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Hassan Idoudi

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Dynamic Population Evacuation

Thèse de doctorat de l'Université Gustave Eiffel

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et Laboratoire d'Informatique Gaspard-Monge (LIGM)

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"We are at the very beginning of time for the human race. It is not unreasonable that we grapple with problems. But there are tens of thousands of years in the future. Our responsibility is to do what we can, learn what we can improve the solutions, and pass them on."

-Richard Feynman
Theoretical physicist

Abstract

This thesis aims to improve planning and executing population evacuations by integrating advanced simulation techniques within urban road networks. Although much research has been conducted using analytical methods, this thesis addresses specific gaps, especially in destination and route choices. It further introduces vehicular communication into evacuation planning, providing a more adaptive and realistic approach to various evacuation scenarios.

The work underscores simulation as a pivotal tool, enabling dynamic modeling of population evacuations. It links shelter allocation and traffic assignment to replicate the movement patterns of individuals across transport networks. Moreover, this study emphasizes the significant role of vehicular communication technology in amplifying the efficiency of evacuation planning and execution. It highlights the importance of real-time coordination and adaptive management in ever-changing conditions.

By exploring multiple scenarios, we show that online management, paired with vehicular communication technology, can enhance the efficiency of evacuation processes. This is especially true when integrated with well-structured Vehicular Ad-hoc Network (VANET) architectures. The research also suggests that various VANET architectures can influence the reliability of vehicular communication in emergencies, offering critical insights for designing vehicular networks ideal for emergency evacuations.

Furthermore, this thesis successfully introduces dynamic risk modelling of hazard propagation, facilitating a more detailed and adaptive approach to evacuee simulations. By incorporating dynamic risk factors, the potential for more advantageous outcomes in evacuation planning and real-time operational management is unveiled, especially in rapidly changing conditions.

Keywords: *Dynamic Traffic Assignment, VANET, User Equilibrium, Inter-vehicle Communication, Multi-agent System, Cloud Computing, Fog Computing, Simulation, System Optimal, Optimization, Operations Research.*

Résumé

Cette thèse vise à améliorer la planification et l'exécution des évacuations de population en intégrant des techniques de simulation avancées dans les réseaux routiers urbains. Bien que de nombreuses recherches aient été menées à l'aide de méthodes analytiques, cette thèse aborde des lacunes spécifiques, notamment en ce qui concerne les choix de destinations et d'itinéraires. Elle introduit en outre la communication véhiculaire dans la planification des évacuations, ce qui permet une approche plus adaptative et plus réaliste des différents scénarios d'évacuation.

Le travail souligne que la simulation est un outil essentiel, permettant une modélisation dynamique des évacuations de population. Elle relie l'attribution des abris et l'affectation du trafic afin de reproduire les schémas de déplacement des individus dans les réseaux de transport. En outre, cette étude souligne le rôle significatif de la technologie de communication véhiculaire dans l'amélioration de l'efficacité de la planification et de l'exécution des évacuations. Elle souligne l'importance de la coordination en temps réel et de la gestion adaptative dans des conditions en constante évolution.

En explorant plusieurs scénarios, nous montrons que la gestion en ligne, associée à la technologie de communication véhiculaire, peut améliorer l'efficacité des processus d'évacuation. Cela est particulièrement vrai lorsqu'ils sont intégrés à des architectures de réseaux ad hoc véhiculaires (VANET) bien structurées. La recherche suggère également que diverses architectures VANET peuvent influencer la fiabilité de la communication véhiculaire dans les situations d'urgence, offrant ainsi des perspectives essentielles pour la conception de réseaux véhiculaires idéaux pour les évacuations d'urgence.

En outre, cette thèse introduit une modélisation dynamique de la propagation des risques, facilitant une approche plus détaillée et adaptative des simulations d'évacuation. En incorporant des facteurs de risque dynamiques, le potentiel pour des solutions plus efficaces dans la planification de l'évacuation et la gestion opérationnelle en temps-réel est mis en lumière, en particulier dans des conditions qui changent rapidement.

Mots-Clés : *Affectation dynamique du trafic, VANET, équilibre utilisateur, Communication inter-véhiculaire, Système multi-agent, Cloud Computing, Fog Computing, simulation, Système optimal, Optimisation, Recherche Opérationnelle*

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List of Acronyms

DPE	Dynamic Population Evacuation
DTA	Dynamic Traffic Assignment
DSRC	Dedicated Short Range Communication
ITS	Intelligent Transport Systems
IVC	Inter-vehicle Communications
MANET	Mobile Ad-Hoc Networks
NA	Nearest Allocation
OBU	On Board unit
OMNeT ++	Objective Modular Network Test bed in C++
SAP	Shelter Allocation Problem
SO	System Optimal
STA	Static Traffic Assignment
SUMO	Simulation of Urban MObility
SUE	Stochastic User Equilibrium
TraCI	Traffic Control Interface
UE	User Equilibrium
VANET	Vehicular Ad hoc Network
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-everything
VCC	Vehicular Cloud Computing
VFC	Vehicular Fog Computing
RSU	Road Side Unit
WAVE	Wireless Access in Vehicular Environments

