THE UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

FAIRNESS- BASED TRANSPORTATION RESILIENCE FOR COMMUNITIES UNDER TSUNAMI HAZARD

A THESIS

SUBMITTED TO THE GRADUATE FACULTY

In partial fulfilment of the requirements for the

Degree of

MASTER OF SCIENCE

By

Rasha Jnad

Norman, Oklahoma
2021

FAIRNESS- BASED TRANSPORTATION RESILIENCE FOR COMMUNITIES UNDER TSUNAMI HAZARD

A THESIS APPROVED FOR THE
GALLOGLY COLLEGE OF ENGINEERING

BY THE COMMITTEE CONSISTING OF

Dr. Andrés D. González, Chair

Dr. Charles Nicholson

Dr. Kash Barker

To my family, my mentors, and my friends

ACKNOWLEDGEMENTS

To begin, I'd want to express my deepest gratitude to Dr. González for advising my master's thesis. I don't think all of this would be possible without his assistance and guidance. Dr. Gonzalez was one of the most committed to his profession and concerned about his students' interests. I'd want to thank him for his patience and support, as well as for pushing me further than I thought possible. Dr. Gonzalez was not just my advisor, but also a trustworthy person who I could consult and trust for advice during my whole master's degree, and it was my good fortune that he accepted me as his research student. Moreover, thank you so much for my committee for their help and assistance.

Also, I would like to express my gratitude to my colleague Himadri Sen Gupta for his help You're a great person to work with and I truly appreciate the time and effort you put it.

Finally, I'd want to convey my gratefulness and thanks to my family and husband for always believing in me. Nothing would be achievable without your support.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Abstract

Natural disasters such as tsunamis have catastrophic impacts on the functionality and resilience of transportation networks in impacted areas, and they can damage coastal regions hundreds of kilometers away from the earthquake that caused them, resulting in a significant number of casualties. As a result, the ultimate goal of this study was to develop a fair-based evacuation model under tsunami hazards. The suggested fairness-based evacuation model employed in this study sought to provide evacuees with equitable access to the emergency facility centers and assembly areas.

To demonstrate the suggested model, we provided a practical case study based on the Seaside, Oregon transportation network and the disruptive impacts of tsunami on the efficiency of the evacuation process. The results showed that the suggested model was efficient in decreasing the total average deviation across demand nodes and ensuring that most of the demand nodes received the minimum required service level. Moreover, after applying the fair distribution strategy, we were able to evacuate most of the threatened population to safer areas. Finally, we did sensitivity analysis to see how determining the best values of a few factors would improve the efficiency of the evacuation process. The findings showed that the value of the minimum required service level assisted in minimizing the total average deviation of the unmet demand in the demand nodes. Secondly, the changes in the upper capacities of arcs showed that: (a) as we raised the capacity of the links, we were able to increase the number of transported evacuees until we were able to dislocate 100 % of the whole population that needed to be displaced, (b) increasing the maximum capacity of each arc allowed us to reduce the total average deviation of the unmet demand of the demand nodes, (c) when we increased the upper maximum capacities of arcs, evacuees needed to travel for shorter distances to reach the safer areas.

1. Introduction:

Numerous individuals live in locations and regions that are vulnerable to natural disasters. At the moment, coastal areas are home to a sizable proportion of the world's population (Oktari et al., 2020). According to Neumann et al. (2015), coastal zones have always attracted humans due to their availability of subsistence supplies, access points to maritime trade and transportation, and recreational or cultural activities. Coastal zone development and utilization have risen significantly in recent decades, and coasts are undergoing huge socioeconomic and environmental changes a trend that is projected to continue in the future. The United States is a good example in this regard since its coastal areas are also significantly more densely inhabited than the rest of the nation; population density in coastal shoreline counties is more than five times that of the rest of the country (US Department of Commerce, 2019). Coastal areas, on the other hand, are the most exposed to natural catastrophe impacts owing to their proximity to the coasts. As a result, these areas are particularly vulnerable to the effects of global climate change, such as tsunamis, earthquakes, erosion, and storm surges (Oktari et al., 2020). The consequences of coastal hazards severely harm the social, cultural, and natural assets, as well as critical resources, for populations living in low-lying coastal areas.

Transportation networks are one of the most essential parts of life that would almost certainly be completely interrupted by natural catastrophes. Roads and bridges, for example, are critical to our everyday operations and activities in many cultures. Its significance is evident throughout the tsunami's post-event reaction and recovery. These transportation assets may be vulnerable to tsunami impacts, particularly in coastal locations, which might result in their destruction and a reduction in service levels (Williams et al., 2020). The transportation networks are crucial in the evacuation procedure. People utilize these networks to leave damaged regions and attempt to reach safety. Further, the capacity of the transportation network to function efficiently is critical for the delivery of help and the transfer of essential supplies and commodities (Akiyama et al., 2013).

The 2011 Tohoku-Oki earthquake is one illustration of the severity of natural disaster consequences (also known as the Off the Pacific Coast of Tohoku Region, Japan, earthquake). This earthquake, which caused a massive tsunami, caused significant damage to many towns, creating significant disruption to numerous coastal communities such as residential and commercial buildings, infrastructures, bridges, and key port facilities (Fujii et al., 2011). Furthermore, at least 200 bridges sustained significant damage as a result of the tsunami, while some bridges were entirely swept away (Akiyama et al., 2013).

Based on the preceding ideas, evacuation may be the greatest choice to consider to secure the safety of the community and decrease the number of casualties (Charnkol & Tanaboriboon, 2006). Evacuation may be described as the movement of people or objects from dangerous locations to safer ones, which is critical in order to preserve lives. As a result, evacuation preparations should be well researched because failing to do so increases the likelihood of additional dangers and fatalities (Bin Obaid et al., 2020).

Tsunamis, in general, require between 20 and 40 minutes to reach coastal communities and create damage. Various evacuation behaviors will exist during this lead period since each individual will react differently to the information that he got. Proactive conduct during the lead period is one item that would decrease tsunami dangers and greatly reduce the loss of human life, especially in mega-tsunamis. Thus, understanding human behavior during tsunamis will thus give significant information to consider when developing evacuation methods (Makinoshima et al., 2020). Many research and mathematical models have been developed in this sector over the last several decades to assist planners in reaching an effective solution that provides for the protection of lives while also reducing the time necessary to reach the safest locations. However, while these studies may give answers and simulation models to solve these problems, they fall short of delivering an ideal solution due to the intrinsic complexity of the dynamic transportation process (Bin Obaid et al., 2020).

Finally, the final objective of this article is to apply a mathematical problem that reduces evacuation time, increases the number of evacuees, and eliminates conflicts throughout the network. Furthermore, the placements of bridges will be carefully studied since they are vulnerable to being entirely devastated by tsunami impact because not all bridges are resistant to earthquakes and tsunamis. Furthermore, different restrictions, parameters, decision variables, and objective functions must be clearly described to have complete knowledge of what should be done to obtain the best solution in the impacted regions.

The following is the format of this paper: Section 2 includes an overview of the literature on transportation resilience in the face of disruptive events, network evacuation models, and the consideration of fairness in this context. Section 3 discusses the proposed model in depth. The results and analysis connected with an exemplary case study: the evacuation procedure in coastal Oregon, are then presented in Section 4. Section 5 finally discusses the findings and next work.

2. Literature review

2.1. Impact of disruptive events on transportation networks

Natural disasters have a significant negative impact on transportation systems as well as other critical essential civil infrastructures such as the economic, social, and power distribution sectors. Depending on a system's resilience and the severity of the disruptive natural events, the consequences can range from traffic disruptions to the complete devastation of transportation infrastructures (Ahmed & Dey, 2020). What happened in Tokyo, Japan in 2011 is an example of the severity of these events on transportation systems. One of the most disruptive earthquakes to occur in Tokyo because the magnitude was 9.0, resulting in a historical tsunami with a height of more than 39 m. More than 24,000 people were reported dead or missing as a result of this tragic event (Mimura et al., 2011).

The United States' coasts are vulnerable to far-field and near-field tsunami hazards (Titus et al. 1984). According to Atwatar et al. (2005), the most significant near-field hazards are linked to subduction zones in Cascadia, Alaska, and the Caribbean, and subsidence caused by a repeat of the massive 1700 Cascadia earthquake would result in a relative sea-level rise of up to one meter along with parts of coastal Oregon, Washington, and northern California. In addition, Atwatar et al. (2005) stated that when the 9.0 magnitude earthquake struck there, the main coastal highway, U.S. 101, became largely impassable, isolating people and making the evacuation process much more difficult. Furthermore, the Indian Ocean tsunami, which was produced by a deep-sea earthquake in northern Sumatra on December 26, 2004, was the greatest natural disaster of its type in recorded human history, killing about 350,000 people. This catastrophe serves as a good lesson on the significance of having an effective disaster management strategy (Athukorala et al., 2005).

Unpredictable disruptions (e.g., earthquakes, tsunamis, floods, landslides, traffic crashes, roadway/bridge failures) can have an impact on transportation network performance by reducing roadway capacity where the incident occurs, resulting in delays, built-up queues, and spillovers to surrounding areas in the network. (Konduri et al., 2013). According to Jenelius et al. (2011), if there is a partial decrease or complete loss of capacity on a bridge link or a road, travel time may increase, network mobility may suffer, and several changes in evacuee behavior may occur. As a result, several existing research efforts focused primarily on reconstruction methodologies, accessibility in disrupted networks, and efficient resource distribution systems to address these issues.

Sánchez-Silva et al. (2005) have proposed a resource optimization model based on transport network system operating reliability. Several possible actions can be used to optimize the distribution of resources. These measures are presented for each link concerning failures and repair rates. Therefore, if this model improves resource allocation, the accessibility of a disturbed network will be maximized. This study also showed that modeling of a decision process can consider the user's behavior as he/she travels between two centroids. Therefore, to optimize resources allocation to improve the reliability of all transport network systems, the suggested model provides a solid environment.

Another key idea is that extensive tsunami penetration inland can lead to challenges in recognizing its influence after its creation. Therefore, the widespread impact of major tsunamis has increased the need for social technologies. As a result, Koshimura et al., 2020 presented an overview of how remote sensing methods have evolved to aid in disaster response following a tsunami. The performance assessments of remote sensing technologies are reviewed with the demands of tsunami catastrophe response with a future viewpoint. Furthermore, Koshimura et al., 2020 mentioned that the strong growth of ML (machine learning) and DL (deep learning) approaches indicates a significant potential to apply a technical framework to comprehensively identify the consequences of natural catastrophes, the frequency of which has increased in recent years.

2.2. Transportation resilience

Many concepts have been used and studied to study the performance of transportation systems, especially when they are vulnerable and susceptible to multiple and different disturbances ranging from a day to day fluctuation to rare natural disasters, such as reliability, robustness, flexibility, and resilience, and when compared to other terms, resilience focuses more on the performance reduction and resilience (Zhou et al., 2019). When confronted with potential activity-interrupting disturbances, infrastructure resilience is defined as its ability to maintain normal and pre-disruption levels of functionality. As a result, for the system to be resilient, it must be able to return to pre-disturbance performance levels or higher (Middleton & Latty, 2016).

The term "resilience" is derived from the Latin word "resiliere," which means to leap, recoil, or spring back. The resilient concept has been introduced to a variety of disciplines and fields, including economics, organization, engineering, social science, and supply chain management. Although there are various explanations for resilience in various fields, the majority of these interpretations are based on the same idea: resilience is a system's ability to return to its normal state after being subjected to disruptions that change its state (Zhou et al., 2019). According to D'Lima and Medda (2015), resilience is a measure of how long a system can withstand disturbances and changes while maintaining the same relationships between state variables and populations. Furthermore, a system is resilient when it can adjust its functioning before, during, and after interruptions and disturbances, allowing it to continue to function as needed after a disruption and in the presence of ongoing stresses (Dekker et al., 2008). In addition, when discussing the resilience approach, two important aspects must be mentioned: criticality and exposure. The criticality of a segment refers to how important it is for the transportation of people and commodities while allowing access to vulnerable populations. Furthermore, the criticality of a transportation network asset determines the system's impact if that asset is disrupted. Thus, the system's resilience is determined by the exposure and criticality of these assets to various hazards and disturbances (Weilant et al., 2019).

