under normal driving conditions but under emergency evacuation conditions as well (Dulebenets et al., 2017). In order to address this challenge in the modeling framework, this project relied on the findings from their previous research, where the driving simulator was deployed to calibrate the travel time function under emergency evacuation conditions, taking into account representative characteristics of evacuees, evacuation route characteristics, driving conditions, and traffic characteristics (Dulebenets et al., 2017, 2019a, 2019b; Abioye et al., 2020; Dulebenets et al., 2020) – see Figure 6.

Figure 6 Previous driving simulator experiments for evacuation time calibration.

In particular, as a part of the conducted driving simulation experiments, a large variety of representative characteristics of evacuees, evacuation route characteristics, driving conditions, and traffic characteristics were investigated, and statistically significant factors were used for travel time computation during travel conditions representing emergency evacuations (Dulebenets et al., 2017, 2019a; Abioye et al., 2020). 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) were identified as the main factors influencing the travel time of evacuees under evacuation settings. Denote $l_r, r \in R$ as length of evacuation route r. Then, the travel time of evacuees used in objective function $\boldsymbol{F}_1$ can be estimated using the following relationship (Dulebenets et al., 2017, 2019a; Abioye et al., 2020).

$$\boldsymbol{t}_{er} = \sum_{p \in P} [(11.9658 + 0.0107 \cdot Age_e - 0.0649 \cdot Dr\_Freq_e - 0.0286 \cdot Dist\_Dr_e - 0.4187 \cdot Diff\_Ev_e - 0.2555 \cdot Ab\_QDec_e - 0.0625 \cdot Sim\_Exp_e + 0.0015 \cdot Avg\_SpHead_e) \cdot (\frac{l_r}{10}) \cdot \boldsymbol{x}_{erp}] \; \forall e \in E, r \in R \tag{13}$$

4. SOLUTION ALGORITHM DEVELOPMENT

Designing an emergency evacuation model that accounts for pandemic conditions presents distinctive complexities requiring a carefully structured solution strategy. This section outlines the methodological rationale for the proposed solution approach and provides comprehensive implementation details. The developed optimization framework targets two key objectives: reducing the total time required for evacuation while simultaneously minimizing disease transmission risk through balanced shelter distribution. The complexity of these dual objectives demands an advanced multi-objective optimization methodology that forms a central component of this project. When dealing with multi-objective optimization involving competing goals, achieving a singular solution that optimizes all the objectives concurrently becomes theoretically impossible (Elmi et al., 2023a; Elmi et al., 2023b). An improvement in one objective typically requires a compromise in another due to their inherent contradictions. One objective's optimal value might correspond to another objective's least favorable outcome, highlighting the intricate balance required in such scenarios. Consequently, instead of pursuing a single optimal answer, we aim to develop a collection of non-dominated solutions that together create a Pareto front (Dulebenets, 2018; Deb et al., 2002).

Within the multi-objective optimization field, methodologies generally fall into two primary categories: those that do not use Pareto principles and those that do (Deb et al., 2002; Hughes, 2003; Li et al., 2015; Safaeian et al., 2023). Methods not based on Pareto principles, such as the widely adopted weighted sum approach, avoid an explicit Pareto front creation. These methods typically consolidate multiple objectives into a unified function, frequently employing importance-based weighting systems. In contrast, Pareto-based approaches deliberately construct a Pareto front, enabling a more thorough exploration of objective trade-offs. The present research adopts a Pareto-based methodology, as it will be able to offer deeper insights into the solution landscape for complex scenarios like pandemic-era evacuation planning.

To demonstrate the competing objectives within the EEPPS decision framework, consider a Pareto front visualization comprising six distinct solutions shown in Figure 7. This graphical representation effectively illustrates the inherent trade-offs in pandemic-era evacuation planning. At one extreme, solution point "1" on the Pareto front represents the configuration achieving minimal total evacuation duration (optimal $\boldsymbol{F_1}$). Although this rapid evacuation strategy offers clear time advantages, it simultaneously produces the largest variation in shelter occupancy rates. Implementing this solution may result in overcrowded shelter conditions, substantially elevating virus transmission probability during pandemic circumstances, as evacuees are directed to reach their nearest available shelters.

Conversely, solution point "6" occupies the opposite end of the spectrum. This arrangement minimizes shelter utilization variation (optimal $\boldsymbol{F_2}$), thereby reducing disease transmission risk. However, the emphasis on balanced shelter usage extends the overall evacuation timeline, potentially resulting in traffic bottlenecks and delays across certain evacuation pathways. While points "1" and "6" exemplify contrasting approaches that prioritize one objective while compromising the other, more balanced alternatives exist along the Pareto front's middle region. Specifically, solutions "4" and "5" present more moderate compromises, achieving acceptable performance in both shelter distribution evenness and total evacuation duration.

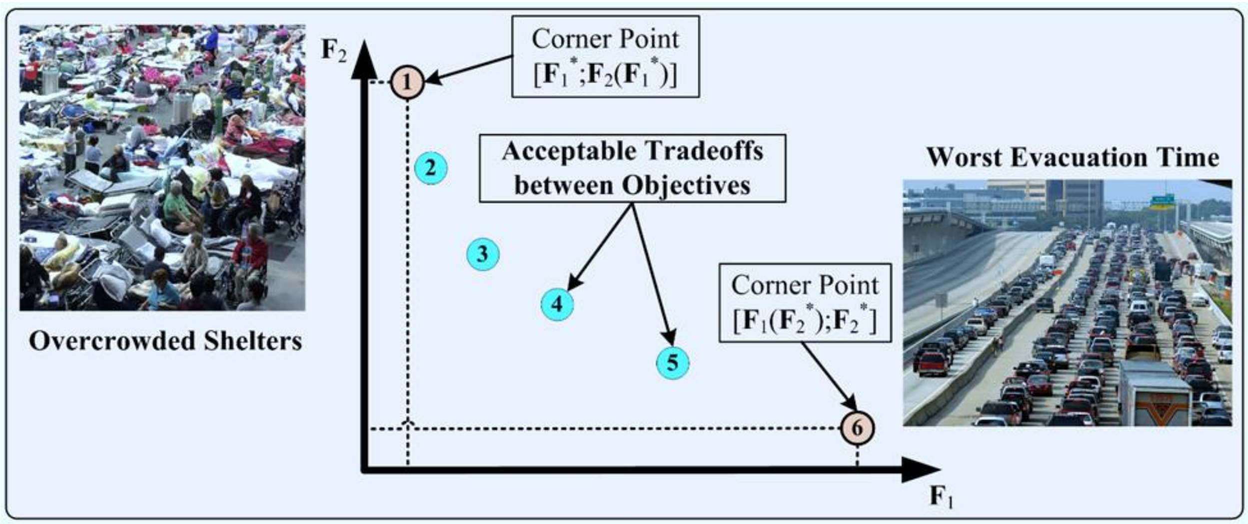


Figure 7 Illustration of a Pareto front featuring competing objectives in pandemic scenarios.

The research on planning emergency evacuations has increasingly incorporated optimization methodologies to tackle both single and multiple objective challenges. Research literature demonstrates diverse solution approaches, each crafted to manage the specific complexities and restrictions inherent in evacuation scenarios. Various metaheuristic methods have become increasingly prevalent, including non-dominated sorting genetic algorithm II (NSGA-II), multi-objective particle swarm optimization (MOPSO), quantum ant colony algorithm (QACA), multi-objective grey wolf optimizer (MOGWO), multi-objective artificial bee colony (MOABC), and other advanced algorithms (Zhang et al., 2013; Karasi and Rathod, 2016; Hajjem et al., 2017; Huang et al., 2020; Samany et al., 2021; Dulebenets, 2022). These approaches have gained traction due to their adaptability and effectiveness in handling extensive problem sets. Traditional exact optimization algorithms frequently encounter difficulties with large-scale evacuation scenarios involving substantial numbers of evacuees, routes, and shelters, resulting in impractical computation times for real-world applications (Dulebenets et al., 2019a). However, it should be acknowledged that while metaheuristics offer computational efficiency, they cannot guarantee optimal solutions within the Pareto frontier.

The present research presents a new algorithmic solution, the decomposition-based epsilon-constraint (DECON) methodology, specifically engineered to enhance the EEPPS framework. This approach extends and refines the established epsilon-constraint method (ECON) developed by Mavrotas (2009), which is recognized for its effectiveness in solving complex multi-objective optimization challenges. The traditional ECON methodology operates by focusing on one primary objective while placing constraints on secondary goals, iteratively constructing the Pareto frontier (PF). However, when considering real-world EEPPS applications with large-scale evacuation scenarios involving substantial numbers of evacuees and multiple routes and shelter locations, the standard ECON method becomes computationally intensive and impractical for generating optimal Pareto frontiers. To overcome this computational barrier, our DECON algorithm implements an innovative solution: it strategically divides the evacuee population into smaller, manageable subgroups, establishes clear priority hierarchies among these groups, and then applies the ECON methodology individually to each subgroup to optimize their respective multi-objective solutions efficiently.

Algorithm 1 Decomposition-based Epsilon-Constraint Algorithm (DECON)

$\boldsymbol{DECON}(Data, t^0, C^{route}, C^{shelter}, PF^{size}, gr^{size}, \varepsilon_1, \varepsilon_2)$

in: $Data$ - the EEPPS input data; t^0 - unit evacuation time; C^{route} - capacities of evacuation routes; $C^{shelter}$ - capacities of shelters; PF^{size} - PF size; gr^{size} - group size; ε_1 - upper bound on $\boldsymbol{F}_1$; ε_2 - upper bound on $\boldsymbol{F}_2$

out: PF^{all} - PF for each evacuee group; $SolutionData^{all}$ - main variable values for each evacuee group

0: $PF^{all} \leftarrow \varnothing; SolutionData^{all} \leftarrow \varnothing$ ◅ Initializing the relevant data structures
1: $E^{sort} \leftarrow \boldsymbol{sort}(Data, t^0)$ ◅ Sorting all the evacuating individuals using the unit evacuation time
2: **while** $E^{sort} \neq \varnothing$ **do**
3: $E^{group} \leftarrow E^{sort}_{gr^{size}}$ ◅ Selecting the following group of evacuating individuals based on gr^{size}
4: $[PF, SolutionData] \leftarrow \boldsymbol{ECON}(Data, E^{group}, C^{route}, C^{shelter}, PF^{size}, \varepsilon_1, \varepsilon_2)$ ◅ Launching ECON
5: $PF^{all} \leftarrow PF^{all} \cup PF$ ◅ Adding the new PF generated by ECON
6: $SolutionData^{all} \leftarrow SolutionData^{all} \cup SolutionData$ ◅ Adding the new solution data
7: $[\boldsymbol{F}_1, \boldsymbol{F}_2] \leftarrow PF$ ◅ Retrieving $\boldsymbol{F}_1$ and $\boldsymbol{F}_2$ from the recently generated PF
8: $j \leftarrow 1$ ◅ Starting the counter of iterations for the MID calculation
9: **while** $j \leq PF^{size}$ **do**
10: $\boldsymbol{F}_1^{component} \leftarrow (\boldsymbol{F}_{1j} - min(\boldsymbol{F}_1))/(max(\boldsymbol{F}_1) - min(\boldsymbol{F}_1))$ ◅ Estimating $\boldsymbol{F}_1^{component}$
11: $\boldsymbol{F}_2^{component} \leftarrow (\boldsymbol{F}_{2j} - min(\boldsymbol{F}_2))/(max(\boldsymbol{F}_2) - min(\boldsymbol{F}_2))$ ◅ Estimating $\boldsymbol{F}_2^{component}$
12: $MID_j \leftarrow \sqrt{(\boldsymbol{F}_1^{component})^2 + (\boldsymbol{F}_2^{component})^2}$ ◅ Estimating MID
13: $j \leftarrow j + 1$ ◅ Updating the counter of iterations
14: **end while**
15: $[\boldsymbol{x}, \boldsymbol{z}] \leftarrow SolutionData_{argmin(MID)}$ ◅ Retrieving $\boldsymbol{x}$ and $\boldsymbol{z}$ for the PF point with $min(MID)$
16: $r \leftarrow 1; p \leftarrow 1$
17: **for all** $r \in R$ **do**
18: **for all** $p \in P$ **do**
19: $C^{route}_{rp} \leftarrow C^{route}_{rp} - \sum_{e \in E^{group}}(\boldsymbol{x}_{erp})$ ◅ Updating the evacuation route capacities
20: $r \leftarrow r + 1; p \leftarrow p + 1$
21: **end for**
22: **end for**
23: $s \leftarrow 1$
24: **for all** $s \in S$ **do**
25: $C^{shelter}_s \leftarrow C^{shelter}_s - \sum_{e \in E^{group}}(q_e \cdot \boldsymbol{z}_{es})$ ◅ Updating the emergency shelter capacities
26: $s \leftarrow s + 1$
27: **end for**
28: $E^{sort} \leftarrow E^{sort} - E^{group}$ ◅ Updating the set of sorted evacuating individuals
29: **end while**
30: **return** $[PF^{all}, SolutionData^{all}]$

The primary stages of the DECON methodology are outlined in Algorithm 1. The procedure initiates with the establishment of data structures designed to maintain the Pareto front and solution data across all evacuee groupings (step 0). The process continues with evacuee organization based on their per-mile evacuation duration in descending sequence (step 1), computed using equation (13). This ordering strategy prioritizes evacuation for individuals requiring extended evacuation times, particularly populations with special accommodation needs. Following this initialization, DECON progresses through a primary sequence of steps spanning steps 2 through 29. Within this sequence, step 3 establishes the initial evacuee group according to the predetermined maximum group size parameter. Step 4 then applies the EEPPS-specific ECON methodology to this newly formed group. Algorithm 2 provides detailed steps of the ECON method specifically adapted for the EEPPS model. Furthermore, this section of the manuscript presents comprehensive mathematical formulations for both EEPPS-1 and EEPPS-2 optimization models, which serve as direct inputs for the ECON methodology.