Chapter 1

General Introduction

1.1 Disaster impact

Natural disasters are adverse events of significant scale that arise from the Earth's inherent processes, encompassing geological and meteorological phenomena. These occurrences encompass a range of disasters, such as tornadoes, severe storms, earthquakes, volcanic eruptions, hurricanes, tropical storms, wildfires, floods, tsunamis, and droughts. The consequences of these events often involve fatalities, traumatic experiences, and extensive property destruction. According to the International Disaster Database, recorded natural disasters have experienced an upsurge since the mid-20th century [Kokai et al., 2004]. Since 1970, the global occurrence of natural disasters has surpassed 9,800 incidents, resulting in a devastating toll. Tragically, these events have claimed the lives of over 3.7 million individuals and have affected a shocking 5.8 billion people. The estimated economic damages stemming from these disasters exceed a staggering \$1.7 trillion [Kellenberg and Mobarak, 2011]. Notable recent events, including the Indian Ocean tsunami in 2004, Hurricane Katrina in 2005, the Sichuan earthquake in China in 2008, the Haitian earthquake in 2009, and the Japanese earthquake and tsunami in 2011, stand as vivid illustrations of the immense economic ramifications triggered by such calamities [Kellenberg and Mobarak, 2011]. In the summer of 2005, Hurricane Katrina's flooding, which caused more than \$108 billion in damages, constituted the costliest natural disaster in U.S. history [Douglas et al., 2008, Glago, 2021].

Natural disasters have exerted impacts in regions across the globe, emerging as a matter of immense relevance in contemporary society. For instance, the occurrence of hurricanes Katrina and Rita in 2005 within the Gulf of Mexico region inflicted extensive damages upon approximately 611 industrial assets, including offshore platforms, oil pipelines, and storage tanks [Krausmann and Cruz, 2017]. Despite being historically perceived as low-probability events, these incidents exhibit significant impact and complexity in risk management, owing to their cascading nature [Nascimento and Alencar, 2016]. However, the frequency of such events has demonstrated temporal variation, with a higher probability of occurrence observed in recent decades (cf Figure 1.1).

1.2 Evacuation as a solution

Over the last two decades, transportation has emerged as a crucial component in the field of emergency management. When faced with various hazardous incidents, evacuations have become the predominant approach to safeguard the well-being of a substantial number of individuals [Wong et al., 2021]. The implementation of evacuations plays a crucial role in preserving lives during disasters, mitigating the need for extensive search and rescue operations, and enhancing the overall quality of life. Over the



Figure 1.1: Number of reported disaster events [Mesa-Gómez et al., 2020]

past few years, a substantial number of large-scale evacuations have been conducted in response to hurricanes [Maul, 2018], wildfires [Seto et al., 2022], and human-made incidents [Huang et al., 2021]. Furthermore, projections indicate that certain natural events are poised to worsen in the coming decades. While climate change has been associated with storm types such as hurricanes, tornadoes, and winter storms, the current state of research does not yet offer a comprehensive understanding or firm consensus on the matter [Impacts, 2018]. Devastating wildfires in California and worldwide have imparted profound lessons, underscoring the need for heightened awareness and preparedness [Soga et al., 2021]. Unlike other hazards like hurricanes, wildfires pose unique challenges as they are difficult to predict and leave minimal time for evacuation. In certain regions of California, the frequency of wildfires has escalated to the extent that they can no longer be considered low-probability events [Str, 2019]. However, due to housing shortages, relocating from high-risk areas is often not feasible for many residents. Consequently, individuals must rely on proactive measures, such as utilizing fire-resistant construction materials and creating defensible space around their properties. Furthermore, being familiar with evacuation routes, devising written evacuation plans, and preparing emergency kits assume paramount importance in situations that necessitate abrupt and chaotic evacuations.

1.3 Evacuation and traffic management

Ensuring the safety of individuals in the face of potential disasters primarily relies on the widely employed strategy of evacuation from affected areas [10]. Evacuation planning and management constitute essential aspects of disaster management activities, encompassing preparedness and response phases. According to reports from the US Federal Emergency Management Agency (FEMA), approximately 45-75 disasters necessitate evacuations each year [Board, 2008]. Effective traffic management is prominent among the core capabilities required for the mass evacuation of people, as outlined in the National Response Framework [Nat,]. The management of evacuation traffic assumes critical importance [Yao et al., 2009], given the inherent risk to people’s lives. If not meticulously planned and executed, the surge in traffic demand, exceeding the transportation network’s capacity [Dixit and Wolshon, 2014], can lead to congestion and leave evacuees