According to Holling (1973), resilient infrastructure systems are those that maintain their functionality while also exhibiting an adaptive response to disruptive events. In light of the importance of transportation in emergency response, policymakers are paying closer attention to the resilience of transportation networks. Since infrastructure can be defined as a group of components that must interact and interconnect with one another for a system to function and achieve the desired result, these components must work in a way that increases a system's efficiency and makes it more resilient to natural hazards (Alderson et al., 2015).

Several attempts and studies have been established to study and measure the resiliency of supply chain networks during and after disruptions. Their efforts were concentrated on analyzing the performance of the SCNs and how these systems would function in the face of these disruptive events. Simonovic and Peck (2013) introduced the quantitative resilience measure, and Cutter did as well (41Cutter et al., 2008). This quantitative measure is distinguished by two characteristics. The first quality is “inherit” (here, the system will function normally during non-disaster periods), and the second is “adaptive” (systems well respond flexibly during disastrous events). These techniques can be used to assess social systems, physical environments, economic systems, and governance networks. Another study proposed matrices for measuring resiliency based on the expected degradation in a system's equality by quantifying redundancy, resourcefulness, robustness, and rabidity to recovery (Bruneau & Reinhorn, 2007). Regarding Simonovic and Peck (2013), it was proposed an approach to adapt multiple scenario simulations using the CBRS (Coastal Megacity Resilience Simulator) model to aid in the development of various adaptation policies, resource allocation decisions, and the prioritization of disaster management investment to increase network resilience.

Furthermore, another study proposed a method to measure network resilience based on the observation that resilient systems reduce the likelihood of failure and increase recovery, and as a result, resilience can be measured by the performance of an infrastructure system after an external chock, including the time required to return to the initial level of performance (Tierney & Bruneau, 2007). To deal with localized interruptions, Fang et al. (2019) presented a p-robust optimization model for infrastructure networks. The proposed model aims to improve network resilience by not only reducing system vulnerability to hazards but also incorporating the order of the repair sequence of destructed components under limited repair resources into pre-event system planning, which will protect the system from an immediate performance drop following an interruption event.

Another essential point to emphasize here is the influence of tsunami and earthquake pressures on coastal buildings, particularly bridges in Oregon state. More than 7,500 highway bridges in Oregon are listed in the 2013 National Bridge Inventory FHWA (2015), with more than half of those constructed before 1975 and designed with seismic demand much lower than contemporary seismic requirements and projected seismic activity in the region. This is significant because geologic data suggests that there is a 37% chance of a subduction zone earthquake of magnitude 8.0 or larger near the southern Oregon coast (Burns et al., 2021). Moreover, according to Goldfinger et al. (2012), there is a 15% chance that an earthquake of 9.0 magnitude or greater would strike the region encompassing Oregon, British Columbia, and Washington in the next 50 years. A magnitude 9.0 earthquake will not only cause massive damage to bridges as a result of ground shaking but will also cause severe ground collapses and wave flooding. As a result, owing to bridge damage along the shore, the transportation network will be affected (FHWA, 2015).

There are several initiatives underway to offer risk assessments and anticipate the consequences of probable disruptive events to bridges in a high-way network owing to seismic risks. The Risk of Earthquake Damage for Roadway Systems is one of the methods used by Werner et al. (2006) to forecast possible seismic losses and prioritize bridge retrofits and considerations for bridge reconstruction. Another tool is the FEMA program HAZUS-MH, which is frequently used by government organizations to prioritize funding (FEMA, 2010). Another major method has been taken in analyzing the possible seismic reaction of bridges, and the projected amount of damage is depicted as fragility curves (Shinozuka et al., 2000). However, one of the crucial data requirements is the link between the level of devastation to a bridge and the resultant loss of functionality of the network component, which is significant and important in understanding the repercussions of an earthquake occurrence (Padgett & DesRoches, 2007). In general, these techniques aid in the development of frameworks for analyzing transportation network disruptions, allowing for the prediction of restricted access to emergency routes, economic losses due to disrupted traffic flow, and network damage in general (Padgett & DesRoches, 2007).

Another important notion that should be highlighted here is that Kameshwar et al. (2019) focused on increasing the resilience of communities under multiple disruptive events. To do so, the proposed a probabilistic decision support framework for this purpose. The framework evaluates the impact of decision support choices such as hazard selection, resilience objectives, and mitigation and response methods to find solutions that can enhance infrastructure performance and achieve community-defined resilience goals. By using Monte Carlo simulation, they were able to propagate restoration, uncertainties in damage, and economic losses in a framework. They then use the Monte Carlo simulation findings to build a Bayesian network. The findings highlight the significance of considering multiple performance targets as well as the interdependence of diverse infrastructure systems in terms of infrastructure resilience.

2.3. Evacuation strategies

Following a discussion of the impact of natural disasters on various aspects of life and the severity of these events on the functionality of transportation networks, well-developed evacuation plans are critical and essential during these disruptive events such as tsunamis, earthquakes, floods, hurricanes, and so on. This is because many individuals just do not know what to do in the event of a grave emergency or what the best evacuation strategy is to be followed. The evacuation procedure may be characterized as a temporary movement of individuals from a dangerous area to a safer location. Every 2-3 weeks, an evacuation of 1000 persons or more takes occurs in the United States (Dotson & Jones, 2005). Although, the evacuation procedure is an efficient technique since it assists in removing people from the dangers of natural catastrophes such as tsunamis, earthquakes, and floods, Lindell (2013) stated that it cannot be always regarded as the right reaction to all dangerous circumstances. Lindell (2013) explained that by stating that in certain cases, the hazard's characteristics, such as earthquakes and tsunamis, preclude evacuation. As an example, earthquakes and tsunamis often give little forewarning, making pre-impact escape impossible. Furthermore, certain tornadoes, hazardous chemicals, and radioactive occurrences have such a quick start and brief duration that evacuation might enhance rather than lessen the risk to inhabitants in the risk region. Evacuation would also be inadvisable in any situation when the danger of mobility outweighed the risk of remaining in place, such as when evacuating intensive care patients. Therefore, a wide range of evacuation models with varying objectives has been tested.

There are two types of evacuation models: structural evacuation and vehicle-based evacuation. Structure evacuation refers to the procedure of evacuating pedestrians from structures such as theaters, skyscrapers, and stadiums (Bin Obaid et al, 2020). An illustration of the structural evacuation process proposed by (Kisko & Francis, 1985). Kisko and Francis (1985) presented a computer algorithm in this study to find the best building evacuation strategies. This approach provides the best method for removing individuals from risky regions as quickly as feasible. Car-based evacuation, on the other hand, includes both private vehicle evacuation and mass-transit evacuation, such as the bus-based evacuation plan given by (Margulis et al., 2006). Margulis et al. (2006) created a scalable and adaptable deterministic evacuation decision support model that would allow the development of a comprehensive decision support system that would allow decision-makers to optimize the number of persons evacuated during disruptive occurrences.

Moreover, according to Bish et al. (2014), an evacuation model was developed to determine traffic flows using the CTM (cell transmission model) proposed by Daganzo (1994) and modified to be utilized in LP (linear programming) by Ziliaskopoulos (Ziliaskopoulos, 2000). This LP framework is an excellent choice for a strategic planning model since it gives a clear depiction of traffic flows while being analytically tractable, allowing it to be utilized as a foundation in other evacuation studies. Finally, Mostafizi et al. (2019) propose an agent-based multi-modal near-field tsunami evacuation modeling framework in Netlogo to study how decision time, mode of transportation, and other variables (i.e., walking speed and driving speed) will impact the estimation of casualties under tsunami hazard. This novel agent-based modeling framework is used to detect and categorize the criticality of network links based on their failure impact on evacuation mortality rates, and so it is used to create the ideal retrofitting strategy for the network's critical links.

2.4. Fairness in evacuation planning:

In the aftermath of natural disasters, the primary goal is to effectively relocate the threatened population to safer areas. The performance of traffic networks may be reduced as a result of the drastic changes in traffic demand that occur during or after a disruptive event. Furthermore, depending on the nature of the natural disaster, some entities in the transportation network may become inoperable, affecting the network's connectivity, reliability, capacity, and safety. As a result, proper emergency evacuation management and planning are critical to mitigating the devastation caused by natural disasters (Aalami & Kattan, 2020).

In general, there are two types of emergency evacuation modeling approaches: analytical and simulation-based. Analytical models provide answers to questions like "what to do?" to create a proper evacuation plan, whereas simulation-based models provide answers like "what if?" As a result, analytical evacuation models can be used directly to find the most efficient evacuation plans, whereas simulation-based evacuation strategies are more convenient for evaluating evacuation plans but do not directly create them (Osorio & Bierlaire, 2013). Depending on the type and severity of natural disasters, different objectives for evacuation planning can be established. According to Oxendine et al. (2012) and Rabbani et al. (2016), one of the most common objectives studied by researchers is minimizing both total evacuation time and loss of life and property, particularly in neighborhoods with high population densities. Furthermore, minimizing total in-network time and network clearance, as presented by Zhang and Haghani (2016), and maximizing the number of evacuees relocated to safer areas in a given time window, as illustrated by Pillac et al. (2016), are two of the most important goals that have captured the attention of researchers in this field. Furthermore, resource allocation is crucial and fundamental in emergency evacuation planning. This critical strategy is a hotly debated topic in academia. Even the most straightforward cases end with the debate over fairness versus efficiency (Zukerman et al., 2005).

Another critical point to emphasize here is that when tsunamis occur, evacuees are usually advised to go to the nearest shelter with the shortest route. However, to avoid inundation, it is sometimes necessary to take a detour that may result in more time for safe evacuation rather than taking the shortest route of the evacuation process. Thus, Kitamura et al. (2020) conducted a study to develop an allocation strategy for evacuees and evacuation routes to reduce the number of casualties in all tsunami scenarios. In their study, the proposed model calculates the amount of time left for each evacuee to reach a safe location using various combinations of shelters and routes. The combination that provides the greatest amount of time for each evacuee is then chosen, and an evacuation plan for all evacuees is obtained. Following that, this process is repeated for other possible tsunami scenarios, and several evacuation simulations are performed for all obtained plans with other tsunami scenarios, and the number of fatalities is calculated. Then, as the optimal plan with the fewest accumulated casualties, an evacuation plan is selected. This method was proven to be effective because it reduced the number of fatalities by approximately 40% on average.

According to Flötteröd and Lämmel (2010), several factors, such as traffic, technical, hydraulic, hydrological, and social characteristics, influence the fairness and efficiency of the flood-induced evacuation process of urban areas. The evacuation plan must include, in particular, hard infrastructure that protects people from natural disasters such as earthquakes and tsunamis (Yamuri & Sugiyama, 2020). As a result, several evacuation studies have optimized the properties of the shelters, such as their locations, numbers, and capacity, due to their importance and ability to reduce the required time of the evacuation process, increasing its efficiency (Yin et al., 2014). To elaborate, previous research has shown that shelter capacity has a significant impact on the effectiveness of evacuation management (Lim et al., 2013). Although in some cases, shelter capacity may be less important to the efficiency of the evacuation process, such as when evacuees can either stay at their homes or evacuate to higher ground, as explained by Johnstone (2012), numerous studies have defined shelter capacity as a constraint in location-allocation models of evacuation problems because of the distribution of shelter capacity (Kongsomsaksakul et al., 2005). As an example of the previous concept presented by Oh et al. (2021), a model was developed to investigate the impact of shelter capacity on the fairness of the evacuation process. According to the findings, the distribution of shelter capacity has a greater impact on the efficiency (evacuation duration) of the evacuation process, whereas fairness changes more noticeably to the evacuation priority assigned to the divided zones in staged evacuation.

Finally, Yan et al. (2018) considered both efficiency and social fairness in an emergency evacuation, initially proposing and embedding in system optimal (SO) objective function a weight function consisting of risk evaluation index as variable and managers' emphasis degree on social fairness principle as a coefficient. The linear program (LP) model was developed to simulate dynamic traffic assignment in the emergency evacuation by combining the weight function and additional restrictions based on an expanded cell transmission model (CTM).

3. Fair-evacuation distribution model

The used fairness-based evacuation distribution model was developed in this part by (Abushaega et al., 2021). We enhanced this model by incorporating different modes of transportation (such as pedestrians and cars) and implementing the proposed fairness-based distribution strategy on a Seaside. OR transportation network.