Algorithm 2 Epsilon-Constraint Algorithm (ECON)

$\boldsymbol{ECON}(Data, E^{group}, C^{route}, C^{shelter}, PF^{size}, \varepsilon_1, \varepsilon_2)$
in: $Data$ - the EEPPS input data; E^{group} - data for evacuee groups; C^{route} - capacities of evacuation routes; $C^{shelter}$ - capacities of shelters; PF^{size} - PF size; ε_1 - upper bound on $\boldsymbol{F}_1$; ε_2 - upper bound on $\boldsymbol{F}_2$
out: PF - PF for a specific evacuee group; $SolutionData$ - main variable values for a specific evacuee group

$PF \leftarrow \emptyset; SolutionData \leftarrow \emptyset$ ⊲ Initializing the relevant data structures
$[Solution_1; \boldsymbol{F}_1{}^*; \boldsymbol{F}_2(\boldsymbol{F}_1{}^*)] \leftarrow \boldsymbol{EEPPS\text{-}1}(E^{group}, Data, C^{route}, C^{shelter}, \varepsilon_2)$ ⊲ Determining $\boldsymbol{F}_1{}^*$
$[Solution_2; \boldsymbol{F}_1(\boldsymbol{F}_2{}^*); \boldsymbol{F}_2{}^*] \leftarrow \boldsymbol{EEPPS\text{-}2}(E^{group}, Data, C^{route}, C^{shelter}, \varepsilon_1)$ ⊲ Determining $\boldsymbol{F}_2{}^*$
$\varepsilon \leftarrow (\boldsymbol{F}_1(\boldsymbol{F}_2{}^*) - \boldsymbol{F}_1{}^*)/(PF^{size} - 1)$ ⊲ Calculating the upper bound interval for $\boldsymbol{F}_1$
$i \leftarrow 1$ ⊲ Starting the counter of iterations for PF construction
$\varepsilon_{1i} \leftarrow \boldsymbol{F}_1{}^*$ ⊲ Setting the first upper bound on $\boldsymbol{F}_1$
$PF \leftarrow PF \cup [\boldsymbol{F}_1{}^*; \boldsymbol{F}_2(\boldsymbol{F}_1{}^*)]$ ⊲ Adding the $\boldsymbol{F}_1{}^*$ corner point
$SolutionData \leftarrow SolutionData \cup Solution_1$ ⊲ Adding the $\boldsymbol{F}_1{}^*$ solution data
while $i \leq (PF^{size} - 2)$ **do**
    $i \leftarrow i + 1$ ⊲ Updating the counter of iterations
    $\varepsilon_{1i} \leftarrow \varepsilon_{1(i-1)} + \varepsilon$ ⊲ Updating the upper bound on $\boldsymbol{F}_1$
    $[Solution_{2i}, \boldsymbol{F}_1(\boldsymbol{F}_{2i}{}^*); \boldsymbol{F}_{2i}{}^*] \leftarrow \boldsymbol{EEPPS\text{-}2}(E^{group}, Data, C^{route}, C^{shelter}, \varepsilon_{1i})$
    $PF \leftarrow PF \cup [\boldsymbol{F}_1(\boldsymbol{F}_{2i}{}^*); \boldsymbol{F}_{2i}{}^*]$ ⊲ Adding the newly generated PF point to the PF
    $SolutionData \leftarrow SolutionData \cup Solution_{2i}$ ⊲ Adding the new solution data
end while
$PF \leftarrow PF \cup [\boldsymbol{F}_1(\boldsymbol{F}_2{}^*); \boldsymbol{F}_2{}^*]$ ⊲ Adding the $\boldsymbol{F}_2{}^*$ corner point
$SolutionData \leftarrow SolutionData \cup Solution_2$ ⊲ Adding the $\boldsymbol{F}_2{}^*$ solution data
return $[PF, SolutionData]$

The key outputs from the ECON algorithm, including the Pareto frontier and associated solution data for the EEPPS model's core variables, are documented in phases 5 and 6 of the process. The algorithm then proceeds to phase 7, where it extracts the reference points from the computed Pareto frontier. These reference values are utilized through phases 8-14 to compute the mean ideal distance for each solution point along the newly computed frontier. This distance measurement is widely recognized as an evaluation criterion for analyzing multi-objective optimization results with Pareto frontiers (Hasani Goodarzi et al., 2018; Pasha et al., 2022). The solution that achieves the best equilibrium $[min(MID)]$ among different objectives is subsequently applied to adjust the capacity parameters of both evacuation pathways (phases 16-22) and emergency refuge facilities (phases 23-27). This particular solution with $min(MID)$ is chosen for its ability to achieve an effective balance between conflicting goals, as detailed in section 5 of this technical report. However, planners retain the flexibility to select different points along the Pareto frontier depending on their specific priorities. For instance, if they wish to prioritize minimizing disease transmission over rapid evacuation times, an appropriate solution should be selected from the Pareto frontier accordingly. In phase 28, the DECON system updates its evacuee database by eliminating groups that have already received route and shelter assignments. This iterative process continues through phases 3-28, repeating until every evacuee has been classified in an evacuation group and successfully matched with appropriate evacuation routes and emergency shelters.

Emergency Evacuation Planning under Pandemic Settings with the $\boldsymbol{F}_1$ Minimization (EEPPS-1):

$$min\ \boldsymbol{F}_1 = \sum_{e \in E} \sum_{r \in R} q_e \cdot \boldsymbol{t}_{er} \tag{14}$$

Subject to: Constraints (3)-(13) (15)

$$\boldsymbol{F}_2 = \sum_{s \in S} \sigma_s \cdot \Delta \boldsymbol{U}_s \tag{16}$$

$$\boldsymbol{F}_2 \leq \varepsilon_2 \tag{17}$$

Emergency Evacuation Planning under Pandemic Settings with the $\boldsymbol{F}_2$ Minimization (EEPPS-2):

$$min\ \boldsymbol{F}_2 = \sum_{s \in S} \sigma_s \cdot \Delta \boldsymbol{U}_s \tag{18}$$

Subject to: Constraints (3)-(13) (19)

$$\boldsymbol{F}_1 = \sum_{e \in E} \sum_{r \in R} q_e \cdot \boldsymbol{t}_{er} \tag{20}$$

$$\boldsymbol{F}_1 \leq \varepsilon_1 \tag{21}$$

5. NUMERICAL EXPERIMENT

Section 5 of this technical report examines the implementation details and results derived from the conducted investigation. The section commences with a comprehensive description of the selected study area and the corresponding datasets employed throughout the experimental investigation. Subsequently, it provides an assessment of the computational performance exhibited by the innovative DECON algorithm, which was specifically engineered to tackle the complex bi-objective optimization challenges inherent in the planning of emergency evacuations during pandemic conditions. The section concludes with a presentation of significant managerial insights extracted from the experimental findings, providing practical guidance and recommendations for emergency management professionals and decision-makers.

5.1. Study Area Description and Adopted Numerical Data

To enable robust computational analysis, a detailed set of parameters was determined to configure both the EEPPS mathematical framework and the DECON solution methodology. These input parameters were strategically selected to simulate real-world evacuation conditions and evaluate the efficiency of the optimization methodology. The coastal territories of the United States, which extend along the Atlantic and Pacific Oceans as well as the Gulf of Mexico, face significant risks from various natural calamities, including tropical cyclones, severe weather systems, and other meteorological events. The South Florida region experiences a particularly high frequency of such occurrences, making efficient emergency evacuation protocols essential. This research examines evacuation planning within Palm Beach County, a densely populated area in South Florida with a documented population of 1,492,191 residents based on the 2020 census information (U.S. Census Bureau, 2023). Given its susceptibility to natural disasters, this county serves as an ideal test environment for analyzing emergency evacuation strategies under varying scenarios, especially considering pandemic-related constraints.

The representative information for the population residing in Palm Beach County was sourced from the U.S. Census Bureau's publicly accessible database (U.S. Census Bureau, 2023), which was used to retrieve the evacuee age distribution data. Regarding other travel time prediction factors utilized in equation (13), including driving patterns, weekly mileage, evacuation complexity perception, response time in decision-making, simulator familiarity, and spacing between vehicles, our research employed maximum-risk scenarios. These conservative estimates were based on parameter ranges established in prior simulator-based research (Dulebenets et al. 2019b), as precise measurements for these variables were not accessible through public demographic databases. This cautious methodology was selected to generate more conservative travel time estimates during evacuation. Should decision-makers have access to more precise data, different parameter values could be incorporated into the analysis accordingly.

The present research implemented a sequential evacuation approach across a defined planning timeframe to reduce traffic bottlenecks and optimize available roadway capacity. This methodical strategy, referred to as time period-based or staged evacuation, facilitates more systematic and effective population movement. The entire evacuation timeline is segmented into multiple intervals, with each period typically representing sixty minutes. This temporal division enables precise capacity planning for evacuation routes, with estimations conducted on an hourly basis. Utilizing hourly intervals corresponds with established traffic management protocols and supports more reliable forecasting of roadway conditions throughout the evacuation sequence.

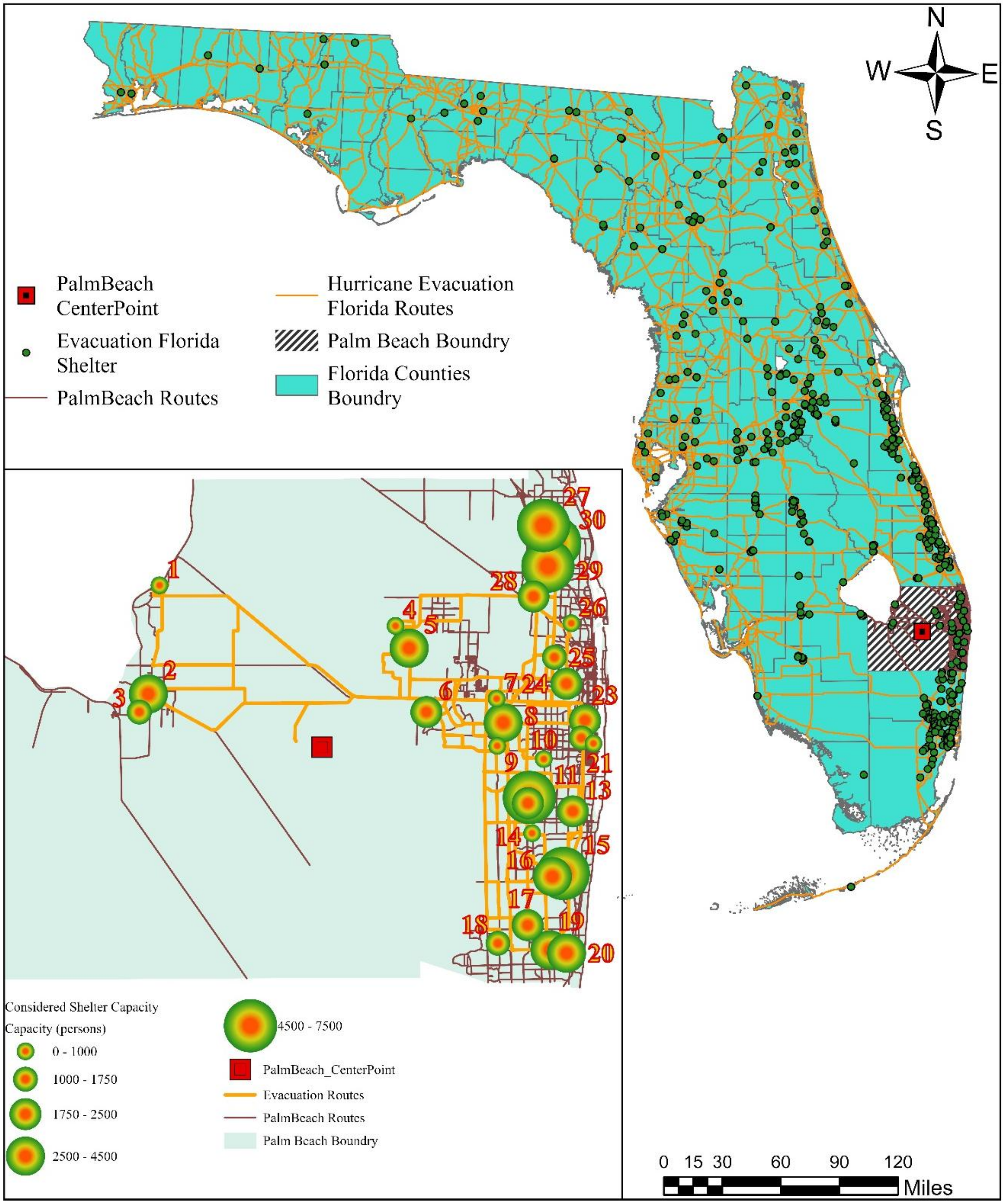


Figure 8 Palm Beach County's evacuation shelters and routes taken into account.

ArcGIS Pro was utilized to model Florida's transportation network, incorporating interstates, U.S. highways, state roads, and local thoroughfares, providing an accurate representation of available evacuation infrastructure. The study determined up to four most direct pathways from the Palm Beach County's center to each emergency shelter location to optimize route selection. The analysis incorporated 30 emergency shelters, consisting of 16 general purpose and 14 special needs facilities that have varying capacities, with facility information obtained from the Florida Division of Emergency Management (FDEM, 2024) (see Figure 8). This methodology identified 119 viable evacuation routes, creating a comprehensive evacuation network. Route capacities were calculated following the Highway Capacity Manual (HCM) standards, with Level of Service (LOS) D chosen as the reference point to reflect typical early-stage evacuation traffic patterns (HCM, 2010). This standard provides a balanced assessment of road capacity under emergency conditions. For routes comprising multiple segments, including combinations of freeways, multilane highways, and two-lane roads, the study adopted a conservative estimation approach. The overall route capacity was established based on the lowest capacity segment, typically corresponding to two-lane highway sections (accommodating 550 vehicles per hour). This conservative approach was selected considering the consistently high traffic volumes during evacuations and the presence of two-lane highway segments that often connect to larger roadways.