vulnerable, potentially resulting in further losses. The hurricanes Katrina and Rita in 2005 [Board, 2008] witnessed the evacuation of millions of people, resulting in the largest traffic congestion in US history. Effective evacuation management not only saves lives but also contributes to the community’s swift and smooth recovery, restoring functionality [Perry, 1979]. The authors in [Islam et al., 2023] examine the policies and methodologies related to evacuation planning, preparedness, and response. Their focus lies specifically on command and control strategies, as well as the criteria for implementation and enforcement. Additionally, the authors provide an overview of evacuation management operations, with particular emphasis on contraflow operations and the utilization of intelligent transportation systems, including connected and automated vehicles. In their study, [Liu et al., 2021] aim to determine how to model and pre-plan emergency response while addressing the critical concern of interaction. The study also focuses on reviewing the interaction between the transportation network and facility location, highlighting the critical concerns of the emergency response optimization problem. The effective implementation of evacuation strategies is crucial for ensuring the safety of individuals during potential disasters. Evacuation planning and management play vital roles in disaster management activities, encompassing preparedness and response phases. The importance of effective traffic management cannot be overstated, as it is a core capability required for the mass evacuation of people, as outlined in the National Response Framework. Poorly planned and executed evacuations can lead to congestion and further endanger evacuees, highlighting the need for meticulous planning to accommodate the surge in traffic demand. The study of evacuation policies and methodologies, including command and control strategies, implementation criteria, and contraflow operations, provides valuable insights for enhancing evacuation management. Additionally, modelling and pre-planning emergency response while addressing the interaction between the transportation network and facility location is a critical concern that requires further exploration. Understanding and improving the emergency response process is crucial for effective disaster mitigation, as well as for preserving lives and ensuring the community continues to operate effectively.

1.4 Evacuation Planning

A typical framework of a transportation model in an evacuation context consists of five sub-models [Pel, 2017], as follows:

- **Evacuation Trip distribution:** It focuses on determining the destinations to which people will evacuate.
- **Trip generation:** This sub-model predicts the number of people who will evacuate and determines the timing of their departure.
- **Modal split:** This sub-model identifies the mode of transportation individuals will use for evacuation.
- **Evacuation traffic assignment:** It determines individuals’ specific routes during an evacuation.
- **Evacuation traffic flows:** This sub-model describes the resulting traffic flows in the transport network.

The purpose of the first four sub-models is to predict travel choices made by individuals both before their departure and during their trip. The collective decisions resulting from these sub-models yield travel patterns. Together, these sub-models provide insights

into the decision-making process and help understand the overall travel behaviour during evacuations. This thesis focuses primarily on the trip distribution task, traffic assignment, and traffic flows within the transportation model framework. We have placed particular emphasis on these aspects based on careful considerations. Firstly, the task of trip generation, which involves estimating the number of evacuees and their departure times, has been extensively studied and modelled using a sigmoid distribution.

Moreover, we have opted not to delve deeply into the modal split task within the framework. Instead, we make the assumption that all evacuees rely on private cars as their mode of transportation during the evacuation process. This assumption allows us to streamline our analysis and concentrate on the critical elements of trip distribution, traffic assignment, and traffic flows.

By focusing on these specific aspects, our objective is to provide valuable insights into the distribution of evacuees to different destinations, the efficient assignment of evacuation routes, and the resulting traffic patterns within the transport network. Through this research, we aim to enhance our understanding of evacuation dynamics and contribute to the development of effective strategies for managing and optimizing evacuations during disastrous events.

1.4.1 Shelter Allocation Problem

Different stages of disaster operations management have been studied, including mitigation, preparedness, response, and recovery [Altay and Green III, 2006]. An important part of the preparedness phase is determining the location of emergency shelters. These shelters serve two primary functions: to provide temporary housing for survivors to avoid secondary damage, such as fires and diseases, and to allow first responders to perform rescue operations efficiently.

After the 2010 Haiti earthquake, an estimated three million people were displaced and about one-third of them became homeless [Plastun and Plastun, 2013]. The lack of available shelters forced many victims to live on the streets, where their health and safety were at risk. In contrast, after the 2011 Tohoku earthquake, more than 2,000 shelters were quickly established [Urata and Hato, 2012], providing a safe place for 166,000 evacuees to stay during the post-disaster recovery period. In addition, the shelters helped maintain the dignity and emotional security of the victims, even though their homes had been destroyed.

Despite the significant differences between Haiti and Japan, the planning of emergency shelters should be integrated into urban resilience planning to reduce vulnerability to disasters. This includes considering factors such as the location of shelters, their capacity, and the availability of resources. Location selection has remained an intriguing problem since its initial proposal in 1909 by [Weber and Friedrich, 1929], who concentrated on pinpointing a warehouse optimally positioned near all customers. The importance of facility location spans various fields, contributing to societal progress and finding relevance in disciplines like economics, mathematics, politics, science, and beyond. At first, research on facility location was not systematic, but mainly involved solving problems about living and production. Most early problems looked at choosing a spot for a facility in a continuous space. The author in [Hotbllino, 1929] studied a different situation - finding the locations of two competing companies along a line. Building on this, the authors in [Smithies, 1941] and [Stevens, 1961] studied the problem more deeply by considering elastic demand relative to competitors, who can move but are physically separated.