In this section, we discuss the proposed fairness-based evacuation distribution model, starting with a description of the model's specific goals and related assumptions. Then we provide a detailed model description, including the proposed mathematical formulation as well as the nature of the variables, constraints, and objective functions used.

3.1. Fair-evacuation distribution model discussion

Under the impact of disruptive events such as Tsunami, this model is designed to transfer people from supply nodes (sectors contain the population needed to be dislocated) to demand nodes (emergency facility centers and assembly areas) and fairly distribute them among these facilities while at the same time minimizing the associated costs (i.e. time, priorities, penalties, etc.) of transferring people through the network. Moreover, the fairness concept here is achieved by minimizing both the positive and negative deviations of not fulfilling the required number of evacuees at the demand nodes. This model is structured to ensure that all demand nodes are getting the minimum required service level. The number of evacuees assigned to each emergency facility center and assembly area is what we mean by the minimum required service level of demand nodes. Also, this model calculates the total percentage of unmet demands at the demand nodes, which is then used to calculate the absolute deviation from this percentage for each demand node for each type of people demand, ensuring that all evacuees have equal access to the demand nodes.

3.2. Fair-evacuation distribution model description

The proposed evacuation model considers the different types of people demands that need to be shifted from supply nodes to demand nodes and attempts to provide them with equal access to the demand nodes.

Because we are studying the evacuation process under tsunami hazards, we will deal with a variety of people's demands based on their basic needs in these situations. Some people, for example, must be transferred to hospitals and fire stations due to their conditions and the need for immediate critical care, whereas others must simply reach safer areas, such as assembly areas, to escape the disruptive event. As a result, this approach facilitates in providing evacuees with fair access to demand nodes based on their type of demand. The main sets used in the fair evacuation process model are described in Table 1. Table 2 describes the parameters used in this model, including the supply/demand of people for each node, the upper and lower capacity of each arc, the minimum required service level for each node, and the cost of transporting a single person to a demand node; this cost could be distance, time, penalty number etc. Table 3 shows the decision variables used in this model, such as the number of people transferred using each arc to meet demand nodes, a binary variable based on if the demand node is getting the required number of evacuees, and the positive and negative deviation from the total percentage of having fewer people than the actual demand at the emergency facilities and assembly areas.

Table 1: Sets

A	Set of arcs
N	Set of nodes
N^d	Set of emergency facility centers and assembly areas

N^s A set of nodes containing the number of persons who must be relocated.

K^p Set of people's demand types

M Set of transportation modes

Table 2: Parameters

---

b_{ik} Supply/ Demand of people at Node i ∈ N for type of people demand k ∈ K^p

d_{ij} Distance of arc (i,j) ∈ A

u_{ijm} Maximum capacity of the arc (i,j) ∈ A using transportation mode m ∈ M

l_{ijm} Minimum capacity of the arc (i,j) ∈ A using transportation mode m ∈ M

α_{ik} Minimum required service level of node i ∈ N^d for each type of people demand k ∈ K^p

f_{ik}^{+} Cost of having an excessive number of people at each sector i ∈ N^s for each type of people demand k ∈ K^p

f_{ik}^{-} Cost of having unmet demand at each emergency facility center and assembly area i ∈ N^d for each type of people demand k ∈ K^p

co_{ik} Cost of not meeting the minimum required service level at node i ∈ N^d for each type of people demand k ∈ K^p

c_{ijm} Unit cost of moving single person to emergency facility center j ∈ N^d or assembly area j ∈ from their residence i ∈ N^s using transportation mode m ∈ M

β Total available budget

Table 3: Decision variables

$$y_{ijm} = \begin{cases} 1 & \text{if the arc } (i,j) \in A \text{ is used using transportation mode m} \in M \\ 0 & \text{otherwise} \end{cases}$$

x_{ijkm} The number of people transferred using arc (i,j) ∈ A for each type of people demand k ∈ K^p using transportation mode m ∈ M

μ_{ik}^{+} Positive deviation from the total percentage of having fewer people than the actual required demand at the emergency facility center and assembly area i $\in N^d$ for each type of people demand k $\in K^p$

μ_{ik}^{-} Negative deviation from the total percentage of having fewer people than the actual demand at each emergency facility center and assembly area i $\in N^d$ for each type of people demand k $\in K^p$

s_{ik}^{+} Excessive number of people at each supply node i $\in N^s$ for each type of people demand k $\in K^p$

s_{ik}^{-} Unmet demand at each emergency facility center and assembly area i $\in N^d$ for each type of people demand k $\in K^p$

$$\delta_{ik} = \begin{cases} 1 \; if \; node \text{ i} \in N^d didn't get \; minimum \; service \; level \; of \; each \text{ type of people demand } \text{k} \in K^p \\ 0 \quad otherwise \end{cases}$$

γ_k Total percentage of unmet demand at the emergency facility centers and assembly areas for each type of people demand k $\in K^p$

The goal of this model is to use the concept of a fairness-based distribution strategy to improve the efficiency of the evacuation process in Seaside, Oregon, which is under threat from a tsunami. This model aims to provide evacuees with fair access to demand nodes based on their type of demand. As a result, this fair evacuation model aims to satisfy two objective functions to accomplish the desired result.

The first objective function, designated by O1, is to minimize the associated costs, which include the cost of transferring evacuees from supply to demand nodes as well as the penalties associated with failing to supply the required number of people or meeting the desired service level at emergency facility centers. The corresponding objective function is represented by Eq (1). The first term in Eq (1) represents the per-mile flow cost of transporting a single person to an emergency facility center for each type of people demand. The cost of not satisfying the requisite demand at each demand node is the second term in Eq (1). The third term in Eq (1) reflects the cost of having surplus supply at each supply node for each sort of people demand. Finally, the cost of not meeting the minimum required service level for each type of people demand in each demand node is associated with the last term of Eq (1).

Minimize

$$O1 = \sum_{m \in M} \sum_{k \in K^p} \sum_{(i,j) \in A} x_{ijkm} \cdot d_{ij} \cdot c_{ijm} + \sum_{k \in K^p} \sum_{i \in N^s} s_{ik}^{+} \cdot f_{ik}^{+} + \sum_{k \in K^p} \sum_{i \in N^d} s_{ik}^{-} \cdot f_{ik}^{-} + \sum_{k \in K^p} \sum_{i \in N^d} co_{ik} \cdot \delta_{ik} \tag{1}$$

The second objective, denoted by O2, shows the average deviation (the negative and positive deviations) of unmet demand for each type of people demand at each demand node. The significance of having the fairness-based distribution strategy in separate objectives is to compare the obtained results when attempting to reduce total distances that evacuees should travel with and without considering the fairness-based distribution strategy. Because the penalty cost of maintaining the minimum required service level is difficult to quantify and the model is designed to deal with multiple types of people demand, determining the evacuees' distribution without a focus on the fairness-based distribution strategy is difficult. By forcing the model to minimize the total average deviation of unfulfilled demand, the bias towards the nodes with the highest demand is minimized to a minimal minimum.

Minimize

$$O2 = \frac{\sum_{k \in K^p} \sum_{i \in N^d} (\mu_{ik}^{-} + \mu_{ik}^{+})}{| N^d |} \tag{2}$$

This model considers multiple restrictions concerning the effectiveness of the evacuation procedure, reducing the initial network capacity and the tsunami's perturbing effects on the transport network functionality. For example, the effects of this type of disturbance might reduce the number of people traveling over each arc, the inability to supply the number of evacuees, fluctuating demand nodes, and problems in the emergency facilities.

The first constraint is related to the process's available budget (β), as shown in Eq (3). This constraint calculates and assures that the overall costs of transporting people across network arcs for all sorts of people demand for all forms of transportation are less than or equal to the entire budget allocated.

$$\sum_{m \in M} \sum_{k \in K^p} \sum_{(i,j) \in A} x_{ijkm}\, d_{ij}\, c_{ijm} \leq \beta \tag{3}$$

The link capacity constraint, as shown in Eq (4), is the second constraint. This constraint specifies how much flow (x_{ijkm}) can be distributed and travel through each arc in the network for each type of people demand. If the arc is functional, the flow through it should be equal to or greater than the arc's minimum capacity (l_{ijm}). The variable (y_{ijm}) denotes the functionality of each arc and is 1 if the arch is operational and 0 otherwise. Furthermore, the flow through each arc should be less than or equal to the maximum capacity of each arc (u_{ijm})

$$y_{ijm}\, l_{ijm} \leq x_{ijkm} \leq u_{ijm}\, y_{ijm}\,, \qquad \forall\, (i,j) \in A, \forall k \in K^p\,, \forall\, m \in M \tag{4}$$

The flow balance constraint is the third constraint as shown in Eq (5). This constraint computes the value of subtracting the number of evacuees entering each node from the number of evacuees leaving each node, and the sum of these values should equal the required demand of each node, whether it is a supply or demand node. Furthermore, if a node has any unmet demand or excess supply for each type of people demand, these values (s_{ik}^{-}, s_{ik}^{+} respectively) should be added or subtracted to the balance constraint equation to make it balanced depending on whether it is a supply or demand node.

$$\sum_{j:(i,j)\in A} x_{ijkm} - \sum_{j:(j,i)\in A} x_{jikm} = b_{ik} + s_{ik}^{-} - s_{ik}^{+} \qquad \forall\, i \in N^d, \forall k \in K^p, \forall\, m \in M \quad (5)$$

Eq (6) is formulated to ensure that all emergency facility centers and assembly areas will receive at least the minimum required service level (α_{ik}). This can be ensured by calculating the value of subtracting the number of evacuees entering each node from the number of evacuees leaving each node, and the sum of these values should equal to the minimum required service level of each demand node. If the binary variable (δ_{ik}) equals one from this equation, it indicates that the minimum required service level of demand nodes was not satisfied.

$$\sum_{j:(i,j)\in A} x_{ijkm} - \sum_{j:(j,i)\in A} x_{jikm} \leq \alpha_{ik} b_{ik}(1 - \delta_{ik}) \qquad \forall\, i \in N^d, \forall\, k \in K^p, \forall\, m \in M \quad (6)$$

According to Eq (7), the total percentage of having fewer people than the actual demand at all emergency facility centers and assembly areas (γ_k) is equal to the sum of unmet demand at each demand node of each type of evacuees' demand (s_{ik}^{-}) divided by the total demand that needed at the demand nodes for all type of evacuees' demand (b_{ik}).

$$\frac{\sum_{k\in K^p} \sum_{i\, \in\, N^d} s_{ik}^{-}}{\sum_{k\in K^p} \sum_{i\, \in\, N^d} b_{ik}} = \gamma_k \qquad \forall\, k \in K^p \qquad (7)$$

Because this model is intended to provide evacuees with equal access and distribute them fairly between emergency facility centers and assembly areas, the absolute deviation from the percentage of unmet demand at each demand node for each type of people's demands to the total percentage of unmet demand in the whole network is calculated. It indicates that we are measuring the average distance between each unmet demand for each type of people demand in each demand node and the total percentage of unmet demand in the network's demand nodes. As a result, Eq (8) is developed to calculate the absolute deviation in which (μ_{ik}^{+}) and (μ_{ik}^{-}) represent the positive and negative deviations from the total percentage of unmet demand.

$$\frac{s_{ik}^{-}}{b_{ik}} - \gamma_k + \mu_{ik}^{-} - \mu_{ik}^{+} = 0, \qquad \forall\, i \in N^d, \forall\, k \in K^p \tag{8}$$

Finally, Eqs (9) – (16) represent the nature of the decision variables

$$y_{ijm} \in \{0,1\} \qquad \forall\, (i,j) \in A,\ \forall m \in M \tag{9}$$

$$x_{ijkm} \geq 0 \qquad \forall\, (i,j) \in A,\ \forall\, k \in K^p,\ \ \forall\, m \in M \tag{10}$$

$$s_{ik}^{+} \geq 0 \qquad \forall\, i \in N^s,\ \ \forall k \in K^p \tag{11}$$

$$s_{ik}^{-} \geq 0 \qquad \forall\, i \in N^d,\ \ \forall\, k \in K^p \tag{12}$$

$$\mu_{ik}^{+} \geq 0 \qquad \forall\, i \in N^d,\ \ \forall\, k \in K^p \tag{13}$$

$$\mu_{ik}^{-} \geq 0 \qquad \forall\, i \in N^d,\ \ \forall\, k \in K^p \tag{14}$$

$$\gamma_k \geq 0 \qquad \forall\, k \in K^p \tag{15}$$

$$\delta_{ik} \in \{0,1\} \qquad \forall\, i \in N^d,\ \ \forall\, k \in K^p \tag{16}$$

4. Case study

The network utilized in this study to apply the fairness-based evacuation distribution model is connected with Seaside City, Oregon, and includes all of its buildings, transportation network, and emergency facility centers and assembly areas. We chose Seaside City as a tested community because its flat topography and its location along the northern Oregon coast and is especially vulnerable to the Cascadia subduction zone, with about 87 percent of built land falling inside the tsunami inundation zone as shown in Fig. 1 (Wood, 2007). Additionally, Seaside City has a resident population of around 6500 people; but, because it is a tourist destination, its population might surpass 20,000 people which makes it more complex. As seen in Fig. 2a, Seaside has only one hospital, one electric substation, one water treatment facility, and one fire station due to its tiny population. Residents' access to these amenities, however, is dependent on 13 bridges because the city is separated into three sections by a river and a creek (Kameshwar et al., 2019).