The practical implementation of the EEPPS mathematical model required several foundational assumptions to structure input data and enable the DECON solution algorithm's application for evacuee assignment across routes, shelters, and time periods. The primary assumptions encompass the following. The analysis framework positioned the Palm Beach County center point as the primary evacuation source, taking into account demographic spread and current road networks. The model assumed single-vehicle evacuation per family unit, while ensuring transportation alternatives for households without vehicles. Family sizes in evacuating vehicles were modeled using a distribution between 2 and 4 people, representing standard household configurations during emergencies. Only shelters with American Red Cross certification meeting safety protocols and space requirements were incorporated. Emergency facilities were considered ready for immediate operation upon evacuation notification. Priority shelter placement was given to at-risk populations, including seniors and disabled individuals, through special needs (SN) shelter designation. To preserve family unity, when one member required SN accommodation, the entire household was assigned together.

The EEPPS system and the DECON salutation approach were engineered for flexibility. The framework permits parameter adjustments as needed. For example, should precise household location information become obtainable, it can be integrated to enhance travel duration estimates. The system can also be modified for mass transit scenarios by adjusting vehicle capacity variables. The simulation testing employed an XPS 8930 system featuring an Intel Core i7-8700K CPU and 31.8 GB memory, operating on Windows 10 (Version 22H2). The actual testing encompassed 17 unique scenarios, with evacuee numbers ranging from 1,000 to 9,000, increasing by 500-person intervals throughout the planning process. The optimization process utilized CPLEX within GAMS version 24.7.4 to resolve EEPPS-1 and EEPPS-2 models, while the implementation was completed using MATLAB 2023b.

5.2. Solution Algorithm Assessment

The computational experimentation began with a thorough assessment of the DECON algorithm's performance efficiency. Since DECON builds upon the conventional ECON algorithm, its complexity of computational time is dependent on the desired Pareto front point number generated per evacuee group (designated as (PF^{size})). Moreover, as the customized DECON algorithm was specifically developed for the EEPPS bi-objective optimization model requiring evacuee population division into multiple groups, the maximum evacuee allocation per group (designated as (gr^{size})) serves as another critical parameter affecting DECON's computational complexity. To evaluate the impact of both Pareto front size and evacuee group size, the study examined 66 distinct scenarios. These scenarios were created by incrementally adjusting the Pareto front size from five to fifteen points, while simultaneously varying evacuee group sizes from 450 to 200 individuals in 50-person increments. The analysis utilized the first problem scenario comprising 1,000 evacuees. Each scenario underwent three algorithmic replications, with the resulting average computational durations (measured in seconds) documented in Table 3 and illustrated in Figure 9.

Table 3 Time complexity evaluation for DECON (CPU times presented in seconds).

$PF^{size} \backslash gr^{size}$	450	400	350	300	250	200	***Average:***
5	547.5	483.2	502.2	561.8	577.5	448.6	520.1
6	661.7	601.4	610.7	676.4	677.2	534.6	627.0
7	792.4	707.1	732.6	842.0	791.1	651.5	752.8
8	861.3	824.8	840.5	938.2	905.6	740.5	851.8
9	988.3	913.9	955.5	1,046.7	1,064.7	829.9	966.5
10	1,122.1	1,000.8	1,064.6	1,186.9	1,191.9	922.6	1,081.5
11	1,263.3	1,129.4	1,149.2	1,298.8	1,295.5	1,299.0	1,239.2
12	1,354.9	1,195.9	1,290.9	1,465.9	1,424.6	1,390.9	1,353.9
13	1,487.5	1,327.3	1,419.2	1,592.1	1,545.1	1,501.1	1,478.7
14	1,601.3	1,473.2	1,478.8	1,655.9	1,614.8	1,702.4	1,587.8
15	1,688.8	1,734.7	1,618.7	1,786.4	1,792.1	1,746.6	1,727.9
Average:	1,124.5	1,035.6	1,060.3	1,186.5	1,170.9	1,069.8	

The computational performance of the DECON algorithm demonstrated sensitivity to both Pareto front size and evacuee group size parameters. When the Pareto front size was incrementally increased from 5 to 15 points, the algorithm's average computational duration expanded substantially from 520.1 seconds to 1,727.9 seconds across all evacuee group configurations. This represents more than a threefold increase in processing time, highlighting the significant impact of Pareto front size on computational efficiency. The relationship between evacuee group size and computational performance revealed interesting patterns. Across different group sizes (gr^{size} = 450, 400, 350, 300, 250, and 200), computational times exhibited variations ranging from 1,124.5 seconds to 1,069.8 seconds, maintaining relatively consistent patterns across all Pareto front size configurations (as illustrated in Figure 10 through Figure 15). This relatively modest variation in computational time despite significant changes in group size suggests that the algorithm demonstrates good scalability with respect to group size modifications.

A detailed comparative analysis revealed that the Pareto front size parameter exerts a substantially greater influence on the algorithm's computational performance compared to evacuee group size adjustments. This finding has important implications for the optimization process and practical implementation. Through comprehensive evaluation of solution quality and computational efficiency trade-offs, the study identified optimal parameter settings: an evacuee group size of 350 and a Pareto front size of 9 points producing the most favorable balance between solution density and computational efficiency (as demonstrated in Table 3 and Figure 13). While the algorithm technically supports Pareto front sizes with fifteen points and more, the analysis revealed that such an increase would result in a substantial computational burden, extending processing time by approximately 69.41% for PF^{size} = 15 points compared to PF^{size} = 9 points. Importantly, this significant increase in computational resources did not yield proportional improvements in solution quality, as the density of solutions across the Pareto frontier showed a minimal enhancement beyond the 9-point configuration (see Figure 13).

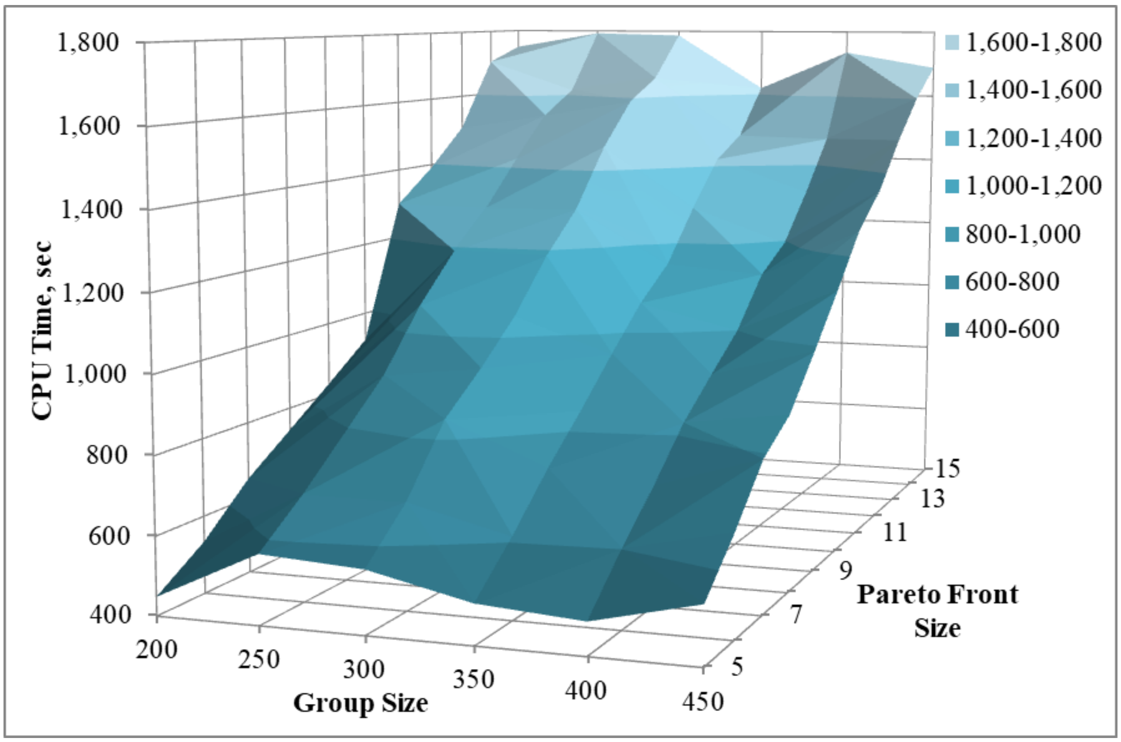


Figure 9 Evaluating the impact of Pareto front size and evacuee group size on DECON's computational time.

These findings underscore the critical importance of thoughtful parameter selection in DECON implementation. The disproportionate impact of Pareto front size on computational performance suggests that this parameter should be carefully optimized, particularly when dealing with large-scale evacuation scenarios where computational efficiency becomes increasingly crucial. The results indicate that while both parameters influence algorithm performance, strategic management of Pareto front size offers the most effective lever for optimizing computational efficiency without compromising solution quality.

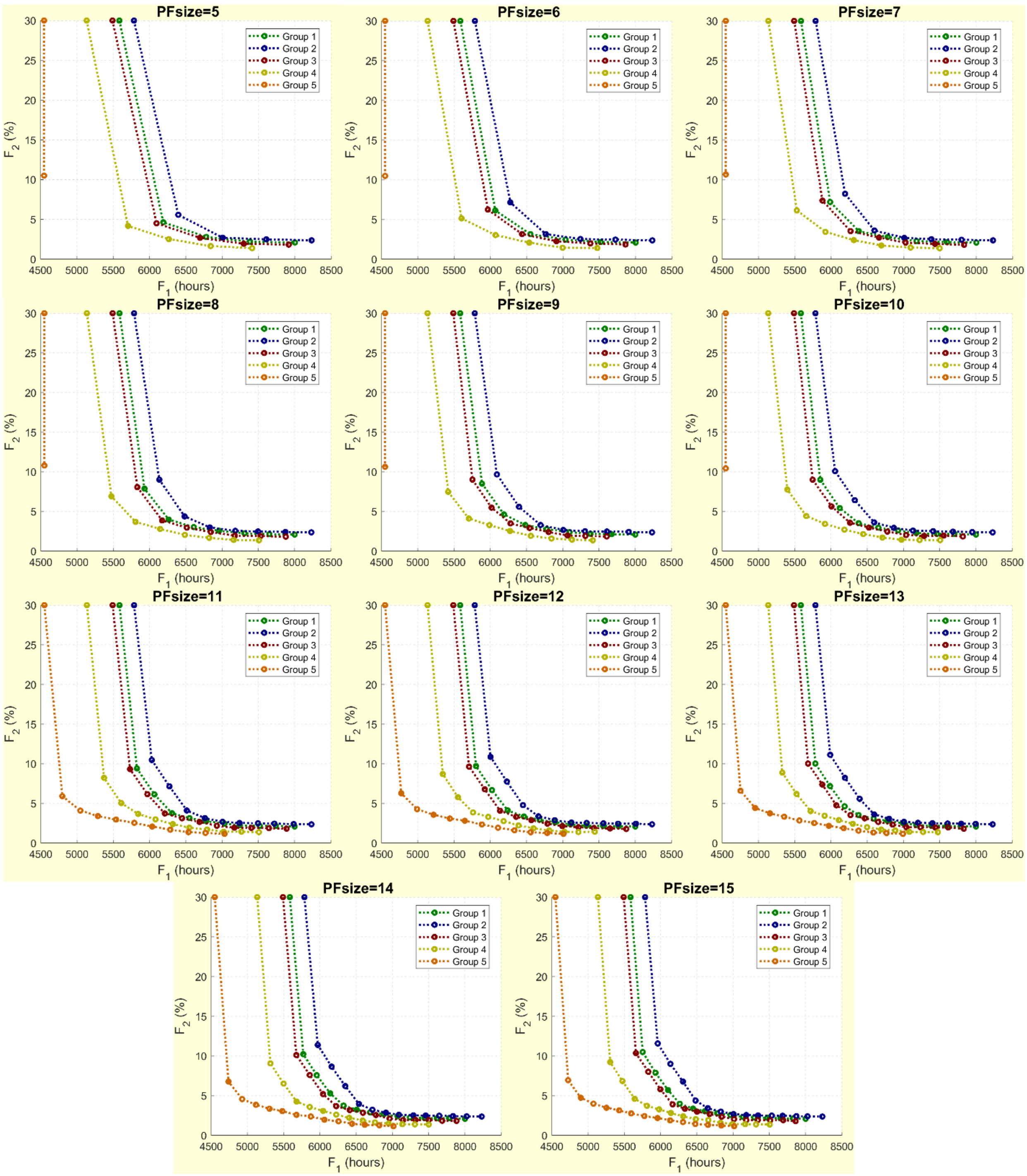


Figure 10 Examining the effects that the size of the Pareto front has on solution density ($\boldsymbol{gr}^{\boldsymbol{size}}$= 200 evacuees).