The collaborative selection of ideal locations from a pool of probable places for numerous facilities has attracted the attention of academic researchers as the complexity of practical difficulties continues to increase. Conventional approaches designed to solve ongoing

problems are no longer appropriate in this situation. The author in [Hakimi, 1964] therefore developed the p-median and p-center approaches in 1964 to address discrete multi-facility location problems inside network frameworks. This significant finding marked a shift in academic discourse toward a more rigorous investigation of facility location. The choice of locations for facilities, shelters, manufacturing plants, warehouses, logistics hubs, and more, is covered under the facility location allocation.

1.4.1.1 p-Center and p-Median

The p-median and p-center location problems are classic discrete optimization models used for facility location planning. As [Jia et al., 2007] explain it, the p-median model aims to minimize the total weighted distance between demand nodes and their nearest facilities, while the p-center model minimizes the maximum distance between a demand node and facility. These models have been extensively studied in operations research. Recent advances have developed more sophisticated solution algorithms, including Lagrangian relaxation, Tabu search, and variable neighborhood search metaheuristics [Brimberg et al., 2000, Irawan et al., 2016].

An important application of p-median and p-center models is planning the locations of emergency shelters and supplies. A study by [Sherali et al., 1991] introduced a hybrid model integrating a p-median approach for shelter placement with a network model. The primary aim was to minimize the duration required for evacuating affected individuals to hurricane shelters. This methodology considers hurricanes' unique attributes and employs a heuristic algorithm to derive optimal shelter locations along with effective evacuation routes. The authors in [Ye et al., 2015] introduced a model to address the challenge of locating emergency warehouses in the context of Chinese national emergency preparedness. The model was built upon the p-center problem framework and took into consideration several constraints, including population distribution, economic factors, transportation considerations, and the need for comprehensive coverage of critical zones. To tackle this complex model, the researchers devised a heuristic algorithm based on a variable neighborhood search approach, which proved effective in solving the formulated problem.

1.4.2 Traffic Assignment Problem

The traffic assignment problem can be likened to a competitive game where each player strives to come out on top. In this game, the players are the travellers (users) and the transportation system itself. The objective is to find an equilibrium, if one exists, which can be seen as a solution to the game.

The diagram in 1.2 illustrates the interconnection between game players. First is the traveller's decisions (the demand side), and the second is the congestion and delays experienced within the system (known as the supply side) in the fundamental traffic assignment problem. Each of these aspects necessitates distinct models. Behavioral models are employed for the demand side, aiming to understand the factors that influence travel choices and how they are influenced. On the other hand, supply-side models commonly draw upon traffic flow theory, queuing theory, computer simulation, or empirical formulas to describe the formation of congestion.

The schema of 1.2 serves as the blueprint for all traffic assignment models, whether static or dynamic. It depicts the reciprocal relationship between travellers' choices, which result in congestion patterns within the network (predicted by traffic flow models), and how these patterns subsequently influence the choices made by travellers. The reciprocal relationship depicted in the schema of 1.2 serves as a crucial link between the traffic assignment models and Wardrop's principles [Wardrop, 1952]. By illustrating how travellers'

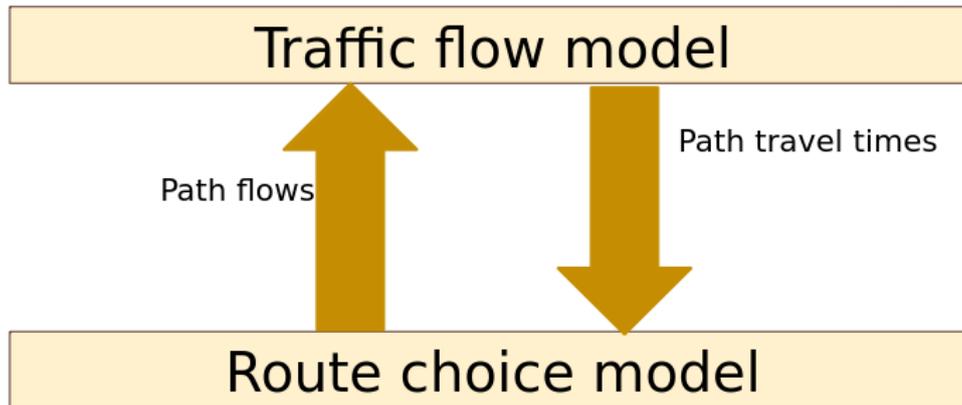


Figure 1.2: Traffic assignment as interacting systems [Boyles et al., 2020]

choices and resulting congestion patterns interact, the schema aligns with the principles established by Wardrop.