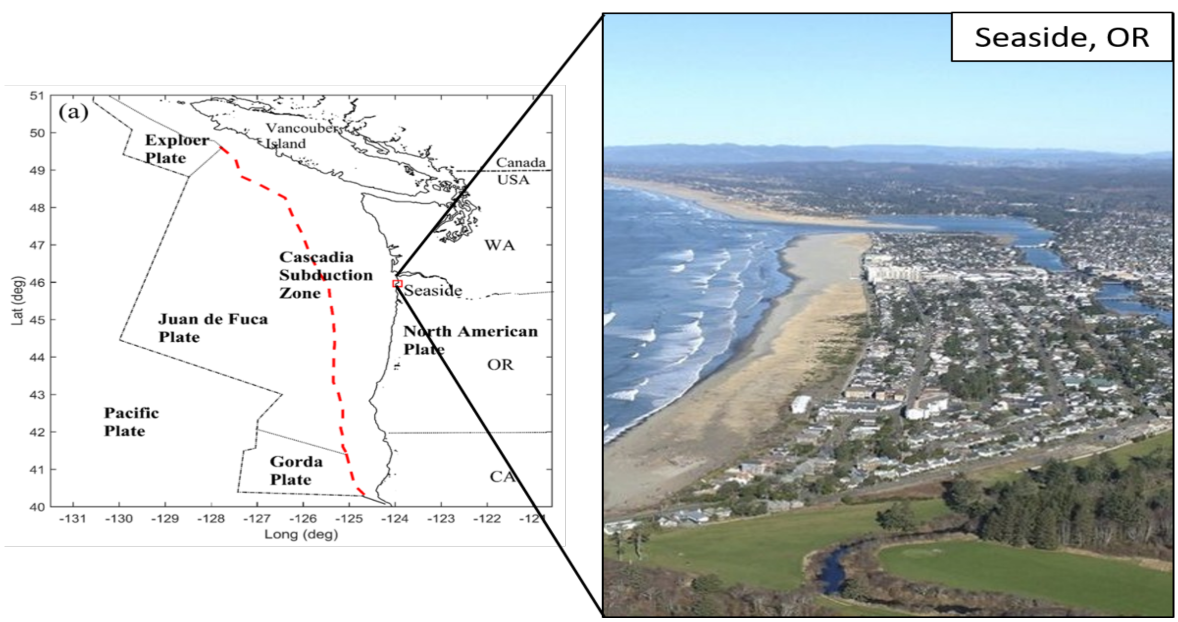

Figure 1. Cascadia subduction Zone site map of the Pacific Northwest Coast (CSZ), *TarunAdluri. (n.d.). Tarunadluri/seaside_optimization. GitHub. Retrieved November 22, 2021, from https://github.com/TarunAdluri/Seaside_Optimization.*

The elevation of the Seaside city from sea level is seen in Fig.2b. We can see that almost the whole city is located in the tsunami inundation zone, making it more vulnerable to tsunami impacts. Numerous studies have been conducted to identify mitigation, response, and recovery strategies that are required to limit the impact of this sort of natural hazard.

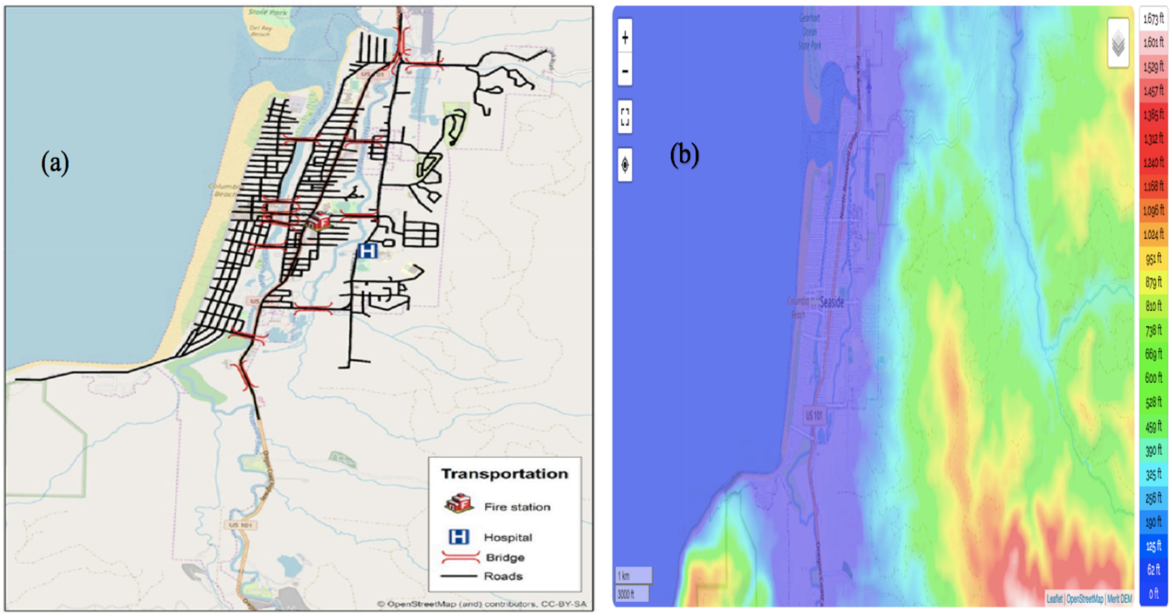

Figure 2. (a) Transportation network in Seaside, OR and the locations of both the hospital and fire station, (b) Seaside, OR elevations https://en-us.topographic-map.com/maps/rug1/Seaside/

Because the supply chain network used in this study is linked to Seaside, OR, we obtained the number of people who need to be evacuated to safer areas from (IN_CORE) which is 3157 people. As illustrated in fig.3a, these persons came from 4453 different buildings. However, to simplify the difficulty of dealing with the 4453 supply nodes, we aggregate these buildings into different sectors based on their addresses we acquired from (IN_CORE). As a result, we got a total of ten sectors that contain all the 4453 buildings, so constructing our supply nodes in our model. These 3157 people should be transported to ten demand nodes, which include eight assembly sites, one hospital, and one fire station, based on their associated capacity and the type of people demands.

Wang et al. (2016) established these eight assembly areas and their locations, which are located outside of the tsunami inundation zone, as shown in Fig.3b.

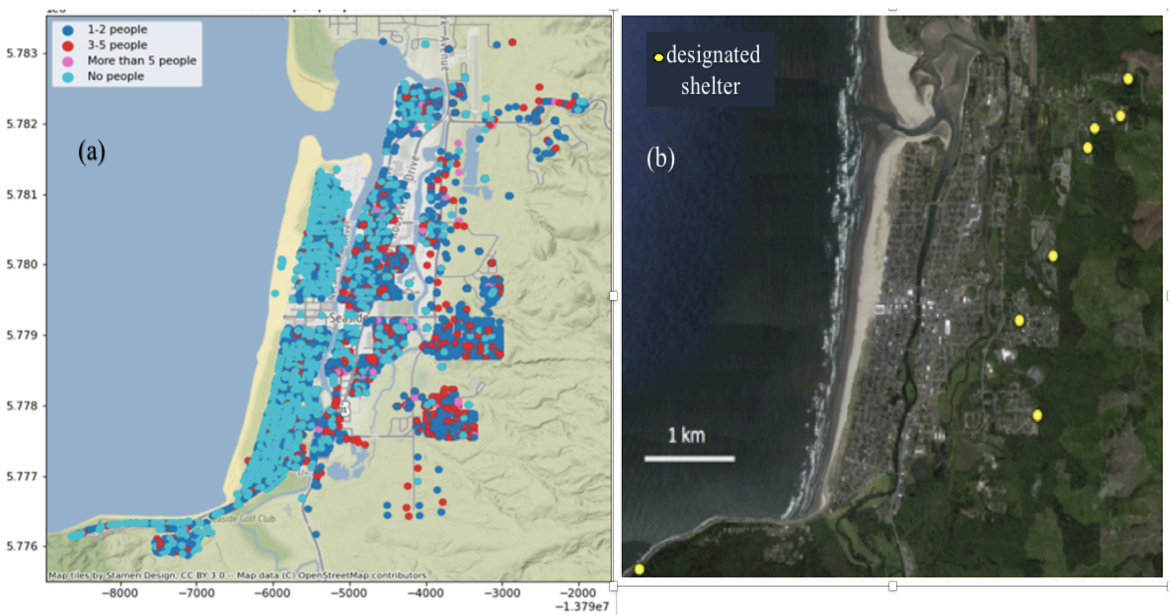

Figure 3. (a) Seaside population that need to be dislocated to safer regions obtained from IN-CORE, (b) The yellow points represent the eight shelters that are located outside the tsunami inundation zone

Moreover, we selected two categories of people demand in this study. The first is associated with persons who require emergency medical assistance and should be sent to a hospital or a fire station. The second type of person demand is for people to be allocated to safe zones, which requires them to be transferred to one of the eight assembly sites or the fire station.

Regarding the transportation modes, we believed that we had two alternatives. The first is that people would walk to safer areas to escape potential congestions and delays. Cars are another means of transportation that can help those who need to be transported as quickly as possible. We were able to establish the maximum and minimum capacity of each link of the transportation network by determining the prior. Furthermore, we calculated efficiency by measuring the number of demand nodes that do not obtain the needed service level for each demand. Additionally, for the four costs that we have in the first objective function, we assume each of them based on the type of people demand, whether it is for excess supply, unmet demand, or the penalty cost associated with failing to maintain the needed service level at each demand node. To highlight further, for those who require emergency critical care, we gave large numbers for costs, whether these costs are due to excess supply, unmet demand, or failure to provide the required service level. As a result, the model will try to reduce these high costs as much as possible, and in doing so, the model is prioritizing this sort of demand and attempting to satisfy it first. Finally, we assumed that the flow cost was proportional to the distance between nodes.

To summarize, the Seaside City network is made up of supply nodes that are divided into ten sectors that include the whole population that has to be evacuated to safer places. There are ten demand indications, which are eight assembly areas located beyond the tsunami inundation zone, one hospital, and one fire station. We have 100 arcs connecting the supply nodes to the demand nodes.

Fig.4a depicts a simulation of persons in each sector being allocated to each of the tenth demand nodes we have, and this would apply to the other sectors. Furthermore, fig.4b depicts Seaside City's transportation network, which connects supply and demand nodes.