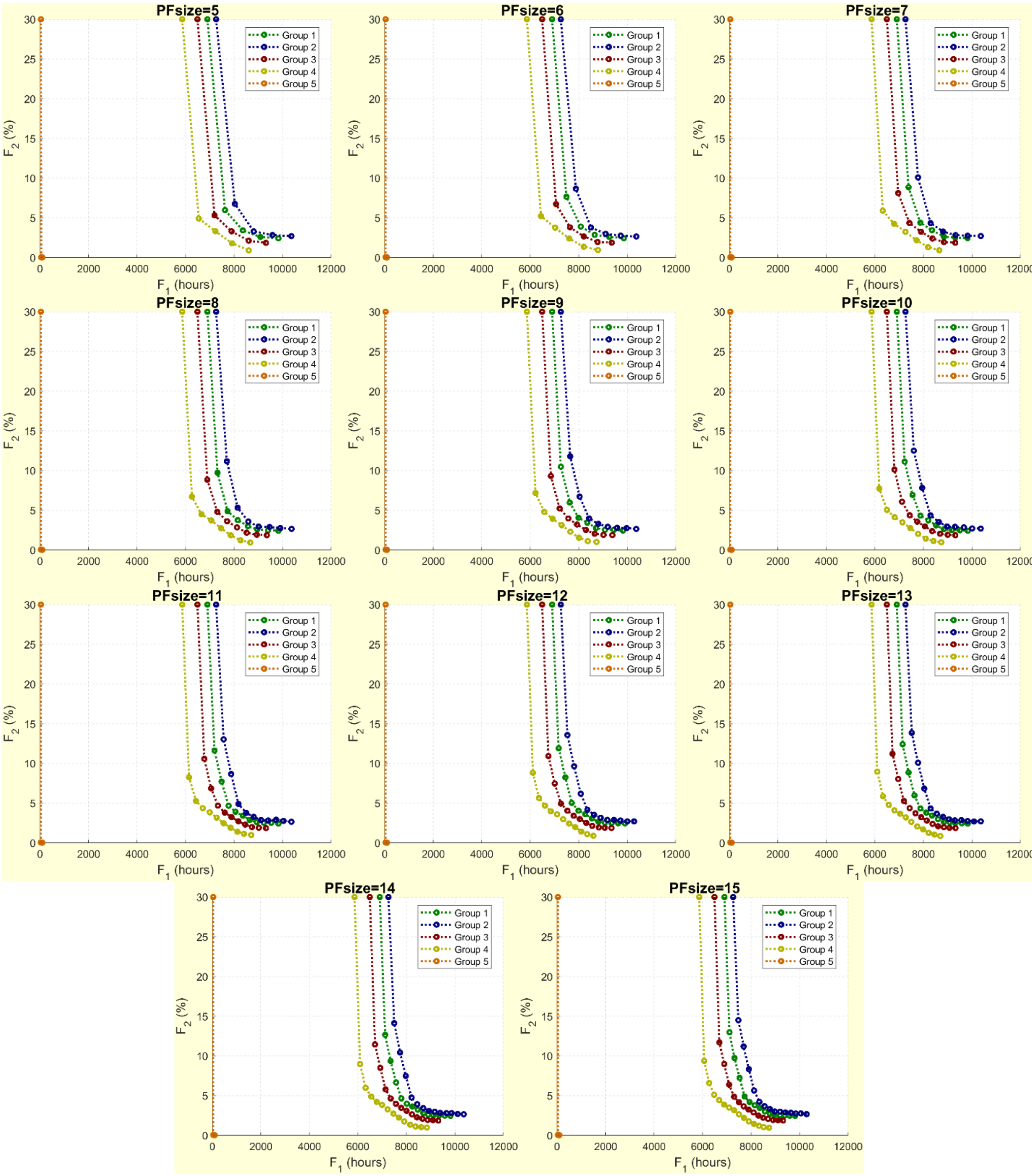


Figure 11 Examining the effects that the size of the Pareto front has on solution density ($\boldsymbol{gr^{size}}$= 250 evacuees).

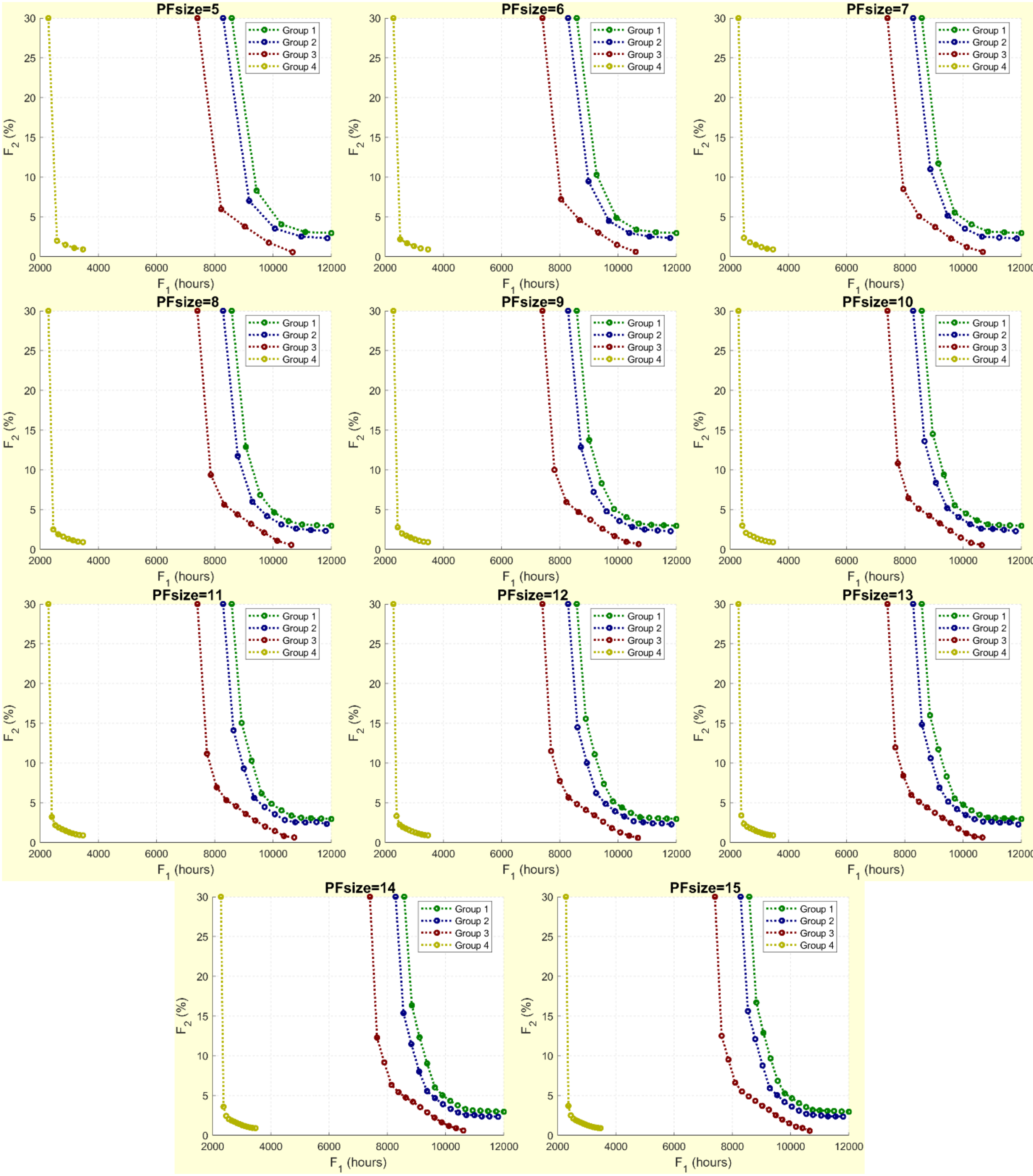


Figure 12 Examining the effects that the size of the Pareto front has on solution density (gr^{size}= 300 evacuees).

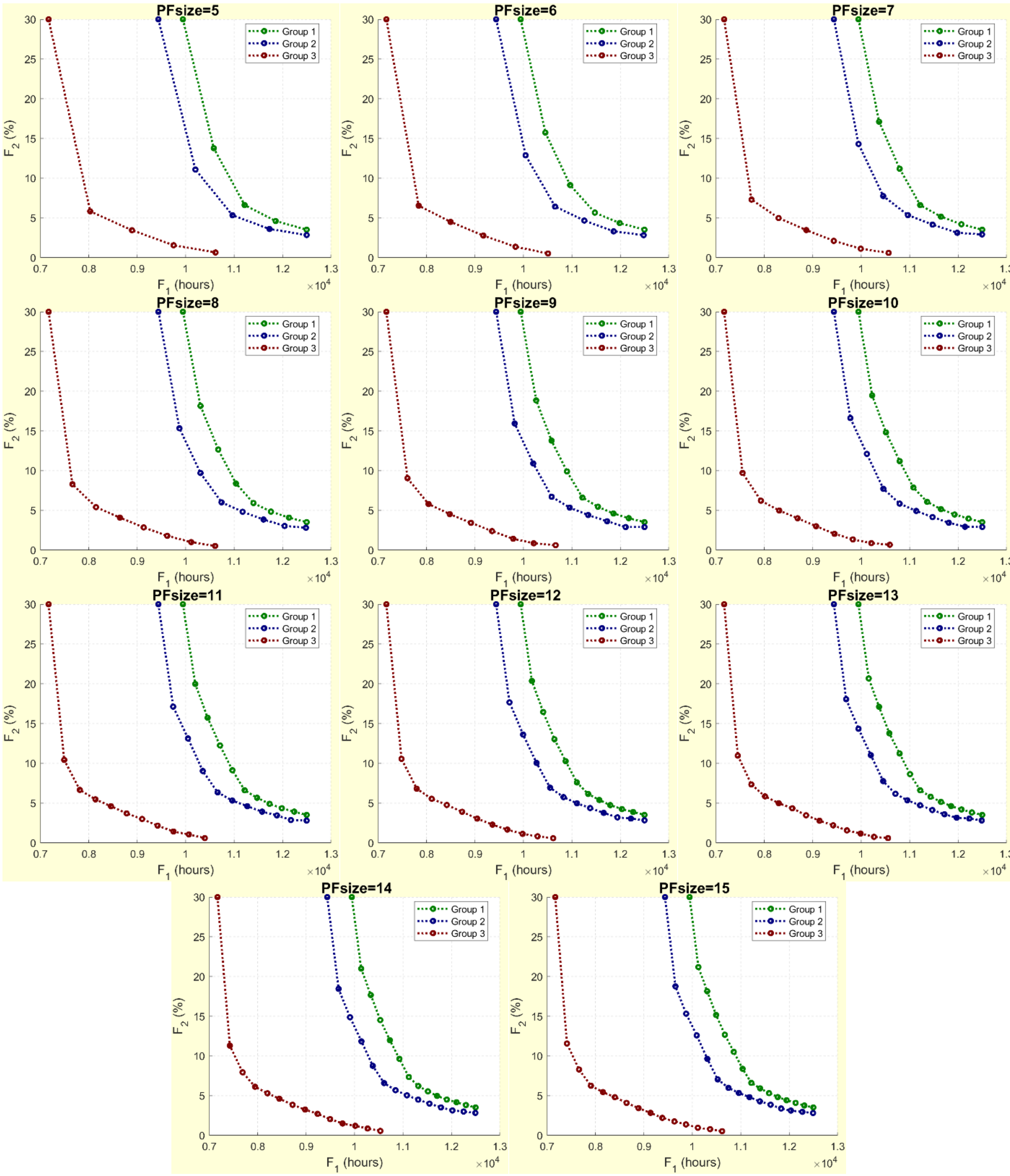


Figure 13 Examining the effects that the size of the Pareto front has on solution density ($\boldsymbol{gr^{size}}$= 350 evacuees).

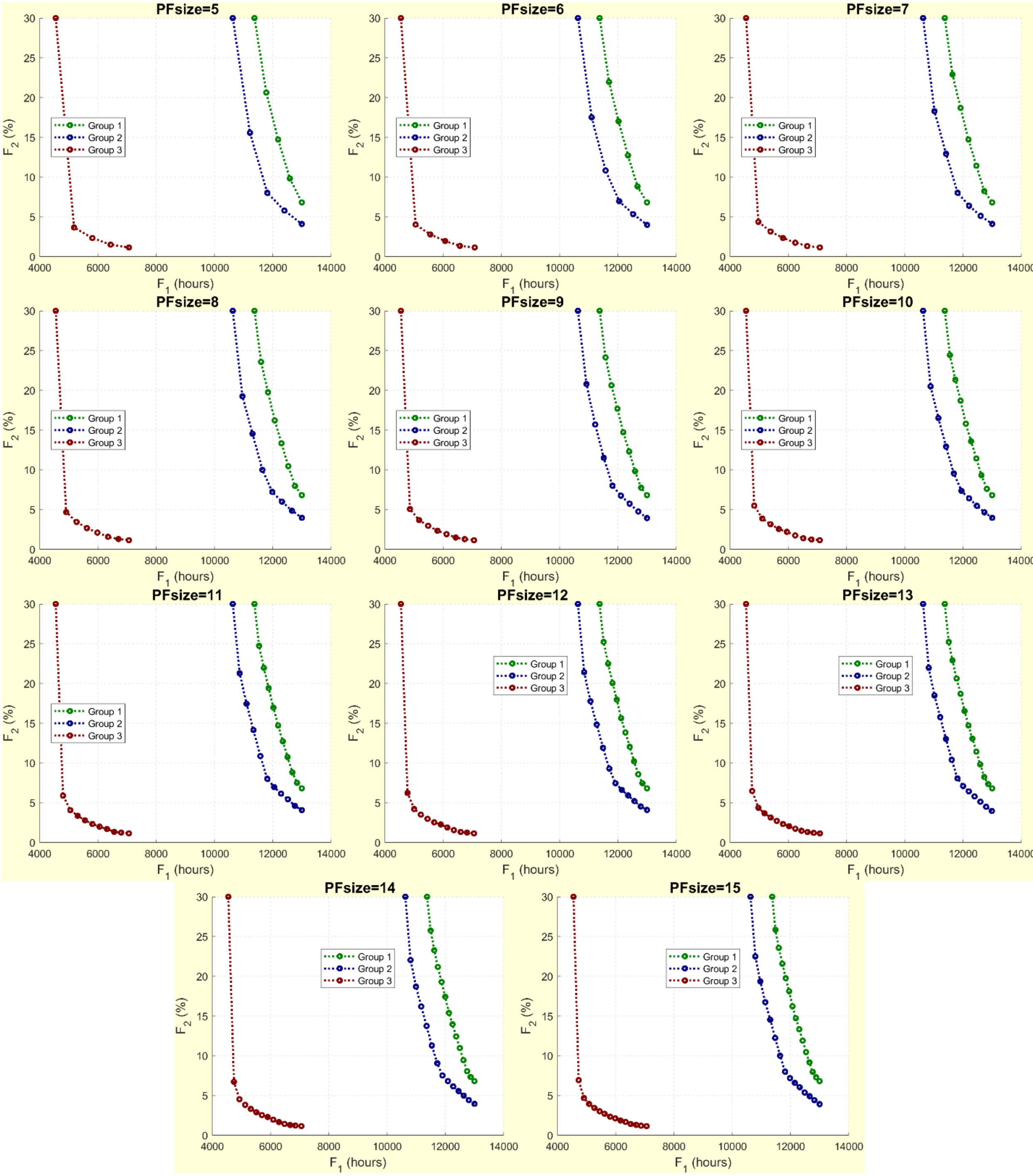


Figure 14 Examining the effects that the size of the Pareto front has on solution density ($\boldsymbol{gr}^{\boldsymbol{size}}$= 400 evacuees).