The formulation of the traffic assignment problem has been significantly influenced by Wardrop’s first and second principles, which were introduced in the early 1950s within the context of traffic dynamics [Wardrop, 1952]. Wardrop’s first principle also referred to as the user optimum principle, posits that travellers act as Nash agents who compete for limited resources within the network, such as road and mode capacity. The user equilibrium represents a state where no user can further decrease their travel costs, reflecting a self-interested scenario.

Wardrop’s second principle, on the other hand, pertains to the system optimum conditions. It characterizes the situation where the total travel cost for all users is minimized. In Wardrop’s own words, the principles can be summarized as follows:

- The User Equilibrium (UE), as expressed by Wardrop’s first principle, states that “the journey times on all routes actually used are equal and less than those which would be experienced by a single vehicle on any unused route.”
- The System Optimum (SO), corresponding to Wardrop’s second principle, refers to the network state that “minimizes the total travel time spent in the network.”

By incorporating these principles, researchers and practitioners can conceive effective strategies for traffic assignment, ensuring optimal utilization of the transportation network and minimizing overall travel time. During a disaster situation, where there is limited information on the road network and congestion levels, evacuees exhibit self-interested behavior, similar to regular traffic conditions in daily life [Jahn et al., 2005, Schulz and Moses, 2003, Correa et al., 2005, Schulz and Stier-Moses, 2006, Correa et al., 2007, Chellapilla et al., 2023]. They tend to choose routes that allow them to reach the pre-designated shelter site quickly.

1.4.2.1 Static and Dynamic

The difference between static and dynamic traffic assignment lies in the traffic flow models used. Historically, static assignment models were the first to be developed, and research into dynamic models arose from the need to improve earlier static models. Dynamic traffic assignment thus has a large number of parallels with the static assignment; but where they differ, this difference is often intentional and important [Boyles et al., 2020].

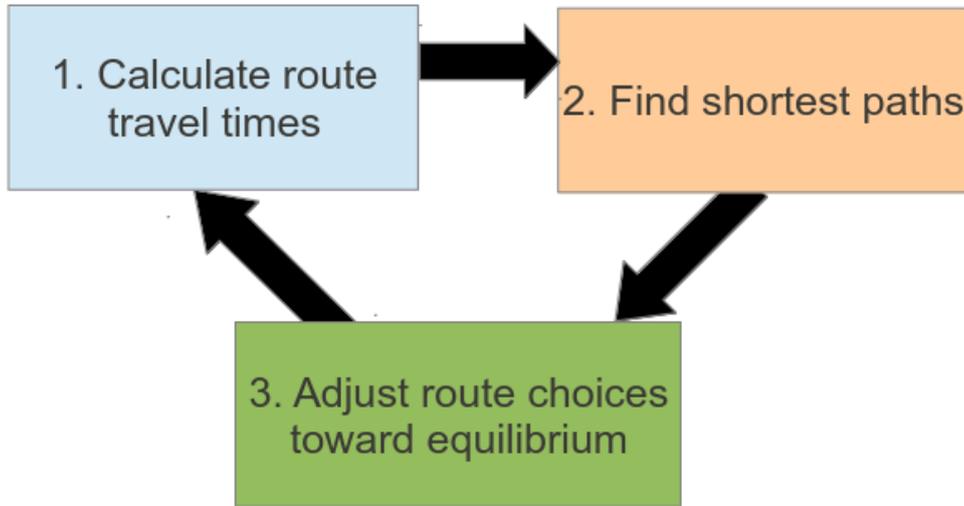


Figure 1.3: Iterative process for dynamic traffic assignment

Static traffic assignment Evacuation models typically rely on traffic assignment models, particularly static models that can be traced back to the formulation initially proposed by Beckmann in [Beckmann et al., 1956]. In the static assignment, the traffic flow model is based on link performance functions, which map the flow on each link to the travel time on that link. A variety of link performance functions exist, but the most popular is the Bureau of Public Roads (BPR) function. The primary benefit of employing link performance functions, such as the BPR function, is the relative ease with which the user equilibrium and system optimum states can be determined, even in complex networks comprising tens of thousands of links. Thanks to efficient algorithms, equilibrium states can be identified within a matter of minutes even on extensive networks. Traffic planners have employed static traffic assignment as a means to assess the present and future utilization of transportation networks [Kalaee, 2010]. For planning purposes, static models yield reasonably accurate estimations, and in cases involving extensive evacuation networks, they can be solved optimally using precise solution methodologies. These models effectively capture no-notice evacuations where evacuees are simultaneously loaded into the evacuation network. However, despite their merits, static models fall short of capturing the intricacies of traffic dynamics, information dissemination, and user behaviour that can vary over time due to changing conditions.