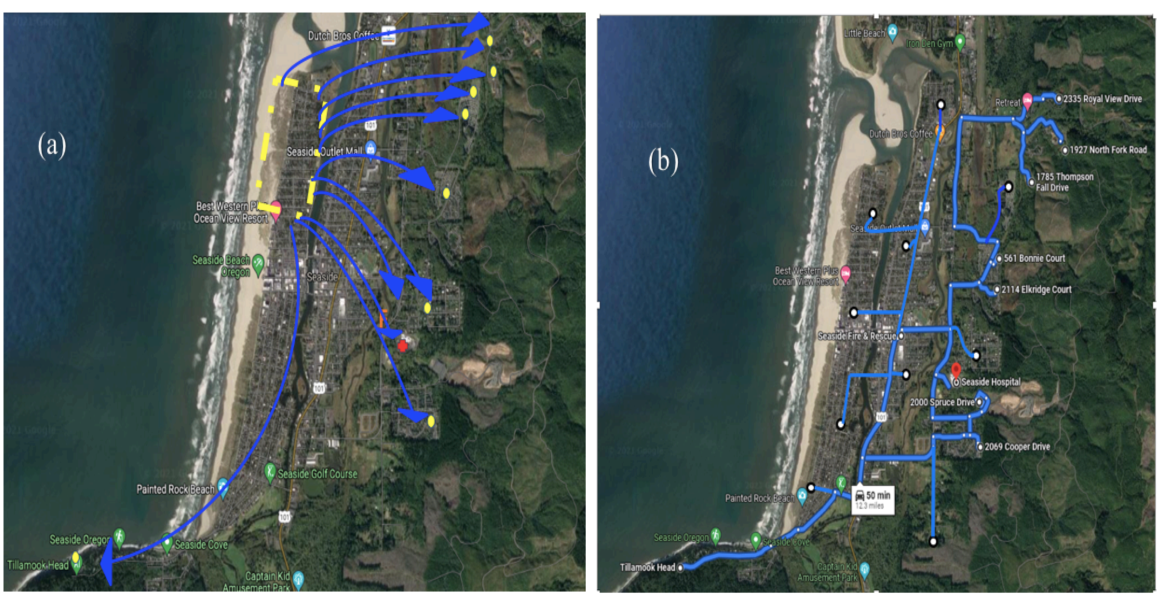

Figure 4. (a) simulation of persons in each sector being allocated to each of the tenth demand node, (b) Seaside City's transportation network, which connects supply and demand node.

4.1. Results and discussion

In this section of our research, first we ran our model without taking the fairness concept into account, merely reducing overall distances and the related surplus supply, unmet demand, and not getting the required service level costs. Then we ran it while considering the fairness distribution strategy, concentrating on aiming to reduce the average deviations of unfulfilled demand nodes for all types of people type of demand in the whole network. Following that, we performed a sensitivity analysis to see how the minimum required service level in each demand node and the upper capacity of each arc affected the overall findings. We chose to conduct these two analyses because the first would provide appropriate direction for decision-makers on how to utilize limited resources and supplies and effectively shift them to meet the needs of evacuees in each assembly area, hospital, and fire station. The second study then assists decision-makers in determining the number of individuals that should pass through each arc to prevent congestion or delays, thus increasing the efficiency of the evacuation process.

4.1.1. Results with and without considering fairness-based distribution strategy

In this section of the research, we used the model to minimize the first objective function, which is the total distances that evacuees must travel to reach safer places. Then we ran it with the second goal function, reducing the average deviations of the whole demand in the demand nodes for all people's demand types. Then we compared the results of both cases in terms of the number of people we were able to transfer, the total distances that should have been traveled to reach safer areas, the total average deviation of unmet demand in demand nodes, and finally the number of demand nodes that did not receive the minimum required service level. The findings are shown in Table 1.

Table 1: Comparison between Objective function1 and Objective function 2 results

Results	Objective function 1	Objective function 2	Improvement (%)
Number of transferred evacuees	2520	3092	22.69
Total distance (mile)	5040	6184	21.95
Total average deviation (%)	98.71	55.38	43.89
Number of demand nodes did not get the minimum required service level	4	2	50

We can see that after implementing the fairness distribution strategy, we were able to evacuate and raise the number of persons that needed to be evacuated to safer locations from 2520 to 3092, but this increased the overall distance traveled from them. Furthermore, the fairness distribution technique helped to reduce the overall average deviation of unmet demand in demand nodes from 98.71 % to 55.38 %, and the number of demand nodes that did not receive the minimum required service level reduced from four demand nodes to only two demand nodes.

Moreover, were then able to collect the outcomes of the unmet demand deviations in the demand nodes. We can observe that all demand nodes have only positive deviations, both with and without considering fairness distribution strategy. This is because all of the observed result deviations surpassed the total percentage of unmet demand in the network's demand nodes.

As shown in fig.5, before implementing the fairness distribution strategy, we obtained high values for positive deviations up to 180 %; however, after implementing the fairness distribution strategy, we were able to reduce these values to less than 40 % in all demand nodes, despite one node having nearly a 100 % positive deviation. This is because this node has the maximum capacity, resulting in the highest related positive deviation value, as seen in fig.6.

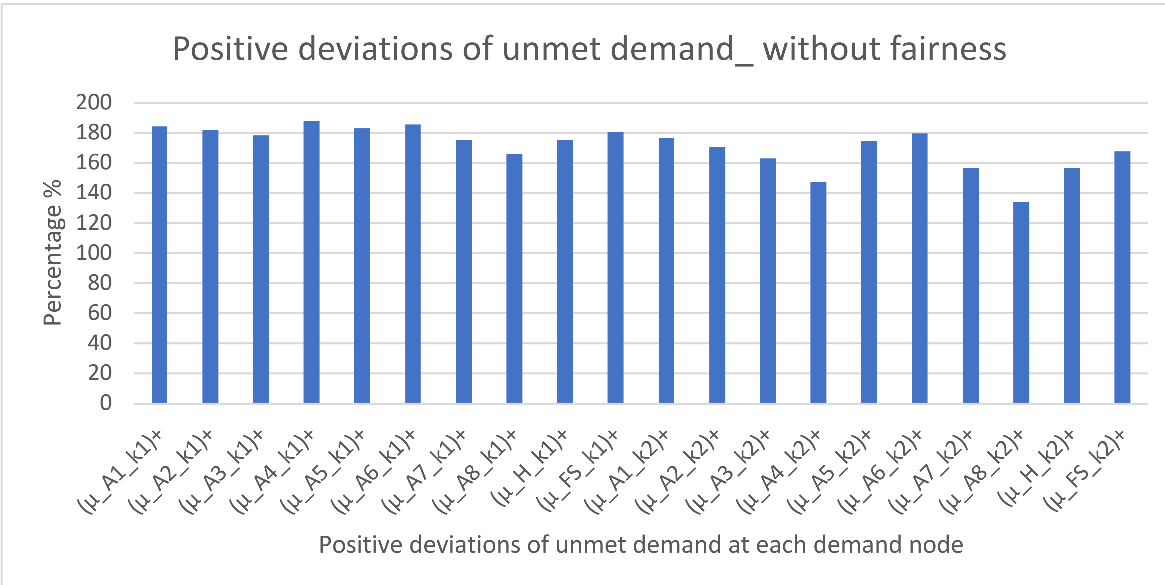

Figure 5. Positive deviations of unmet demand in the demand nodes without applying the fairness concept

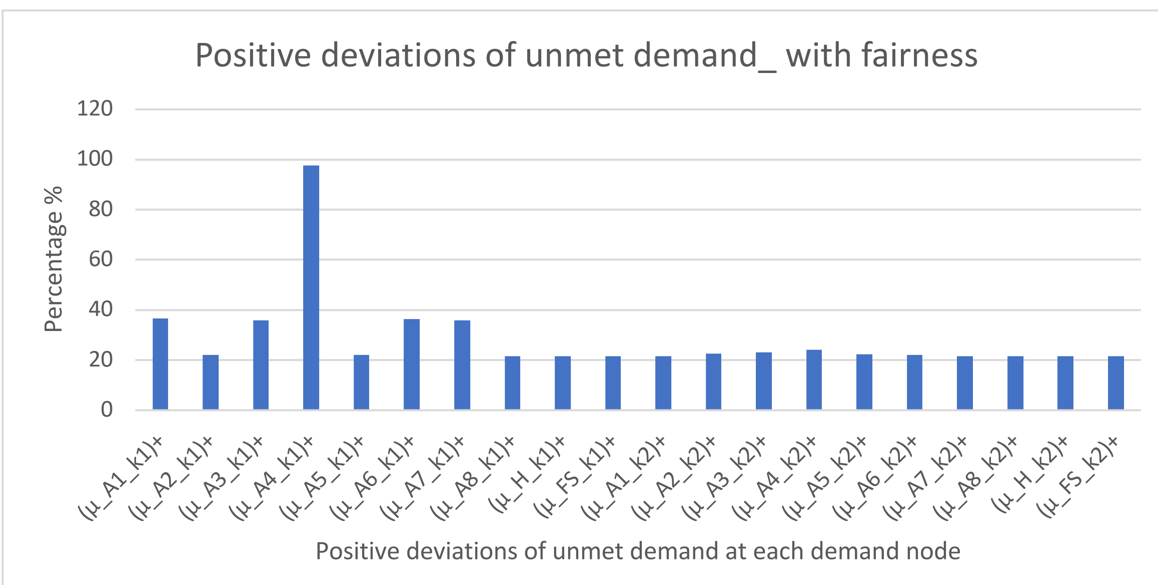

Figure 6. Positive deviations of unmet demand in the demand nodes with applying the fairness concept

To make the previous findings more obvious, we utilized shades that begin with the lightest color, which shows the lowest positive deviation values, and conclude with the darkest color, which shows the highest positive deviation values. Fig. 7 shows that before implementing the fairness distribution strategy, all of the demand nodes have the darkest colors, indicating that all of the demand nodes have large positive deviation values. However, after employing the fairness distribution strategy, all demand nodes have the lightest colors, indicating that these demand nodes have low positive deviation values.

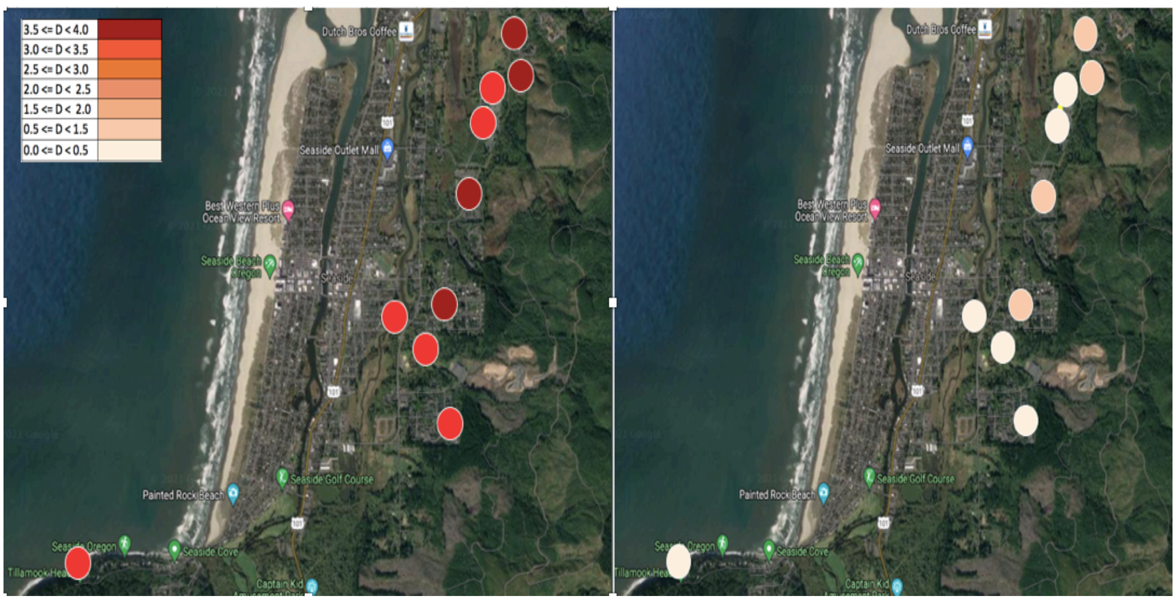

Figure 7. Different shades show the difference between the positive deviation values of unmet demand before and after implementing the fairness distribution strategy

Finally, here in this part of the study, we investigated the relationship between the first objective function and the total average deviation of unfulfilled demand in the demand nodes which is the second objective of this study. As a result, the ε-method was used to run the model with both objectives and to construct the Pareto frontier. We concentrated on minimizing the overall distance that evacuees had to go. The link between total distance that evacuees should travel and the total average deviation of unmet demand in demand nodes is depicted in Fig.7. The vertical axis indicates the average deviation of unfulfilled demand at demand nodes, while the horizontal axis reflects the total distance that evacuees must travel to reach safer places. Furthermore, fig.8 illustrates the findings by demonstrating that when the model prioritizes the first objective function; minimizing total distance, people needed to travel for relatively short distances; however, this meant that we had a few demand nodes that did not receive the minimum required service level, resulting in a higher value for the average deviation of unmet demand in the demand nodes. On the other hand, when we have a smaller value for the total average deviation of unmet demand at the demand nodes, it means that we were able to meet most of the minimum required service level of the demand nodes, while evacuees had to travel a longer distance to reach the emergency facility centers and the assembly areas.