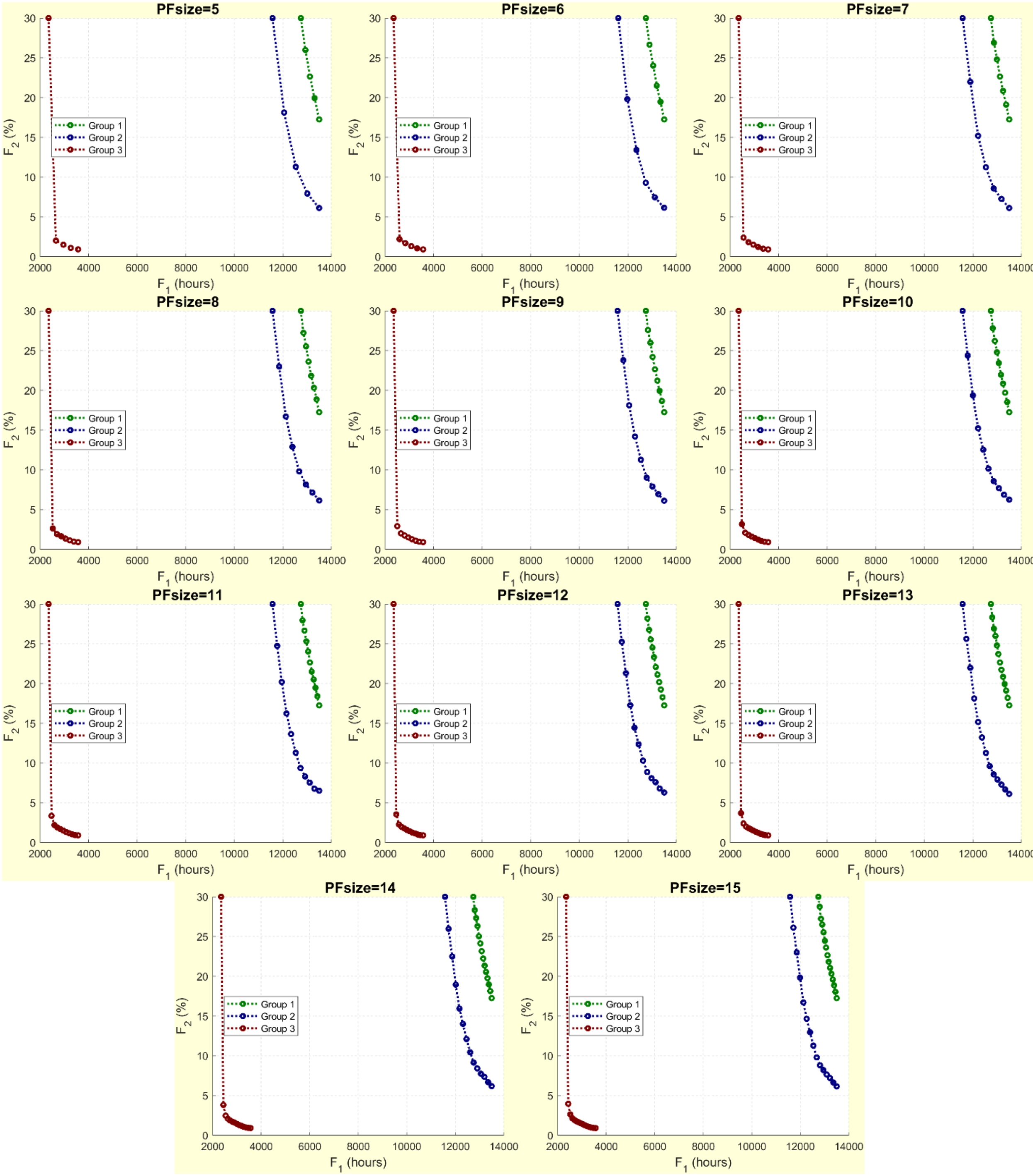


Figure 15 Examining the effects that the size of the Pareto front has on solution density ($\boldsymbol{gr^{size}}$= 450 evacuees).

5.3. Practical Insights

The second experimental phase focused on executing the DECON algorithm across all seventeen generated problem scenarios (with the detailed study area and input data specifications available in section 5.1 of this technical report) to extract valuable managerial insights for pandemic-era evacuation planning. Building upon findings from the initial experimental phase (detailed in section 5.2 of this technical report), the algorithm parameters were optimized with a Pareto front size (PF^{size}) of 9 points and an evacuee group size (gr^{size}) of 350 individuals.

Table 4 presents a comprehensive summary of the DECON algorithm's performance across all problem instances, documenting:

1. Problem scenario identification number;
2. Total evacuation population ($|E|$);
3. Number of evacuee groups proposed by DECON (gr^{num});
4. Maximum and minimum values for both $\boldsymbol{F_1}$ and $\boldsymbol{F_2}$ objectives at the Pareto front corner points;
5. Maximum and minimum values for $\boldsymbol{F_1}$ and $\boldsymbol{F_2}$ objectives at the Pareto front point with the best trade-off solution that has $min(MID)$;
6. DECON's computational duration measured in minutes.

The analysis of the results revealed a direct correlation between population size and the number of required evacuee groups. For instance, the first problem scenario successfully managed the evacuation of 1,000 individuals using three evacuee groups, while the 17th problem scenario required 26 distinct groups to coordinate the evacuation of 9,000 people. This linear scaling demonstrates DECON's adaptability to varying population sizes while maintaining systematic group organization for effective evacuation management. The structured presentation of these results, particularly the inclusion of both corner points and best trade-off solutions, provides emergency planners with comprehensive insights into the range of possible evacuation strategies and their associated outcomes in terms of both objectives ($\boldsymbol{F_1}$ and $\boldsymbol{F_2}$). This detailed analysis offers valuable guidance for real-world evacuation planning scenarios under pandemic conditions.

A more comprehensive analysis of the Pareto frontier (PF) corner points uncovered significant differences in the key metrics. The total evacuation duration, evaluated by the objective function ($\boldsymbol{F_1}$), showed a considerable range, spanning from 291.8 hours at its minimum to 12,500.0 hours at its maximum. Concurrently, the objective function ($\boldsymbol{F_2}$), representing the total deviation in average shelter usage, displayed variability from 0.204% to 30.000%. These extensive ranges can be traced back to the evacuee grouping mechanism within the evacuation planning structure. The values of both ($\boldsymbol{F_1}$) and ($\boldsymbol{F_2}$) are substantially affected by the dynamic allocation of evacuees into different groups, taking into account various factors, including vehicle occupancy rates and the predetermined maximum group size limit (gr^{size}). This flexibility in group formation and composition enables the refinement of evacuation strategies to achieve optimal balance between evacuation timing and shelter occupancy distribution.

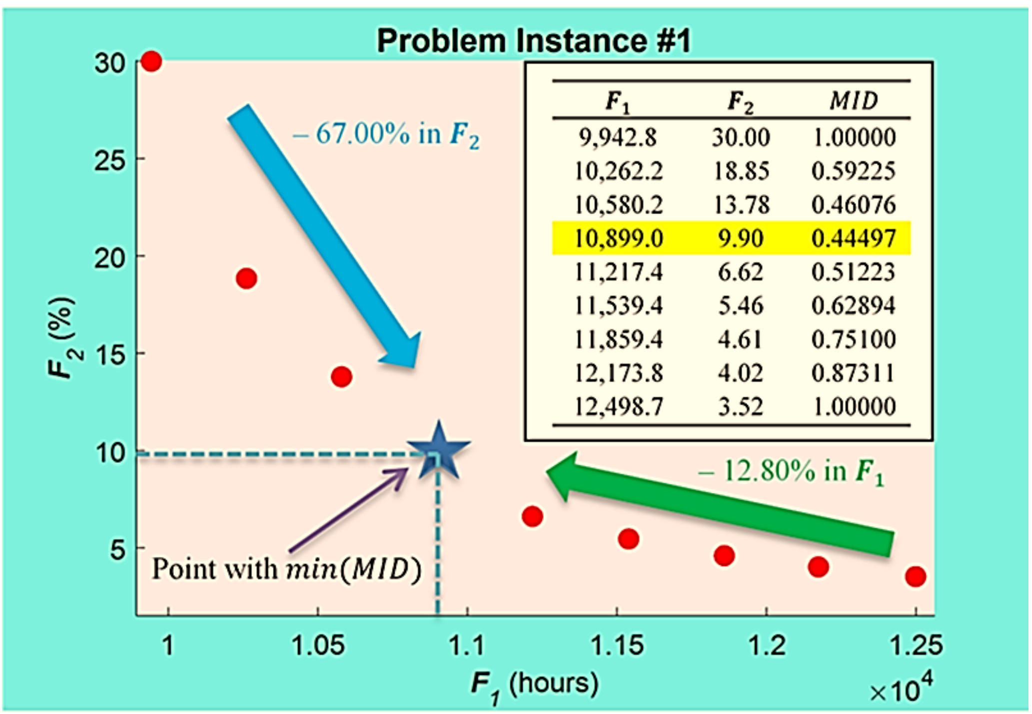
Table 4 Overview of the DECON outcomes for the analyzed problem scenarios.

Scenario	$\|E\|$	gr^{num}	PF Corner Points				PF Point with min (MID)				CPU time, min
			$max(\boldsymbol{F}_1)$	$min(\boldsymbol{F}_1)$	$max(\boldsymbol{F}_2)$	$min(\boldsymbol{F}_2)$	$max(\boldsymbol{F}_1)$	$min(\boldsymbol{F}_1)$	$max(\boldsymbol{F}_2)$	$min(\boldsymbol{F}_2)$	
1	1,000	3	12,498.7	7,168.6	30.000	0.488	10,899.0	8,036.1	10.916	5.745	15.92
2	1,500	5	12,499.4	2,343.2	30.000	0.483	10,940.2	2,501.1	10.333	2.827	25.66
3	2,000	6	12,493.0	5,816.8	30.000	0.736	10,895.8	6,184.7	10.337	7.285	31.67
4	2,500	8	12,494.9	1,370.9	30.000	0.496	11,021.4	1,477.9	11.512	1.728	44.62
5	3,000	9	12,498.9	4,724.6	30.000	0.502	11,073.8	5,056.1	11.949	5.900	54.64
6	3,500	11	12,497.0	291.8	30.000	0.204	11,228.4	319.8	13.785	0.344	64.85
7	4,000	12	12,499.1	3,773.0	30.000	0.515	11,345.8	4,014.7	15.359	5.614	73.04
8	4,500	13	12,500.0	7,193.6	30.000	0.511	11,347.5	8,169.8	15.385	7.051	79.87
9	5,000	15	12,499.9	2,808.8	30.000	0.505	11,312.3	2,995.0	14.859	4.529	92.31
10	5,500	16	12,499.3	6,394.9	30.000	0.501	11,311.9	7,147.0	14.862	6.963	99.43
11	6,000	18	12,500.0	1,752.7	30.000	0.514	11,238.8	1,852.0	13.896	3.396	110.83
12	6,500	19	12,499.7	5,481.3	30.000	0.511	11,203.9	6,120.8	13.436	6.532	115.56
13	7,000	21	12,500.0	646.8	30.000	0.436	11,280.7	712.2	14.372	0.986	129.37
14	7,500	22	12,499.9	4,184.4	30.000	0.515	11,280.3	4,446.7	14.375	7.827	134.61
15	8,000	23	12,500.0	7,491.8	30.000	0.524	11,280.7	8,601.9	14.375	8.043	140.60
16	8,500	25	12,498.9	3,171.5	30.000	0.517	11,281.5	3,400.0	14.375	6.251	152.05
17	9,000	26	12,499.6	6,651.7	30.000	0.555	11,129.3	7,531.1	15.571	8.225	158.69
Minimum:		3	12,493.0	291.8	30.000	0.204	10,895.8	319.8	10.333	0.344	15.92
Maximum:		26	12,500.0	7,491.8	30.000	0.736	11,347.5	8,601.9	15.571	8.225	158.69
Average:		14.82	12,498.7	4,192.1	30.000	0.501	11,180.7	4,621.6	13.512	5.250	89.63

To demonstrate the grouping methodology, the first problem scenario can be examined which involved a total population of 1,000 evacuees. The DECON algorithm strategically distributed these evacuees across three distinct groupings: Group 1 accommodated 348 individuals, Group 2 similarly contained 348 evacuees, while Group 3 comprised the remaining 304 evacuees (calculated as 1,000−348−348=304). This particular distribution pattern was deliberately engineered to achieve an efficient balance in transportation resource allocation while respecting the established maximum group size limitations. Such strategic grouping was designed to maximize the efficiency of vehicle deployment while simultaneously pursuing the dual objectives of minimizing the overall evacuation duration and maintaining balanced shelter occupancy rates. The research findings highlighted the critical importance of evaluating solutions linked to the Pareto front points exhibiting the minimum Mean Ideal Distance (MID). This MID measurement functions as a key metric to find balanced solutions that effectively manage the tension between competing objectives ($\boldsymbol{F}_1$) and ($\boldsymbol{F}_2$). More specifically, when examining solutions associated with the minimum MID, the peak values observed for ($\boldsymbol{F}_1$) and ($\boldsymbol{F}_2$)

remained at 11,347.5 hours and 15.571%, respectively. These results show a notable improvement compared to the values recorded at the Pareto front corner points, which reached 12,500.0 hours for ($\boldsymbol{F}_1$) and 30.000% for ($\boldsymbol{F}_2$).