Dynamic traffic assignment The development of dynamic traffic assignment emerged as an attempt to address the limitations identified in the static assignment, as discussed in the preceding section [Batista et al., 2023]. Although dynamic traffic assignment is increasingly being implemented, it has not entirely replaced static traffic assignment. This can be attributed partially to institutional inertia but also to a few drawbacks associated with employing more realistic traffic flow models. Dynamic traffic assignment involves an iterative procedure wherein route choices are continually updated at each iteration until an approximate dynamic user equilibrium solution is achieved [Ameli et al., 2020c]. This iterative process typically comprises three steps, as illustrated in Figure 1.3:

- **Calculate route travel times:** This procedure involves utilizing a network loading model to determine the time-dependent travel durations on each link, considering the routes chosen and departure times of all drivers as inputs. In contrast to static assignment, this step is more complex, requiring the calculation of link performance functions for each network link.

- **Find shortest paths:** After the completion of network loading, the travel time for each link at every time interval is acquired. Using this information, we can identify the shortest path from each origin to each destination for every departure time.
- **Adjust route choices toward equilibrium:** After determining the time-dependent shortest paths for all origins, destinations, and departure times, vehicles can be redirected from their current routes to these new, optimal paths. However, similar to static assignment, this step must be executed carefully as the act of shifting vehicles will alter the travel times of the paths.

There are two primary approaches to solving Dynamic Traffic Assignment (DTA) problems: analytical and simulation-based approaches. The analytical approach, extensively discussed by [Boyce et al., 2001], offers high accuracy but is primarily applicable to small or medium networks with a limited number of Origin-Destination (OD) pairs. This is due to the necessity of considering all path cost functions per OD pair and incorporating the impacts of travel paths and modes comprehensively [Szeto and Wong, 2012, Ameli et al., 2019]. In the case of large-scale networks with numerous paths per OD pair and a substantial number of ODs, the analytical approach becomes exceedingly challenging due to the complexity arising from multiple flow exchanges at nodes [Ameli et al., 2020b]. Consequently, we adopt the simulation-based approach to tackle DTA problems in large-scale networks. This approach offers a practical solution by simulating and analyzing the dynamic behaviour of traffic flows in a computationally feasible manner [Chen et al., 2021].

1.4.2.2 Analytical and Simulation-based Approaches

Dynamic Traffic Assignment (DTA) models can be broadly classified into two categories: analytical (optimization-based) models and simulation-based models. A comprehensive overview of DTA models is provided in the study [Peeta and Ziliaskopoulos, 2001]. Analytical models have evolved since the work [Merchant and Nemhauser, 1978]. Efforts in this category include mathematical programming formulations, optimal control theory-based formulations, and variational inequality approaches [Aziz, 2019, Bagloee et al., 2017, Bahrami and Roorda, 2020, Wang et al., 2022, Xie and Liu, 2022]. Many analytical models are adaptations of static formulations. However, these models have limitations in accurately representing time-dependent dynamic traffic characteristics and user behaviours, particularly in larger and more realistic networks.

To address these limitations, simulation-based DTA models have been developed at various levels, such as macroscopic, mesoscopic, or microscopic scales. Examples of such models include SUMO [SUM,], NETVAC [Hobeika and Kim, 1998], RouteSim [Ziliaskopoulos and Waller, 2000], and DYNASMART [Mahmassani, 2001]. While these models offer valuable insights, they require substantial time, ample data, extensive effort to set up, and significant computational resources to run effectively [Ameli et al., 2021]. Additionally, the heuristic approaches employed in these models introduce the possibility of converging to suboptimal solutions [Ameli et al., 2022a]. Nevertheless, these simulation-based models are generally well-suited for real-time evacuation management purposes, where capturing realistic traffic dynamics and user behaviours is critical.

1.4.2.3 Deterministic and stochastic

Traffic assignment models (TAMs) are tools that transportation planners use to estimate and forecast traffic flows on road networks. Deterministic models, such as user equilibrium (UE), provide point predictions about traffic volume based on fixed inputs, such as travel demand and network capacity, and assumptions about route choice behavior [Sheffi et al., 1982, Ameli et al., 2022b]. For example, UE predicts travellers will

choose the shortest free-flow travel time path. However, in the real world, traffic flows are subject to inherent variability due to daily changes in demand, weather conditions, accidents, and driver behaviour. Deterministic models are unable to capture this variability.

Stochastic traffic assignment models treat key parameters as random variables. For example, the authors in [Hazelton, 2003] developed a stochastic UE model with random travel demand. Other stochastic extensions model random perceived travel times [Chen and Zhou, 2010], route choice [Frejinger and Bierlaire, 2007], and capacity constraints [Sumalee et al., 2011]. Stochastic models can estimate probability distributions of traffic volumes rather than fixed point flows. Recent research finds that stochastic assignment better replicates empirical traffic patterns than deterministic models.