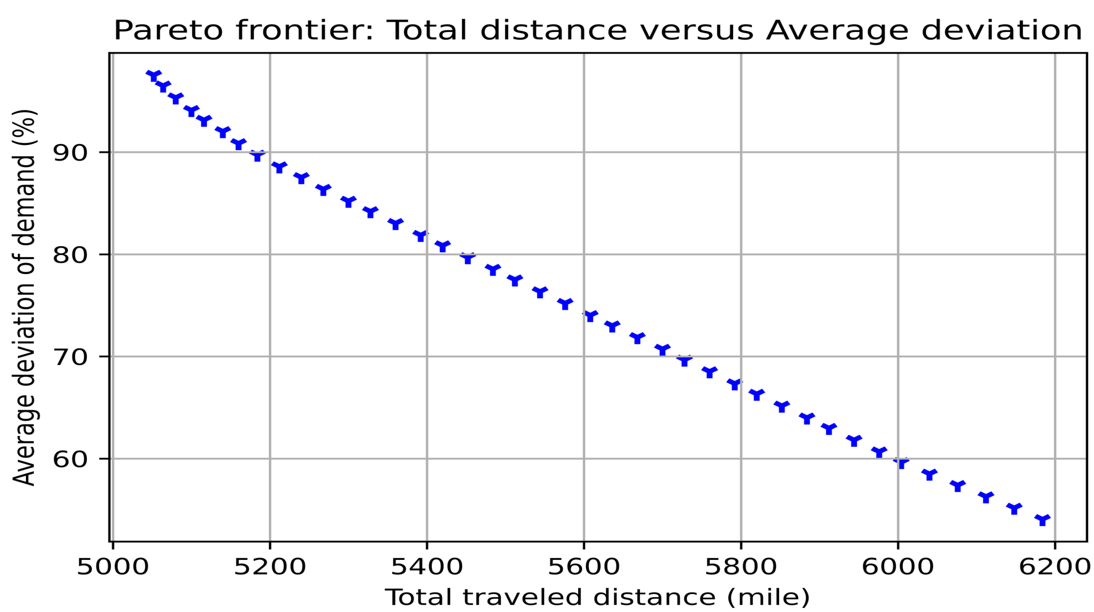

Figure 8. The correlation between the total travelled distance from evacuees and the total average deviations of the unmet demand in the demand nodes

4.1.2. Sensitivity Analysis

4.1.2.1. Minimum required service level and the number of demand nodes that did not get the minimum required service level

The minimum required service level values had been investigated in this section of the study since reducing the number of demand nodes that do not get the minimum required service level is one of the study's final goals. This is significant because identifying the best values for the minimum required service level that should be allocated to each demand node will assist decision-makers in assigning the best values. In other words, obtaining these values would aid in determining how much of the limited supplies should be allocated to each demand node based on the number of evacuees that would be available there. Therefore, we chose different percentages for the minimum required service level starting from 30 % and ending with 100%. What we meant by these percentages was deciding how much of the threatened population should be transferred to each demand node. As shown in Table 2, when we chose 30% as the percentage of each demand node's minimum required service level, we improved by guaranteeing that all demand nodes received the assigned minimum required service level. However, this % means that we were only able to relocate % of the threatened people to safer areas, which would raise the total average deviation of unmet demand in the demand nodes, which is something we were attempting to prevent. As a consequence, we examined several values for the minimum required service level of each demand node, and the final result revealed that 90 % of the threatened population would be the best value for the minimum required service level. This is because we were able to reduce the number of nodes that did not get the minimum required service level from 4 to 2 while also moving a larger portion of the threatened population.

Table 2: The minimum required service level of demand nodes and the number of demand nodes that did not get the minimum required service level

Number of emergency facility centers and assembly areas that did not receive the minimum required service level (SL)			
Test	**Without fairness**	**With fairness**	**Improvement**
30% SL D>S	10 %	0 %	10 %
70% SL D>S	30 %	10 %	20 %
90% SL D>S	40 %	20 %	20%
100% SL D>S	60 %	50 %	10%

4.1.2.2. Minimum required service level and the total average deviation analysis

In this portion of the study, we noticed that the minimum required service level for each demand node for each type of people demand assisted in lowering the total average deviation of unmet demand across all demand nodes. In other words, when we had smaller percentages for the minimum required service level at each demand node; the portion of the threatened population assigned to each demand node, we were only able to transfer a small proportion of the threatened population, resulting in demand nodes not being able to meet their required demand. As a result, large average deviations of unmet demand in demand nodes would be obtained. Fig.9 expands on the preceding notion by demonstrating that when the demand's minimum required service level was low at the demand nodes, the total average deviation was large. This is mostly due to unmet demand in the demand nodes. On the contrary, by increasing the minimum required service level value of the demand node, we were able to reduce the overall average deviation of all demand nodes. In other words, when we had a minimum required service level of 90%, we had the lowest overall deviation value, which was 56%. This means that we evacuated 90% of the population that needed to be evacuated to safer areas while maintaining a reduced average deviation in the demand nodes. Furthermore, we can see certain variations in the line depicting the relationship between the minimum required service level and the average deviation of unmet demand. This is because we were evaluating the best value of the minimum required service level of demand nodes, and some values are not optimal in this regard. These values, however, would be omitted while showing the pareto frontier, which would only exhibit the good values of the minimum required service level of the demand nodes, assisting in lowering the overall average deviations of the unmet demand in the demand nodes.

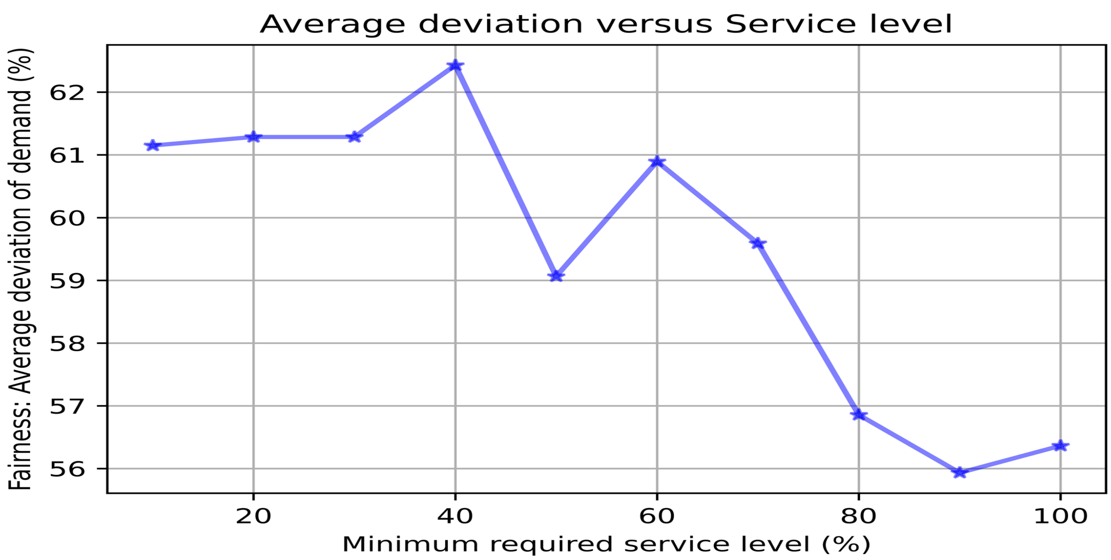

Figure 9. The minimum required service level in demand nodes versus the total average deviation of the unmet demand in the demand nodes

4.1.2.3. Increase in the link's upper capacity and the percentage of transferred people to safer areas

In this test, we wanted to evaluate how the maximum capacity of links influenced the overall number of people transported to safer regions depending on their demands. We tried different capacities for arcs, ranging from small to big capacities until we couldn't see any improvement in the number of people we could transport. Fig.10 displays the outcome by indicating that when we increased the capacities of links to 22 people moved through each arc of the transportation network, we transferred 100% of the threatened population that needed to transfer to safer locations, which was 3157 people. On the contrary, when the upper capacity of each link was limited to a small value, we were unable to evacuate the threatened population to safer areas. We can see that we kept raising the upper capacity of links only to test our concept.

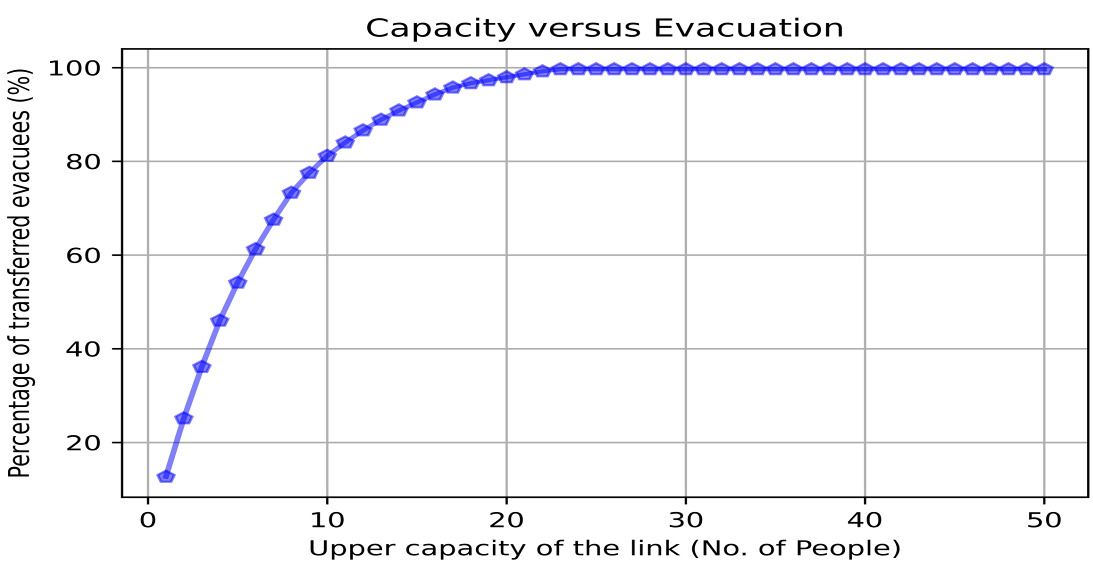

Figure 10. The upper capacity of arcs versus the percentage of transferred people to safer areas.

4.1.2.4. Increase in the link's upper capacity and the total average deviation of unmet demand in demand nodes

In this part of this study, we investigated how the maximum capacity of the arcs influenced the overall average deviation of unmet demand in the demand nodes. In other words, we examined how the upper capacities of arcs would aid in supplying the needed demand in demand nodes, hence lowering the overall average deviations of unmet demand in demand nodes. The findings revealed that increasing the maximum capacity of each arc allowed us to minimize the total average deviation of the unmet demand of the demand nodes. Fig. 11 demonstrates the previous notion by depicting that when the maximum capacities of arcs were assigned to small values, we had the highest value of the total average deviation of unmet demand, which was nearly 350 %. The previous percentage indicates that we could not transfer evacuees and meet the required demand in demand nodes. On the other hand, when links capacities increased, we relocated the majority of the population with small total average deviations of unfulfilled demand at all demand nodes.