An analysis of the first problem scenario demonstrated substantial benefits when selecting the Pareto front point with the minimum MID. The conducted evaluation revealed two key improvements. First, in comparison with the corner point $[\boldsymbol{F}_1^*; \boldsymbol{F}_2(\boldsymbol{F}_1^*)]$ that represents the solution with the optimal $\boldsymbol{F}_1$ (minimum evacuation time) but higher $\boldsymbol{F}_2$, the solution with the minimum MID achieved a 67.00% decrease in the average shelter utilization deviation. Second, in comparison to the corner point $[\boldsymbol{F}_1(\boldsymbol{F}_2^*); \boldsymbol{F}_2^*]$ (which prioritized the minimal shelter deviation but accepted longer evacuation times), the solution with the minimum MID delivered a 12.80% reduction in the total evacuation duration. Figure 16 provides a graphical representation of these outcomes, clearly demonstrating how the minimum MID solution achieves a superior balance and efficiency compared to the extreme solutions at the Pareto front corner points.



F_1	F_2	MID
9,942.8	30.00	1.00000
10,262.2	18.85	0.59225
10,580.2	13.78	0.46076
10,899.0	9.90	0.44497
11,217.4	6.62	0.51223
11,539.4	5.46	0.62894
11,859.4	4.61	0.75100
12,173.8	4.02	0.87311
12,498.7	3.52	1.00000

Figure 16 Determination of the PF point with the minimum value of the mean ideal distance.

The present research included detailed analysis of evacuation route usage patterns across the studied problem scenarios. Figure 17 and Figure 18 illustrate the distribution of evacuees across various evacuation routes (showing the aggregate evacuee numbers over the considered time intervals) for each problem scenario, based on the Pareto front solution with the minimum MID. These scenarios serve as illustrative examples, and it can be observed that similar patterns of route usage were observed across all the problem scenarios. The analysis identified that evacuees utilized 19 different evacuation routes, with significant variations in their usage. Notably, evacuation routes "20" and "107" were predominantly favored. In the first problem scenario, these routes accommodated 118 and 114 evacuating vehicles, respectively. This trend became even more evident in the 17th problem scenario, where routes “20” and “107” handled substantially larger volumes of 1,032 and 1,172 evacuating vehicles, respectively.

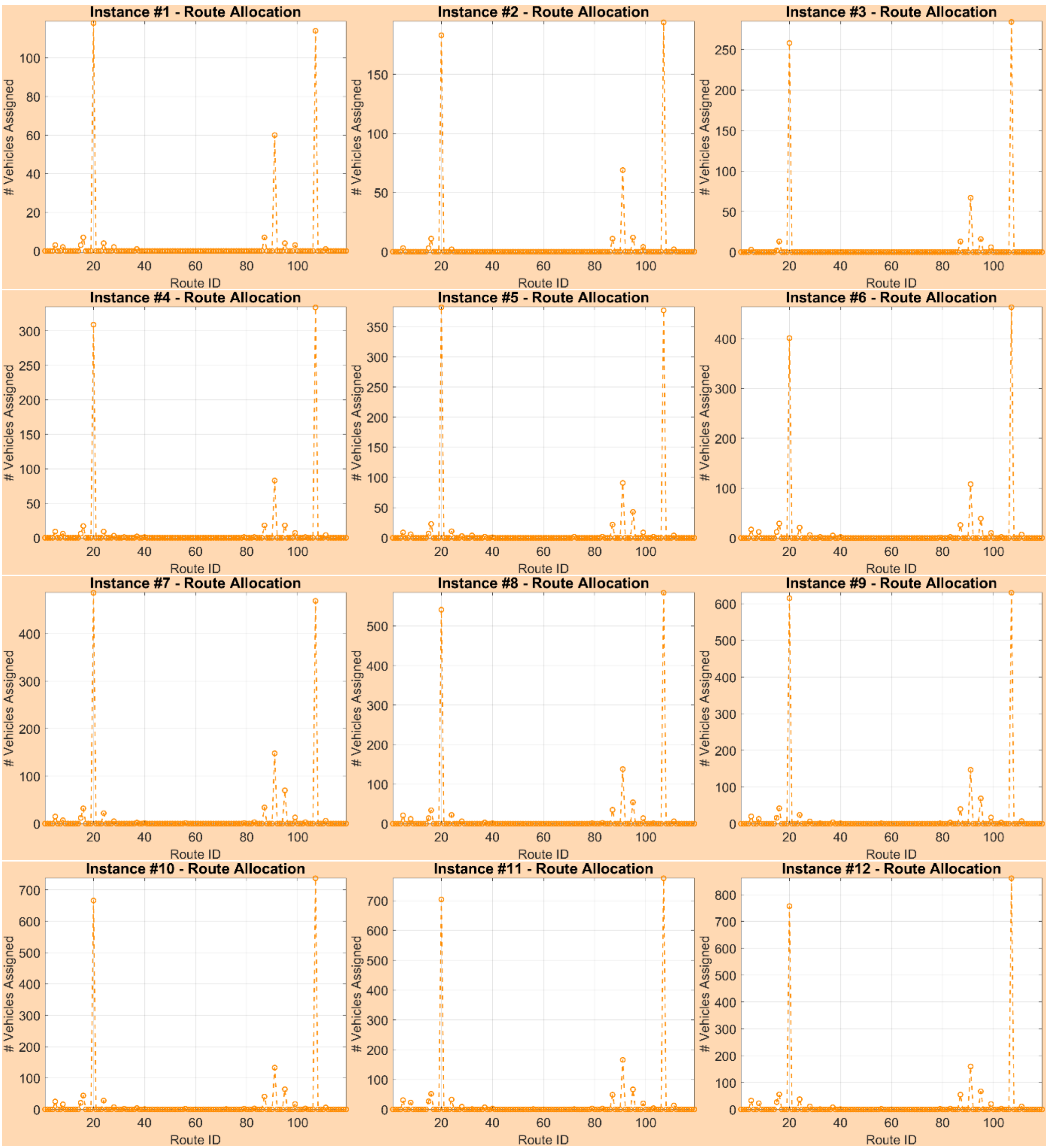


Figure 17 Routing evacuees to designated evacuation paths across problem scenarios “1” through “12”.

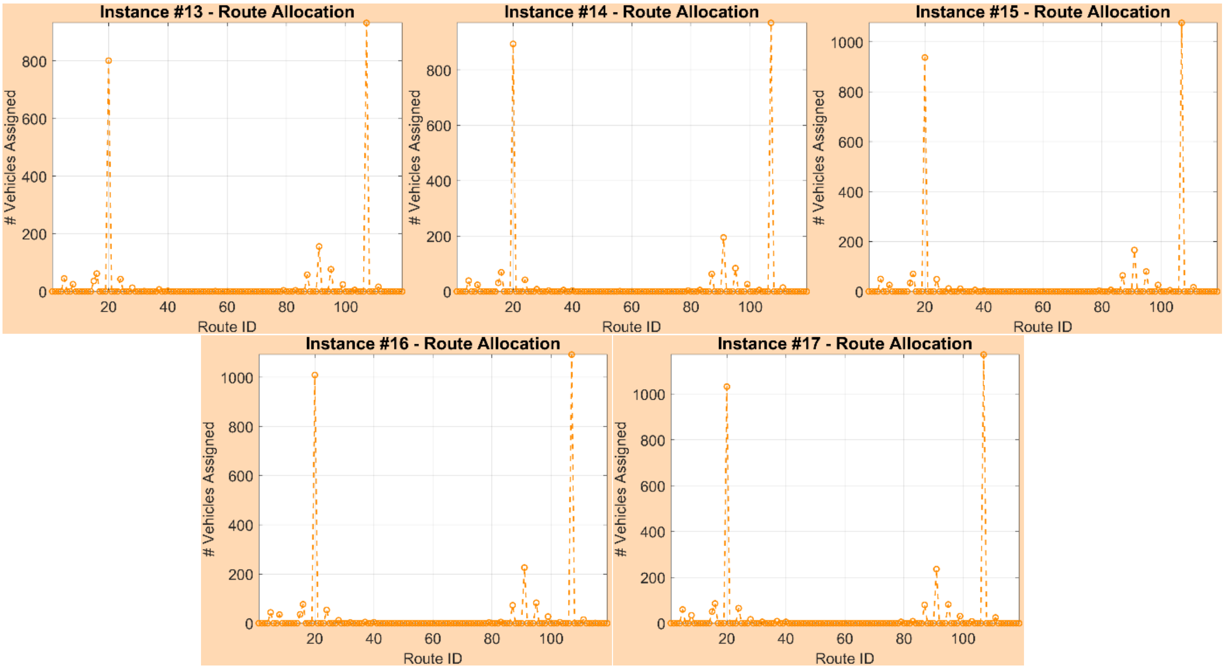


Figure 18 Routing evacuees to designated evacuation paths across problem scenarios “13” through “17”.

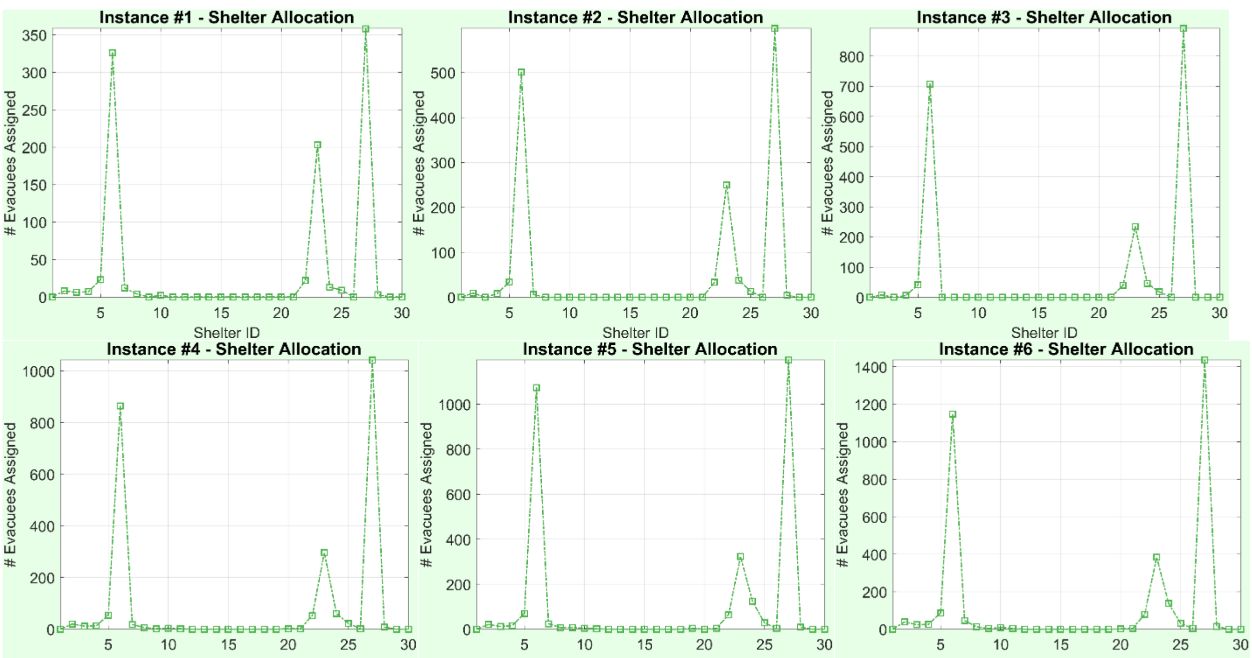


Figure 19 Allocation of evacuees to emergency sheltering facilities across problem scenarios “1” through “6”.

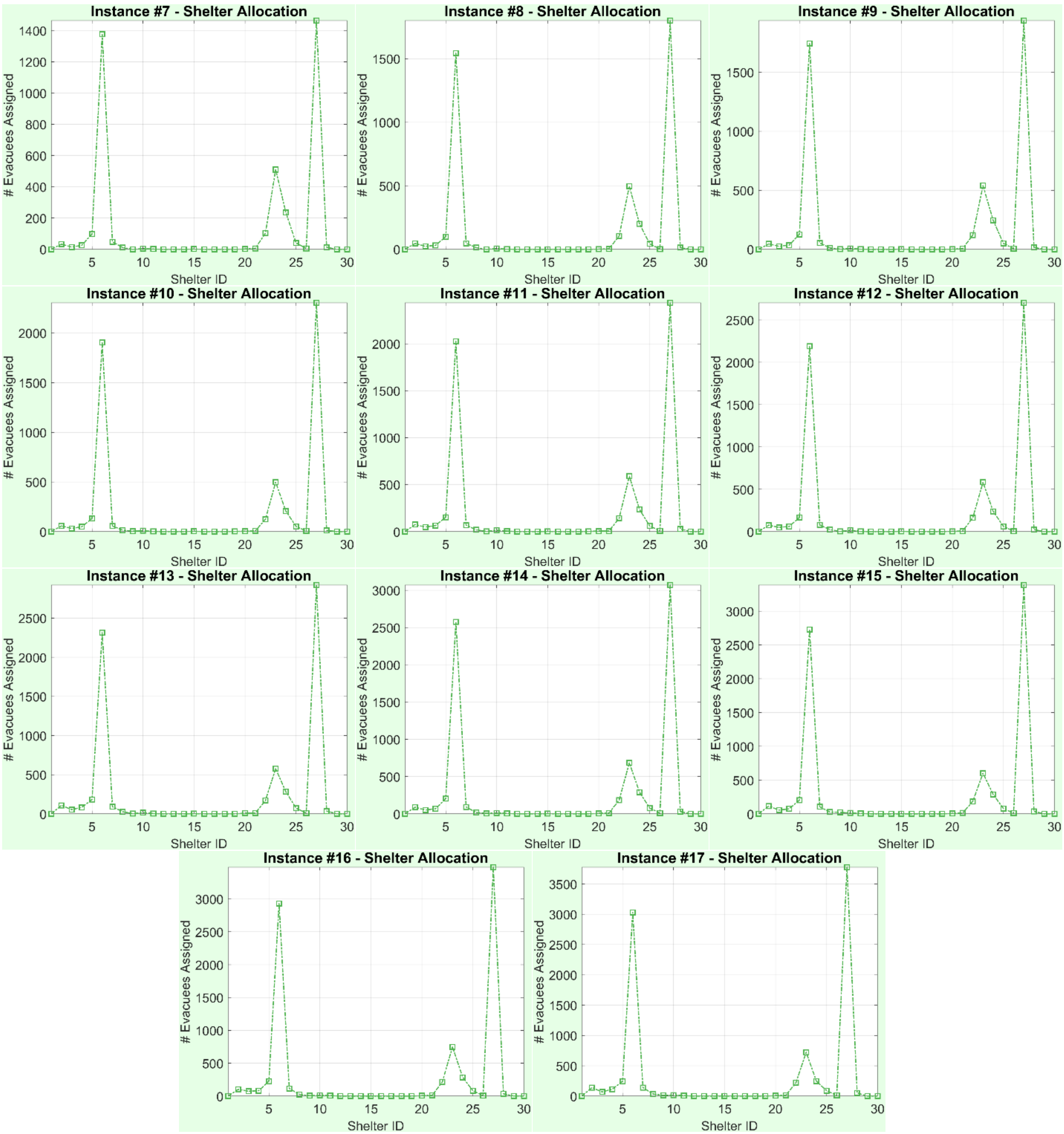


Figure 20 Allocation of evacuees to emergency sheltering facilities across problem scenarios "7" through "17".