In summary, deterministic models are useful for general infrastructure planning but cannot evaluate reliability or system performance under uncertainty like evacuation. Stochastic models provide more behavioural realism and can assess variability in travel times, congestion probabilities, and robustness of traffic control strategies. However, they require complex statistical and computational methods. The appropriate model depends on the specific aims and needs of the transportation planning study.

1.4.3 Application in the Evacuation Context

Researchers have formulated different optimization frameworks for establishing suitable shelter locations (strategic choices), orchestrating car-based evacuations (tactical choices), and treating these as distinct issues. Nevertheless, the determinations emerging from either of these challenges intricately impact the other (e.g., the availability of financial resources and the utilization of road networks). This section aims to provide a concise overview of optimization models that integrate the aspects of initiating shelters and executing evacuations for at-risk communities. Most studies tackle evacuation planning analytically, coupling both shelter allocation and traffic assignment, but never in a simulation-based setting, which obliges a sequential nature of the problem. For analytically tackling evacuation planning, several innovative methodologies have been proposed to address the complex challenges of evacuation and emergency response scenarios. Notably, the authors in [Kongsomsaksakul et al., 2005] introduced a sophisticated two-tiered program specifically tailored for flood scenarios. They successfully resolved the intricate optimization problems inherent in such situations by employing a genetic algorithm. The practical application of their framework was demonstrated on the complex Logan network situated in Utah, USA.

Expanding the horizons of this research domain, the authors in [Alçada-Almeida et al., 2009] undertook the task of formulating a multiobjective optimization model that offers a comprehensive solution encompassing both evacuee travel distance and risk assessment in the face of fire catastrophes. Their pioneering approach took root in Coimbra, Portugal, a setting prone to such events. Their methodology presents a robust decision-making framework, enhancing urban preparedness against potential fire disasters. Shifting the focus towards hurricane scenarios, the authors in [Li et al., 2011a, Lim et al., 2012] devised an intricate scenario-dependent two-tiered program that seamlessly integrated driver route preferences into the optimization process. With hurricanes posing unique challenges in terms of evacuation planning, their model proved particularly invaluable in the state of North Carolina, USA. By accounting for a wide array of variables and preferences, the research offered a comprehensive and adaptable solution for handling hurricane-induced emergencies.

The contributions of these researchers have significantly enhanced our ability to manage disasters and plan evacuations strategically, all while relying on analytical approaches rather than simulation-based methodologies. While many studies have developed com-

plex frameworks for evacuation planning, these plans often lack the flexibility to adjust to unexpected events during a disaster. To enable adaptive decision-making, there is a need for real-time communication with vehicles to update them on new decisions as situations evolve.

1.5 Online Evacuation Management

To optimize the evacuation process to its fullest potential, the integration of real-time online adjustments into the planning framework emerges as a requirement. While creating an offline evacuation plan serves as the foundational step, it is the initial phase of a more complex and dynamic process. Recognizing the ever-changing nature of emergency scenarios, it becomes evident that the ability to modify decisions in real-time is paramount. This pertains not only to the selection of destinations but also to the intricate choices of routes taken by evacuees. The concept of online adjustment encapsulates the notion of adaptability, an indispensable trait when dealing with unpredictable events. The static nature of a preconceived plan, while undoubtedly valuable, may fail in the face of evolving circumstances. Factors such as traffic congestion, road closures, or unexpected developments demand a level of responsiveness that can only be achieved through real-time adjustments. The decision-making process undertaken during the planning phase, though thoroughly informed, can never anticipate the entirety of variables that may arise during an evacuation. Therefore, the introduction of online adjustments stands as an imperative enhancement to the traditional evacuation strategy. At the heart of this advanced approach lies the utilization of intelligent transportation systems (ITS). These systems leverage cutting-edge technologies to facilitate seamless communication and coordination among vehicles. Through interconnectedness, vehicles gain access to up-to-the-minute information regarding traffic conditions, alternative routes, and emerging challenges. This data exchange empowers vehicles to make informed decisions that optimize their trajectories based on prevailing conditions, enhancing overall efficiency. The true potential of online adjustment unfolds within this digital orchestration of cooperation. The profound impact of this integration is evident in the realm of public safety. Timely evacuations can mean the difference between life and death, particularly in the face of natural disasters or other emergencies. By embracing online adjustments, we transition from a static and potentially outdated evacuation plan to an agile and adaptive response system. This transformation ensures that our efforts to safeguard lives are not confined by the limitations of a predetermined course of action.