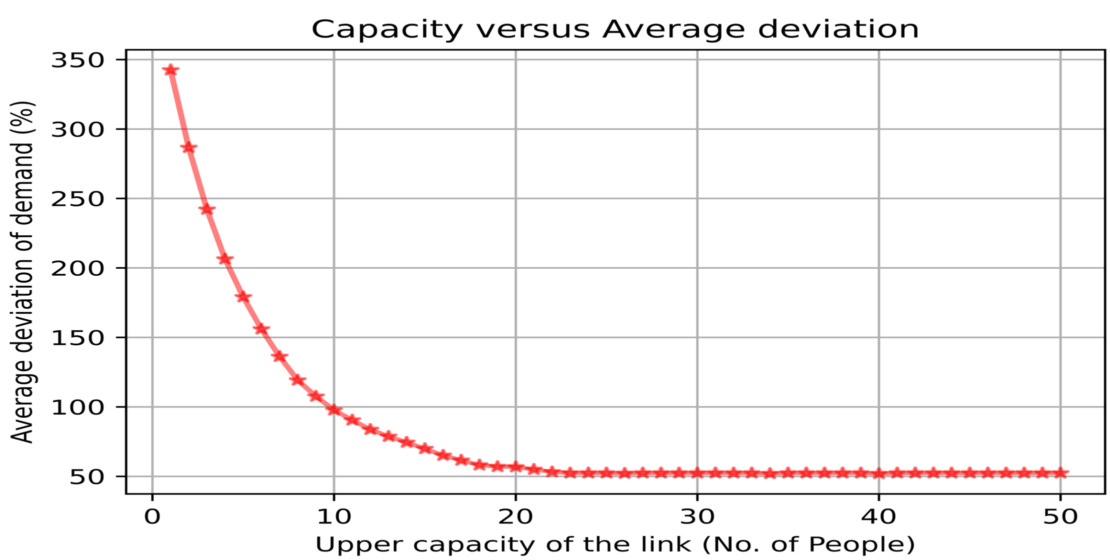

Figure 11. The upper capacity of arcs versus the total average deviation of the unmet demands for all demand nodes

4.1.2.5. Increase in the link’s upper capacity and the total traveled distance from evacuees to reach the safer areas

Finally, in the sensitivity analysis, we tested how increasing the upper capacities of links would affect the total distances that evacuees should travel to reach the safer areas. To do so, we depict the relationship between the total distance that evacuees should travel and the total average deviation of the unmet demand in the demand nodes. Here we were focusing on minimizing the total distance while increasing the upper capacities of links. Fig.12 depicts the previous relationship more clearly. It demonstrated that at the start of the test, when we set low values to the upper capacities of links, we had a high number; more than 6000 miles in all, for the total distances that evacuees should travel to safer places. However, because we evacuated the majority of the people and had little unmet demand at the demand nodes, we had a low value for the total average deviation. After that, we finish this test by providing higher values to the upper capacities of links. Hence, we reduced the total traveled distances by evacuees; to less than 1000 miles in total, while at the same time increasing the total average deviation in the demand nodes since evacuees had to travel to the closest nodes without satisfying the needed demands in the farthest demand nodes.

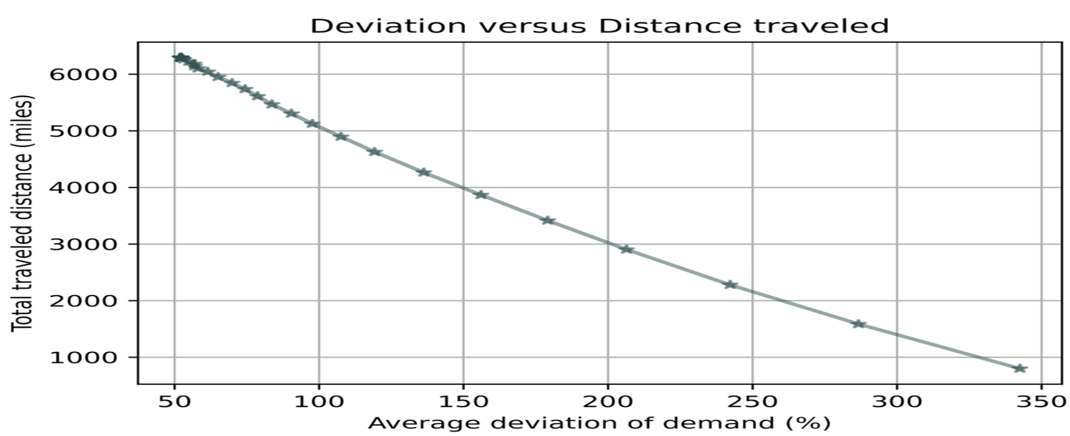

Figure 12. the link’s upper capacity and the total traveled distance from evacuees to reach the safer areas

5. Conclusion and future work

Natural catastrophes have a significant influence on the transportation network's efficiency and operation. When tsunamis strike coastal areas, they can create serious disruptions to the transportation network, affecting the evacuation process and the capacity to evacuate people to safer locations, as well as increasing the number of casualties and injured persons. As a result, numerous previous studies in this field have been investigating and analyzing the resilience of the transportation network under the disruptive impacts of these natural disasters, along with developing evacuation processes that allow people to safely reach regions that are outside the affected areas. Furthermore, tsunami evacuation processes are unique and must be addressed and investigated since these disasters differ from other natural disasters in terms of available time for escape. This is since tsunami warning timeframes are often significantly shorter than those of other natural catastrophes, and may not allow a sufficient enough lead time for evacuation before the disaster occurs.

In this study, we employed a fairness-based evacuation distribution model. Based on the individuals' type of need, whether they were evacuated to shelters or require urgent care, this strategy attempts to relocate evacuees from high-risk regions as a result of unexpected events such as tsunamis and minimize the number of demand nodes that did not receive the minimum required service level. Additionally, this strategy gave evacuees equitable access to emergency facility centers and assembly zones, which was accomplished by lowering the overall average deviation of unmet demand at demand nodes. On the opposite, when the model focused on decreasing the total distances that evacuees must travel, the model prioritized nodes with the highest demand which created high average deviation in other demand nodes. Moreover, the findings demonstrate that the suggested model was efficient in decreasing the total average deviation across demand nodes and ensuring that most of the demand nodes received the minimum required service level. Moreover, we were able to depict the Pareto frontier between the two objective functions. The pareto frontier illustrated that there is an opposite correlation between the total traveled distances by evacuees and the total average deviation of the unmet demand in the demand nodes. To explain more, when the model prioritizes the first objective function; minimizing total traveled distance, people needed to travel for short distances; however, this meant that we had demand nodes that did not receive the minimum required service level, resulting in a higher value for the average deviation of unmet demand in the demand nodes. Furthermore, we did sensitivity analysis and we obtained the following results. First, the minimum required service level for each demand node for each type of people's demands assisted in lowering the total average deviation of unmet demand across all demand nodes. Second, the changes in the upper capacities of arcs showed that (a) as we raised the capacity of the links, we were able to increase the number of transported evacuees until we were able to dislocate 100 % of the whole population that needed to be displaced, (b) increasing the maximum capacity of each arc allowed us to reduce the total average deviation of the unmet demand of the demand nodes, and (c) when we increased the upper maximum capacities of arcs, evacuees needed to travel for shorter distances to reach the safer areas.

Future research will build on current efforts and may expand in a variety of areas. One of these directions may be to consider vertical shelters. Vertical evacuation shelters are structures or earth hills designed to resist earthquake and tsunami impacts, and their height allows people to evacuate above the level of tsunami inundation. This is significant since most people do not have enough time to escape the area, and having these sorts of shelters would increase the number of survivors. Furthermore, due to congestion and blocked roads, while evacuating, people may abandon their cars in the middle of the road and decide to walk to shelters, which would disrupt the entire evacuation process, cause additional congestion, and lengthen the evacuation time. Another area that will be investigated in future works is the time required for the evacuation process and how this factor might increase the efficiency of the evacuation while preventing traffic congestions and blocked roads. Another topic for future research is the expanding population of Seaside, which can exceed 20,000 people during certain times of the year when we only investigate a small portion of the population. As a result of the large increase in population, further studies may be beneficial, such as requiring extra shelters. Finally, we hypothesized that to ensure a fair evacuation, people should have equitable access to the emergency facility centers. However, the concept of fairness is broad and can be interpreted in a variety of ways which would affect the final aimed results.

References:

Aalami, S., & Kattan, L. (2020). Fairness and efficiency in pedestrian emergency evacuation: Modeling and simulation. *Safety Science*, *121*, 373–384. https://doi.org/10.1016/j.ssci.2019.08.020

Abushaega, M., González, A., & Trafalis, T. (2021). Mitigation of Disruption Impacts on Supply Chain Transportation Networks using Fairness-based Distribution Strategies.

Ahmed, S., & Dey, K. (2020). Resilience modeling concepts in transportation systems: A comprehensive review based on mode, and modeling techniques. Journal of Infrastructure Preservation and Resilience, 1(1). doi:10.1186/s43065-020-00008-9

Akiyama, M., Frangopol, D. M., Arai, M., & Koshimura, S. (2013). Reliability of Bridges under Tsunami hazards: Emphasis on the 2011 Tohoku-Oki Earthquake. *Earthquake* Spectra*,* *29*(1_suppl), 295-314. doi:10.1193/1.4000112

Alderson, D. L., Brown, G. G., & Carlyle, W. M. (2015). Operational models of infrastructure resilience. *Risk Analysis, 35*(4), 562-586. doi:10.1111/risa.12333

Athukorala, P.-chandra, & Resosudarmo, B. P. (2005). The Indian Ocean tsunami: Economic impact, disaster management, and lessons. *Asian Economic Papers*, *4*(1), 1–39. https://doi.org/10.1162/asep.2005.4.1.1

Atwater, B. F., Musumi-Rokkaku, S., Satake, K., Tsuji, Y., Ueda, K., & Yamaguchi, D. K. (2005). The orphan tsunami of 1700—japanese clues to a parent earthquake in North America. *Professional Paper*. doi:10.3133/pp1707

Bin Obaid, H. S. (2020). Fair Resource Allocation in Macroscopic Evacuation Planning using Mathematical Programming: Modeling and Optimization

Bish, D. R., Sherali, H. D., & Hobeika, A. G. (2014). Optimal evacuation planning using staging and routing. *Journal of the Operational Research Society, 65*(1), 124-140. doi:10.1057/jors.2013.3

Bruneau, M., & Reinhorn, A. (2007). Exploring the concept of seismic resilience for acute care facilities. *Earthquake Spectra, 23*(1), 41-62. doi:10.1193/1.2431396

Burns, P. O., Barbosa, A. R., Olsen, M. J., & Wang, H. (2021). Multihazard Damage and Loss Assessment of Bridges in a Highway Network Subjected to Earthquake and Tsunami Hazards. *Natural Hazards Review*, *22*(2), 05021002. https://doi.org/10.1061/(asce)nh.1527-6996.0000429

Charnkol, T., & Tanaboriboon, Y. (2006). Tsunami evacuation behavior analysis. IATSS Research, 30(2), 83-96. doi:10.1016/s0386-1112(14)60173-4

Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., & Webb, J. (2008). A place-based model for understanding community resilience to natural disasters. *Global Environmental Change, 18*(4), 598-606. doi: 10.1016/j.gloenvcha.2008.07.013

Daganzo, C. F. (1994). The cell transmission model: A dynamic representation of highway traffic consistent with the hydrodynamic theory. *Transportation Research Part B: Methodological, 28*(4), 269-287. doi:10.1016/0191-2615(94)90002-7

Dekker S, Hollnagel E, Woods D, Cook R (2008) Resilience engineering: new directions for measuring and maintaining safety in complex systems. Lund University School of Aviation

D'Lima, M., & Medda, F. (2015). A new measure of resilience: An application to the London Underground. *Transportation Research Part A: Policy and Practice, 81*, 35-46. doi:10.1016/ j.tra. 2015.05.017

Dotson, L. J., & Jones, J. (2005). Identification and Analysis of Factors Affecting Emergency Evacuations. *Sandia National Laboratories*, *NUREG/CR-6864, Vol. 1 SAND2004-5901*. https://doi.org/https://www.nrc.gov/docs/ML0502/ML050250245.pdf

Fang, Y., Fang, C., Zio, E., & Xie, M. (2019). Resilient critical infrastructure planning under disruptions considering recovery scheduling. *IEEE Transactions on Engineering Management,* 1-15. doi:10.1109/tem.2019.2902916

FEMA. 2010. HAZUS-MH MR5 technical manual—Earthquake model. Washington, DC: FEMA

FHWA (Federal Highway Administration). 2015. "National bridge inventory." Accessed May 17, 2021. http://www.fhwa.dot.gov/bridge /nbi.cfm

Flötteröd G, & Lämmel G. (2010). Evacuation simulation with limited capacity sinks - an evolutionary approach to solve the shelter allocation and capacity assignment problem in a multi-agent evacuation simulation. *Proceedings of the International Conference on Evolutionary Computation*. https://doi.org/10.5220/0003086302490254

Fujii, Y., Satake, K., Sakai, S., Shinohara, M., & Kanazawa, T. (2011). Tsunami source of the 2011 off the Pacific coast of Tohoku earthquake. *Earth, Planets and Space, 63*(7), 815-820. doi:10.5047/eps.2011.06.010

Goldfinger, C., Nelson, C. H., Morey, A. E., Johnson, J. E., Patton, J. R., Karabanov, E. B., …Vallier, T. (2012). Turbidite event history—Methods and implications for Holocene paleoseismicity of the Cascadia subduction zone. Professional Paper.

Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics, 4*(1), 1-23. doi:10.1146/annurev.es.04.110173.000245

INCORE. IN. (n.d.). Retrieved November 19, 2021, from https://incore.ncsa.illinois.edu/.

Jenelius, E., Mattsson, L., & Levinson, D. (2011). Traveler delay costs and value of time with trip chains, flexible activity scheduling and information. *Transportation Research Part B: Methodological, 45*(5), 789-807. doi: 10.1016/j.trb.2011.02.003

Johnstone, W. M. (2012). Life safety modelling framework and performance measures to assess community protection systems: application to tsunami emergency preparedness and dam safety management (T). University of British Columbia. Retrieved from https://open.library.ubc.ca/collections/ubctheses/24/items/1.0073328

Kameshwar, S., Cox, D. T., Barbosa, A. R., Farokhnia, K., Park, H., Alam, M. S., & van de Lindt, J. W. (2019). Probabilistic decision-support framework for community resilience: Incorporating multi-hazards, infrastructure interdependencies, and resilience goals in a Bayesian network. Reliability Engineering & System Safety, 191, 106568. https://doi.org/10.1016/j.ress.2019.106568

Kisko, T. M., & Francis, R. L. (1985). Evacnet+: A computer program to determine optimal building evacuation plans. *Fire Safety Journal, 9*(2), 211-220. doi:10.1016/0379-7112(85)90009-8

Kitamura, F., Inazu, D., Ikeya, T., & Okayasu, A. (2020). An allocating method of tsunami evacuation routes and refuges for minimizing expected casualties. *International Journal of Disaster Risk Reduction*, *45*, 101519. https://doi.org/10.1016/j.ijdrr.2020.101519

Konduri, K. C., Pendyala, R. M., You, D., Chiu, Y.-C., Hickman, M., Noh, H., Gardner, B., Waddell, P., & Wang, L. (2013). A network-sensitive transport modeling framework for evaluating impacts of network disruptions on traveler choices under varying levels of user information provision.

Kongsomsaksakul, S., Yang, C., & Chen, A. (2005). Shelter location-allocation model for flood evacuation planning. *Journal of the Eastern Asia Society for Transportation Studies*, *Vol. 6*(pp. 4237). https://doi.org/10.11175/easts.6.4237

Koshimura, S., Moya, L., Mas, E., & Bai, Y. (2020). Tsunami damage detection with remote sensing: A review. *Geosciences, 10*(5), 177. doi:10.3390/geosciences10050177

Lim, H. R., Lim, M., & Piantanakulchai, M. (2013). A Review of Recent Studies on Flood Evacuation Planning. *Journal of the Eastern Asia Society for Transportation Studies*, *Vol.10*. https://doi.org/10.11175/EASTS.10.147

Lindell, M. K. (2013). Evacuation Planning, Analysis, and Management. Handbook of Emergency Response. Texas A&M University Hazard Reduction & Recovery Center. https://doi.org/10.1201/b15372-8

Makinoshima, F., Imamura, F., & Oishi, Y. (2020). Tsunami evacuation processes based on human behavior in past earthquakes and tsunamis: A literature review. Progress in Disaster Science, 7, 100113. doi: 10.1016/j.pdisas.2020.100113

Margulis, L., Charosky, P., Fernandez, J., & Centeno, M. (2006). Hurricane Evacuation Decision-Support Model for Bus Dispatch. Fourth LACCEI International Latin American and Caribbean Conference for Engineering and Technology (LACCET '2006) "Breaking Frontiers and Barriers in Engineering: Education, Research, and Practice 21-23 June 2006, Mayaguez, Puerto Rico.

Middleton, E. J., & Latty, T. (2016). Resilience in social insect infrastructure systems. *Journal of The Royal Society Interface, 13*(116), 20151022. doi:10.1098/rsif.2015.1022

Mimura, N., Yasuhara, K., Kawagoe, S., Yokoki, H., & Kazama, S. (2011). Damage from the Great East Japan earthquake and tsunami - a quick report. Mitigation and Adaptation Strategies for Global Change, 16(7), 803-818. doi:10.1007/s11027-011-9297-

Mostafizi, A., Wang, H., Cox, D., & Dong, S. (2019). An agent-based vertical evacuation model for a near-field tsunami: Choice behavior, logical shelter locations, and Life Safety. International Journal of Disaster Risk Reduction, 34, 467–479. https://doi.org/10.1016/j.ijdrr.2018.12.018

Neumann, B., Vafeidis, A. T., Zimmermann, J., & Nicholls, R. J. (2015). Future coastal population growth and exposure to sea-level rise and coastal flooding - a global assessment. *PLOS ONE*, *10*(3). https://doi.org/10.1371/journal.pone.0118571

Oh, W. S., Yu, D. J., & Muneepeerakul, R. (2021). Efficiency-fairness trade-offs in evacuation management of urban floods: The effects of the shelter capacity and zone prioritization. PLOS ONE, 16(6). https://doi.org/10.1371/journal.pone.0253395

Oktari, R. S., Syamsidik, Idroes, R., Sofyan, H., & Munadi, K. (2020). City resilience towards coastal hazards: An integrated bottom-up and top-down assessment. *Water, 12*(10), 2823. doi:10.3390/w12102823

Osorio, C., & Bierlaire, M. (2013). A Simulation-Based Optimization Framework for Urban Transportation Problems. *Operations Research*, *61*(6), 1333–1345. https://doi.org/10.1287/opre.2013.1226

Oxendine, C., Sonwalkar, M., & Waters, N. (2012). A Multi-Objective, Multi-Criteria Approach to Improve Situational Awareness in Emergency Evacuation Routing Using Mobile Phone Data. *Transactions in GIS*, *16*(3), 375–396. https://doi.org/10.1111/j.1467-9671.2012.01341.x

Padgett, J. E., & DesRoches, R. (2007). Bridge Functionality Relationships for Improved Seismic Risk Assessment of Transportation Networks. *Earthquake Spectra*, *23*(1), 115–130. https://doi.org/10.1193/1.2431209

Pillac, V., Van Hentenryck, P., & Even, C. (2016). A conflict-based path-generation heuristic for evacuation planning. *Transportation Research Part B: Methodological*, *83*, 136–150. https://doi.org/10.1016/j.trb.2015.09.008

Rabbani, M., Zhalechian, M., & Farshbaf-Geranmayeh, A. (2016). A robust possibilistic programming approach to multiperiod hospital evacuation planning problem under uncertainty. *International Transactions in Operational Research*, *25*(1), 157–189. https://doi.org/10.1111/itor.12331

Sánchez-Silva, M., Daniels, M., Lleras, G., & Patiño, D. (2005). A transport network reliability model for the efficient assignment of resources. *Transportation Research Part B: Methodological, 39*(1), 47-63. doi: 10.1016/j.trb.2004.03.002

Topographic Seaside Topographic map, elevation, relief. topographic. (n.d.). Retrieved November 8, 2021, from https://en-us.topographic-map.com/maps/rug1/Seaside/.

Shinozuka, M., Feng, M. Q., Lee, J., & Naganuma, T. (2000). Statistical Analysis of Fragility Curves. *Journal of Engineering Mechanics*, *126*(12), 1224–1231. https://doi.org/10.1061/(asce)0733-9399(2000)126:12(1224)

Simonovic, S. P., & Peck, A. (2013). Dynamic resilience to climate change caused natural disasters in coastal megacities quantification framework. *British Journal of Environment and Climate Change, 3*(3), 378-401. doi:10.9734/bjecc/2013/2504

Tierney, K., & Bruneau, M. (2007). *Conceptualizing and measuring resilience*. http://onlinepubs.trb.org/onlinepubs/trnews/trnews250_p14-17.pdf.

Titus, J. G., & Barth, M. C. (1984). An overview of the causes and effects of sea level rise. *Greenhouse Effect and Sea Level Rise*, 1–56. https://doi.org/10.1007/978-1-4684-6569-3_1

US Department of Commerce, N. O. and A. A. (2019, October 31). *What percentage of the American population lives near the coast?* NOAA's National Ocean Service. Retrieved September 26, 2021, from https://oceanservice.noaa.gov/facts/population.html.

Wang, H., Mostafizi, A., Cramer, L. A., Cox, D., & Park, H. (2016). An agent-based model of a multimodal near-field tsunami evacuation: Decision-making and life safety. Transportation Research Part C: Emerging Technologies, 64, 86–100. https://doi.org/10.1016/j.trc.2015.11.010

Weilant, S., Strong, A., & Miller, B. (2019). Incorporating resilience into transportation planning and assessment. doi:10.7249/rr3038

Werner, S. D., C. E. Taylor, S. Cho, J. P. Lavoie, C. Huyck, C. Eitzel, H. Chung, and T. Eguchi. 2006. Technical manual: REDARS2 methodology and software for seismic risk analysis of highway systems. Buffalo, NY: Univ. of Buffalo

Williams, J. H., Wilson, T. M., Horspool, N., Paulik, R., Wotherspoon, L., Lane, E. M., & Hughes, M. W. (2020). Assessing transportation vulnerability to tsunamis: Utilizing Post-event field data from the 2011 Tōhoku TSUNAMI, Japan, and the 2015 ILLAPEL tsunami, Chile. *Natural Hazards and Earth System Sciences, 20*(2), 451-470. doi:10.5194/nhess-20-451-2020

Wood, N. (2007). Variations in city exposure and sensitivity to tsunami hazards in Oregon. *Scientific Investigations Report*. https://doi.org/10.3133/sir20075283

Yamori, K., & Sugiyama, T. (2020). Development and social implementation of smartphone app nige-tore for improving tsunami evacuation drills: Synergistic effects between commitment and contingency. *International Journal of Disaster Risk Science*, 11(6), 751–761. https://doi.org/10.1007/s13753-020-00319-1

Yan, X., Liu, X., & Song, Y. (2018). Optimizing evacuation efficiency under emergency with consideration of social fairness based on a cell transmission model. *PLOS ONE*, *13*(11). https://doi.org/10.1371/journal.pone.0207916

Yin, W., Murray-Tuite, P., Ukkusuri, S. V., & Gladwin, H. (2014). An agent-based modeling system for travel demand simulation for hurricane evacuation. *Transportation Research Part C: Emerging Technologies*, *42*, 44–59. https://doi.org/10.1016/j.trc.2014.02.015

Zhang, X., & Haghani, A. (2016). A Two-Stage Optimization Framework for Optimizing Large-Scale Vehicular Evacuation Routing and Scheduling Operation with Uninterrupted Traffic Flow. *International Journal of Transportation*, *4*(2), 47–68.

Zhou, Y., Wang, J., & Yang, H. (2019). Resilience of Transportation Systems: Concepts and comprehensive review. *IEEE Transactions on Intelligent Transportation Systems, 20*(12), 4262-4276. doi:10.1109/tits.2018.2883766

Ziliaskopoulos, A. K. (2000). A linear programming model for the single destination system optimum dynamic traffic assignment problem. *Transportation Science, 34*(1), 37-49. doi:10.1287/trsc.34.1.37.12281

Zukerman, M., Liansheng Tan, Hanwu Wang, & Ouveysi, I. (2005). Efficiency-fairness tradeoff in telecommunications networks. *IEEE Communications Letters*, *9*(7), 643–645. https://doi.org/10.1109/lcomm.2005.1461691