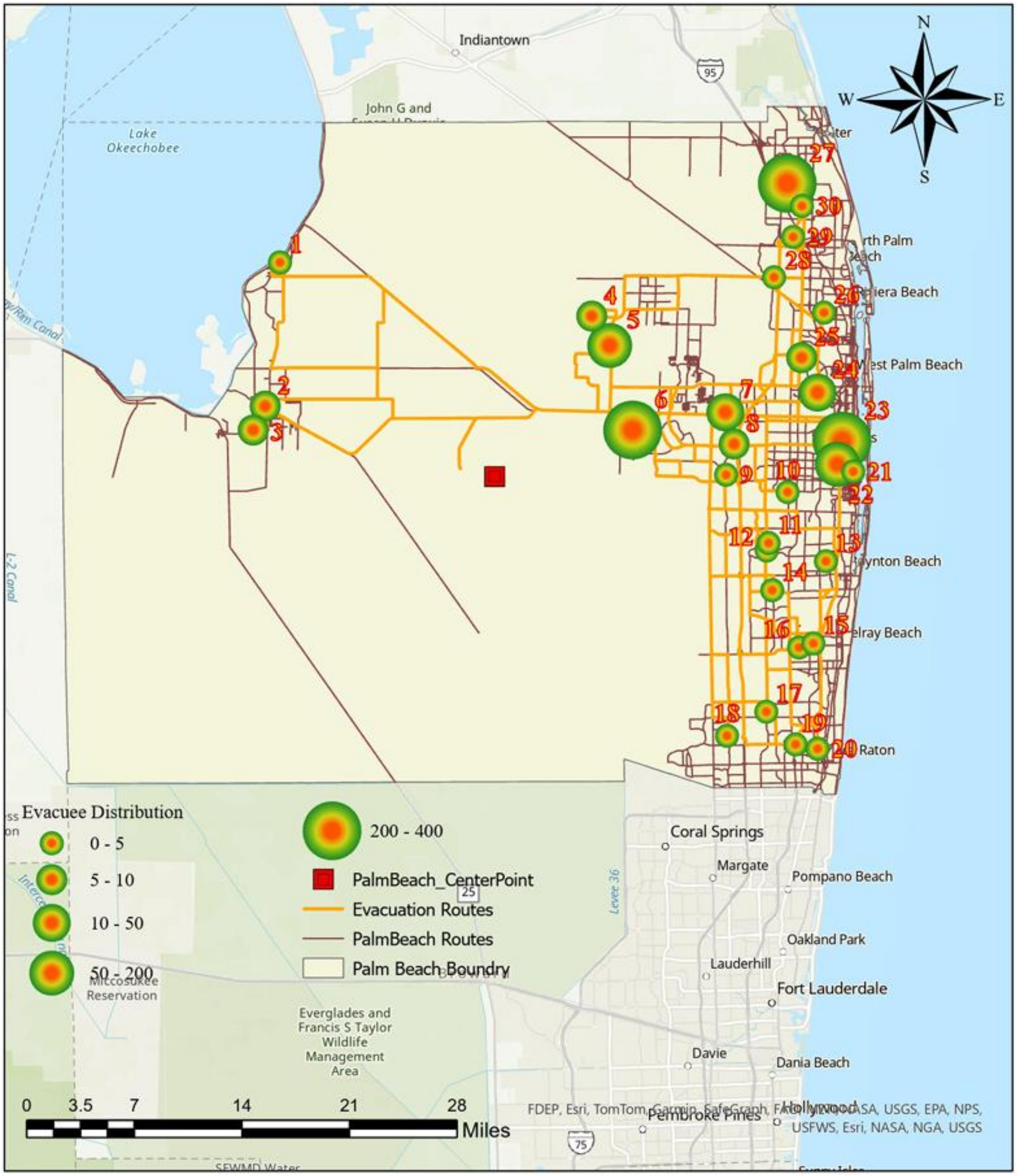


Figure 21 Spatial allocation of evacuees to available emergency sheltering facilities for problem scenario "1".

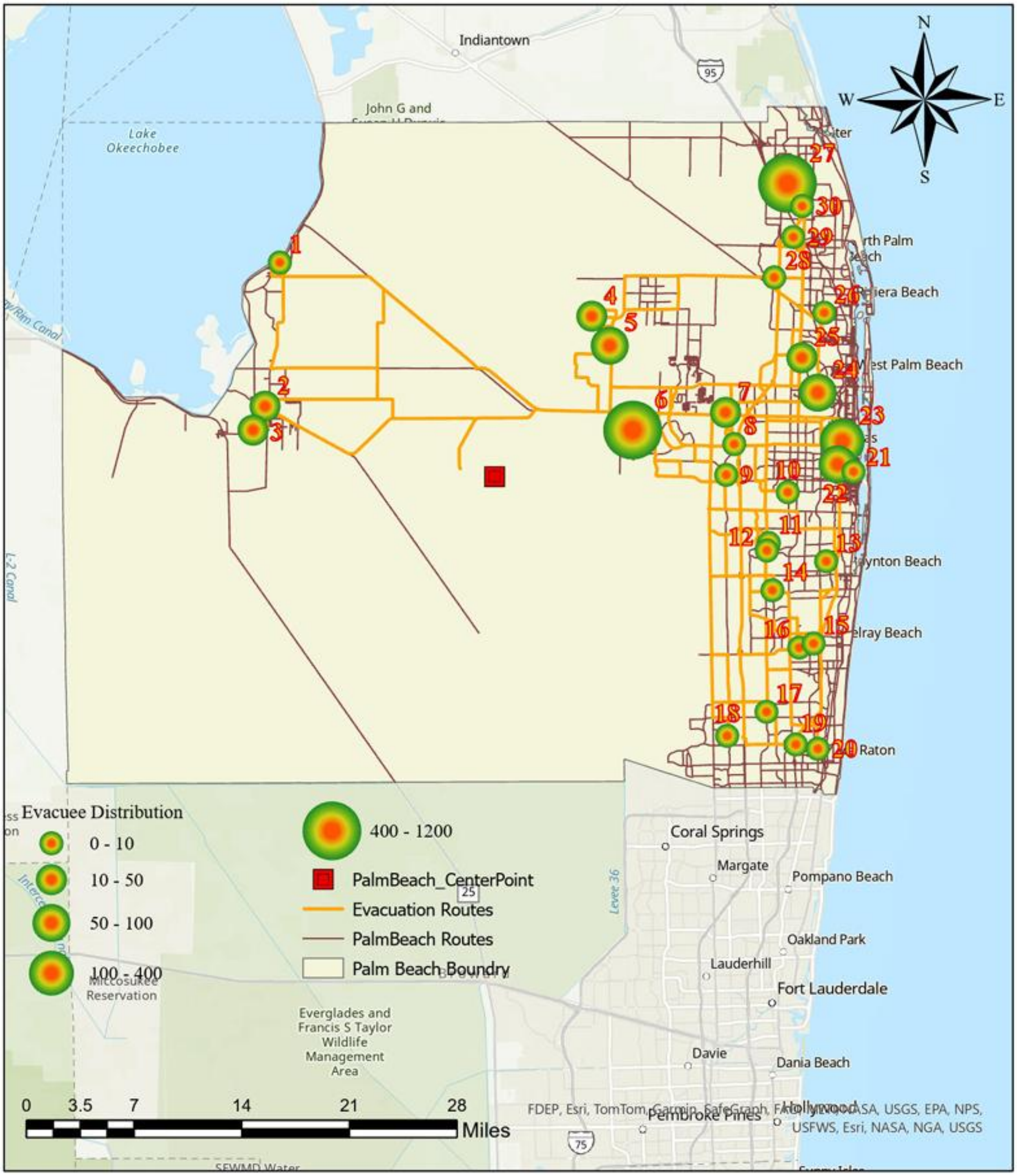


Figure 22 Spatial allocation of evacuees to available emergency sheltering facilities for problem scenario “5”.

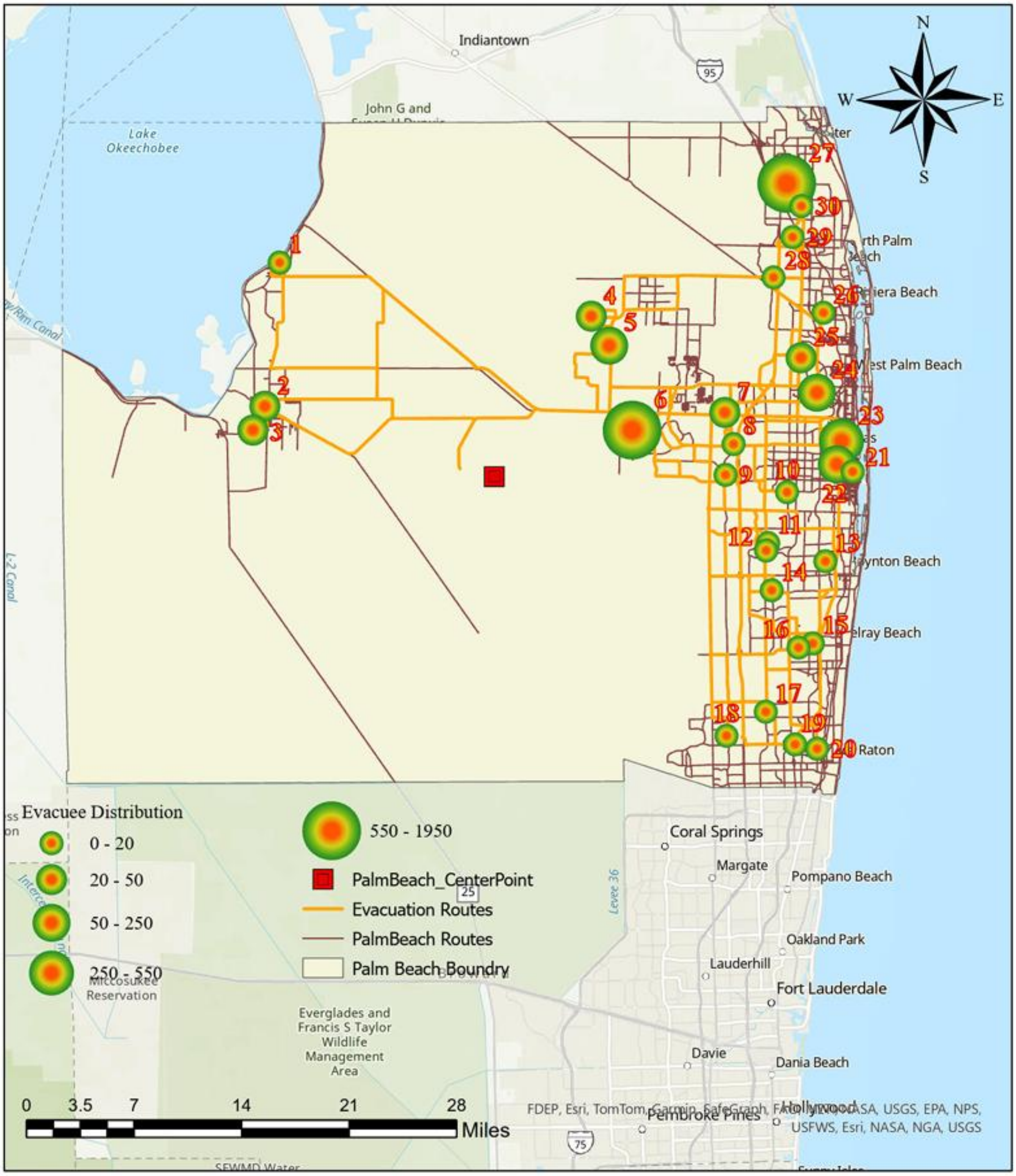


Figure 23 Spatial allocation of evacuees to available emergency sheltering facilities for problem scenario "9".

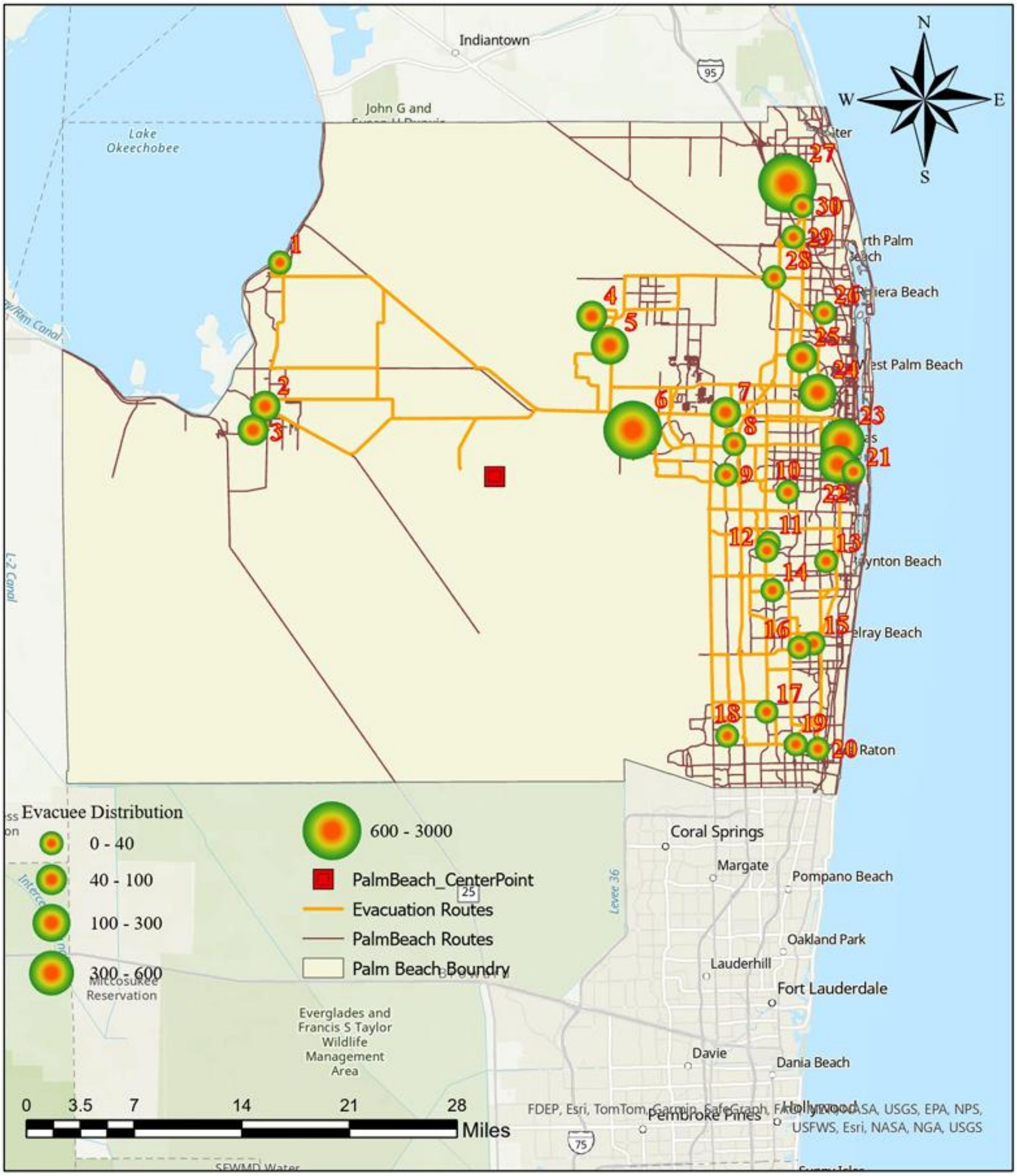


Figure 24 Spatial allocation of evacuees to available emergency sheltering facilities for problem scenario "13".

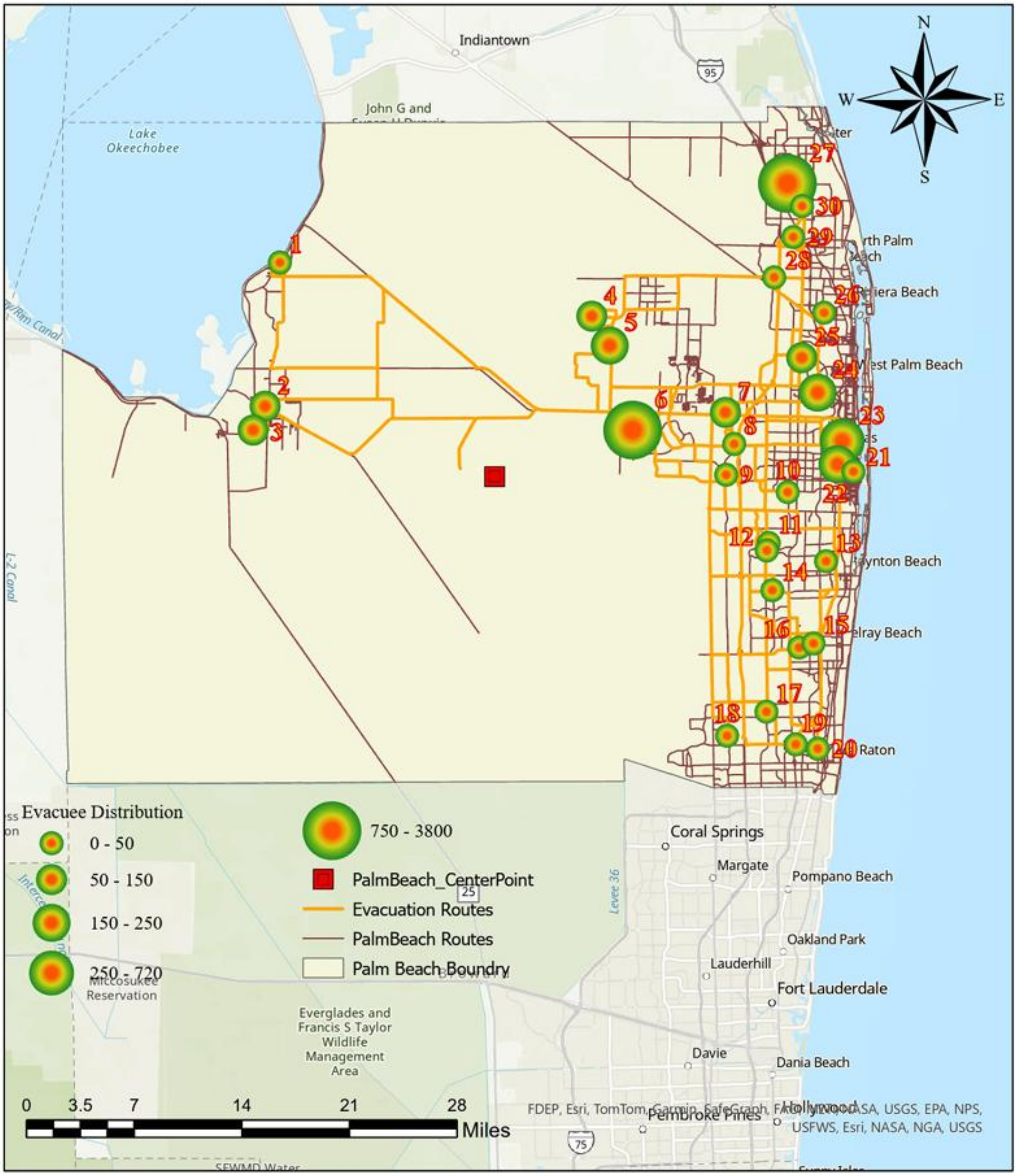


Figure 25 Spatial allocation of evacuees to available emergency sheltering facilities for problem scenario "17".

Beyond the comprehensive examination of evacuation route usage patterns, this project also conducted a detailed investigation of evacuee distribution across emergency shelters. Figure 19 and Figure 20 present the patterns of evacuee allocation to various emergency shelter facilities across all the considered problem scenarios, especially focusing on the Pareto front solutions featuring the minimum MID. The geographic distribution of evacuees across emergency shelter facilities is presented in Figure 21, Figure 22, Figure 23, Figure 24, and Figure 25 for problem scenarios "1", "5", "9", "13", and "17". The analysis revealed that evacuees utilized 19 distinct emergency shelters, with notably uneven usage patterns. Shelters "6" and "27" emerged as the predominantly selected facilities. For the first problem scenario, these shelters accommodated 326 and 358 evacuees, respectively. This pattern was amplified in the 17th problem scenario, where shelters "6" and "27" hosted significantly larger populations of 3,031 and 3,776 evacuees, respectively.

The DECON algorithm demonstrated strong computational performance, effectively handling large-scale situations with up to 9,000 evacuees within reasonable time limits (around 2.5 hours). Computational requirements scaled linearly with evacuee population size. For example, the processing time increased from 15.92 minutes for the first problem scenario (1,000 evacuees) to 158.69 minutes for the 17th problem scenario (9,000 evacuees). For the future research involving substantially larger evacuee populations (e.g., 100,000 individuals), several computational approaches could be considered. One promising strategy involves parallel processing using multiple computers through a "master-slave" model where the evacuee population is distributed across several machines running simultaneous DECON algorithms (Durillo et al. 2008; Yang et al., 2013; Fu et al., 2018; Dulebenets, 2023). Alternatively, different algorithmic approaches (such as heuristics and metaheuristics) could be employed. While these alternative methods might not guarantee the optimal evacuee assignment to routes and shelters for the partitioned evacuee groups like DECON does, they typically offer improved computational efficiency.

6. CONCLUSIONS

Natural hazards are significant environmental events that result from natural processes, including atmospheric, geological, and hydrological phenomena. These events, occurring frequently across various regions globally, have led to considerable economic, social, and environmental impacts, especially in highly populated and infrastructure-dense areas. The United States (U.S.) is especially susceptible to a broad spectrum of natural hazards due to its diverse climate zones and geographic features. Emergency evacuation orders are generally issued in the areas that are expected to have a significant impact from the approaching hazards. Evacuation process is typically challenging due to a variety of issues, including but not limited to congested evacuation route segments, insufficient capacity and availability of emergency shelters, and potential accidents that may occur. Emergency evacuations in rural areas pose additional challenges because of geographical isolation, infrastructural limitations, economic factors, and inadequate resources. Furthermore, the frequent occurrence of infectious disease outbreaks, epidemics, and pandemics in recent years has added significant complexity to emergency evacuation planning. Evacuating to the nearest emergency facilities may not be the best option, as the nearest emergency facilities can be operating at the capacity level and may have an increased virus transmission risk.

Considering the aforementioned challenges, the present project has made substantial contributions within the area of emergency evacuation planning, specifically in dealing with the unprecedented challenges posed by pandemic conditions. This comprehensive investigation has yielded significant insights into optimizing evacuation strategies while maintaining public health safety measures, with particular attention to the unique needs of both urban and rural populations. In the initial phase of the project, an extensive analysis of evacuation challenges was conducted specific to pandemic contexts. Moreover, major challenges encountered by rural populations during emergency evacuations were highlighted as well. These challenges underline the need for advanced decision support systems that can assist rural populations during large-scale evacuations. The present investigation also revealed critical gaps in the existing evacuation models, particularly regarding their inability to account for social distancing requirements and other pandemic-related constraints. In response, the Emergency Evacuation Planning under Pandemic Settings (EEPPS) framework was developed, which represents a unique bi-objective optimization framework that effectively balances evacuation efficiency with health safety considerations. This mathematical model can be viewed a significant advancement in the field, incorporating both traditional evacuation constraints and pandemic-specific considerations in a unified framework.

Moreover, the proposed modeling framework approach enhances the traditional travel time estimations by incorporating representative characteristics of drivers, addressing a significant limitation of the conventional Bureau of Public Roads (BPR) formula. Another methodological contribution of this project centers on the development of the decomposition-based epsilon-constraint (DECON) algorithm. This algorithm was specifically designed to address the complexities of the EEPPS framework. The integration of Pareto-based optimization techniques has proven particularly effective in managing competing objectives, while the proposed novel grouping strategies for evacuee management have successfully balanced transportation efficiency with health safety considerations.

The computational implementation phase demonstrated the robust performance of the developed solution approach across diverse scenarios. Through extensive testing across 17 different problem scenarios, ranging from small to large population sizes, the scalability of the developed methodology was extensively validated. The DECON algorithm efficiently managed scenarios involving up to 9,000 evacuees, with optimal parameter settings identified for both evacuee group size and Pareto front size. The minimum Mean Ideal Distance (MID) approach yielded substantial improvements in both virus transmission rate and evacuation time. A case study of Palm Beach County (Florida) provided a real-world validation of the methodology's practical applicability. This comprehensive analysis incorporated the actual geographic and demographic data from authoritative sources, including the U.S. Census Bureau and local emergency management agencies. The study encompassed 119 viable evacuation routes and 30 emergency shelters, including both general-purpose and special needs facilities. Through the GIS integration and careful consideration of the existing infrastructure, the model's effectiveness was demonstrated in real-world applications.

The results of the conducted investigation are particularly noteworthy. The DECON algorithm achieved remarkable improvements, reducing shelter utilization deviation by 67.0% while simultaneously decreasing evacuation times by 12.8% compared to the extreme points where the emphasis was dedicated either to virus transmission risk minimization or evacuation time minimization. These improvements demonstrate the significant potential of the proposed methodology in enhancing emergency evacuation operations. Furthermore, the model's adaptability to varying pandemic severity levels through adjustable parameters ensures its continued relevance across different emergency scenarios. From a practical perspective, the conducted research has generated valuable insights for emergency management professionals. Optimal distribution patterns were identified for evacuee groups across available shelters and routes, effective strategies were developed for balancing transportation efficiency with social distancing measures, and comprehensive guidelines were established for group-based evacuation planning. Particularly significant is the framework's ability to prioritize populations with special needs while maintaining the overall system efficiency, a critical consideration in emergency management.

The rural dimension of this research addresses a critical gap in emergency evacuation planning. The proposed methodology explicitly considers the unique challenges faced by rural populations, including limited transportation infrastructure and extended distances to emergency facilities. By incorporating special needs shelter requirements and designing strategies that accommodate both rural and urban evacuation needs in a comprehensive way, the proposed approach provides a more comprehensive solution to emergency evacuation planning.

Looking ahead, several promising directions for future research emerge from this work. From a computational perspective, exploring parallel processing methods could support even larger evacuee populations, while investigating alternative heuristics might yield faster computational performance. The integration of real-time data capabilities would enhance dynamic, responsive evacuation management. Model extensions could incorporate additional pandemic factors as new data becomes available, adapt to multi-hazard scenarios, and develop multimodal transportation options to enhance evacuation flexibility (e.g., buses can be used in combination with private vehicle to assist with emergency evacuation). As for implementation strategies, developing userfriendly interfaces for emergency management professionals and establishing standardized protocols for data collection and model updates will be crucial. Training programs for emergency responders and integration with the existing emergency management systems will facilitate practical adoption of the developed tools. Certain practitioners may have adequate knowledge about natural hazards and planning of emergency evacuations but may not have a sufficient background regarding optimization and advanced decomposition algorithms. Therefore, training programs will play an important role for practitioners. The methodology that was developed as part of this project provides a robust foundation for different extensions while maintaining its core strength in balancing multiple, often competing objectives.

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