1.5.1 Intelligent Transportation Systems

Intelligent transportation systems (ITS), as presented in Figure 1.4, are a collection of advanced automated technologies that combine vehicles, people, and infrastructure. ITS first came into focus in 1991 when industry experts began to discuss the potential of electronic technologies to improve road transportation [Zhang et al., 2011, Bapaume et al., 2021, Bapaume et al., 2023]. Many ITS technologies offer trip optimization through route guidance, reducing unnecessary miles, reducing traffic congestion, and improving air quality [Alisoltani et al., 2022, Alisoltani et al., 2019]. ITS has been the focus of considerable attention in recent times. This is largely due to the advantages of wireless devices and various sensing technologies. These have enabled a range of innovations, such as the tracking of freeway traffic [Zhu et al., 2019], the operation of traffic control centres, the automated recognition of incidents, the screening of vehicles, and the implementation of autonomous driving [Valle, 2021].



Figure 1.4: General concept of the Intelligent Transport System [Drilo et al., 2009]

ITS, typically capable of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, are considered the future of Vehicular ad hoc networks (VANET) technology [Moubayed et al., 2020]. ITS are capable of supporting a large number of applications. These applications can provide a variety of services to drivers, including real-time warnings to improve road safety, such as collision warnings, traffic information sharing to avoid traffic jams, intelligent road signs, collaborative incident management, and speeding strategy. detect, etc. [Yang and Pun-Cheng, 2018, Lee and Atkison, 2021]

1.5.2 Vehicular Communication Using VANET

The fundamental description of VANET, which stands for Vehicular Ad-Hoc Network, entails equipping a vehicle with a communication node capable of initiating wireless communication with other nearby communication nodes within its radio coverage. Additionally, an underlying notion is that vehicles are inherently mobile entities. As a result, the network's structure fluctuates unpredictably over time, although in this context, some forecasts can be generated regarding the movement of communication nodes, given that every vehicle is expected to follow predetermined routes and roads [Annoni and Williams, 2015]. The progression of VANET substantially enhances ITS. Equipping vehicles with sensors, global positioning systems (GPS), and communication capabilities enhances transportation safety and efficiency [Zeadally et al., 2020].

1.5.3 VANET Architectures

With the rise of transformative applications that have reshaped our daily routines, coupled with growing driver expectations, vehicles have become increasingly voracious in terms of analytical capacity, processing power, computational ability, and storage capacity. De-

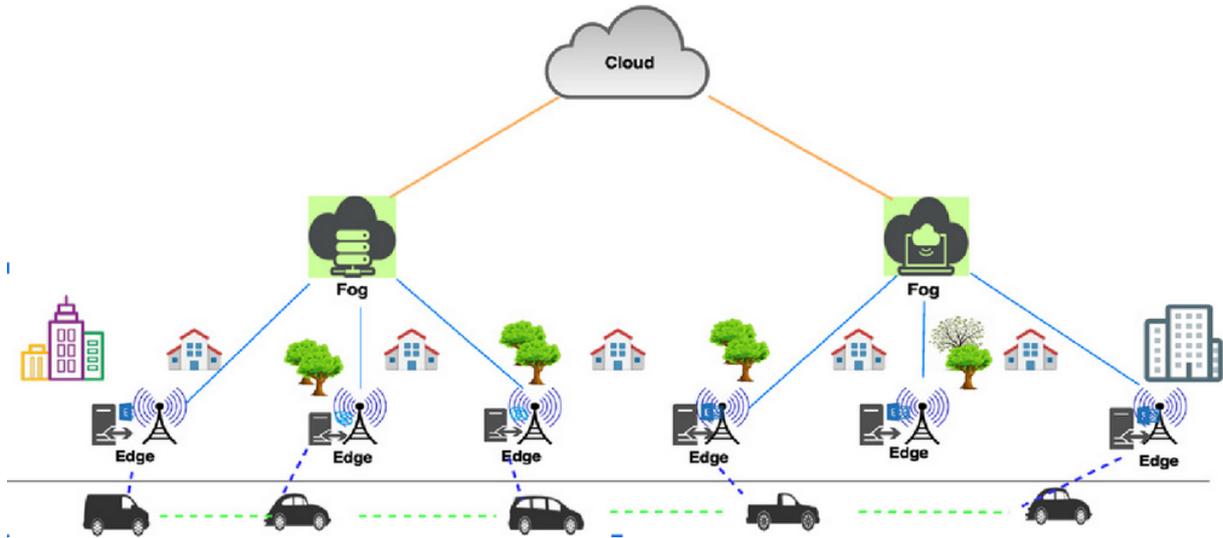


Figure 1.5: VANET Architectures

spite substantial efforts to address these demands, vehicular networks exhibit numerous drawbacks, primarily stemming from the high mobility of nodes (vehicles), resulting in elevated communication costs [Qin et al., 2012].

This pressing challenge necessitated a significant augmentation of vehicle resources to accommodate and cater to all driver applications, ensuring their comfort and safety, among other needs. Consequently, the concept of vehicular cloud computing (VCC) emerged, enabling vehicles to tap into the advantages of cloud computing to fulfil specific requirements [Pitsillides et al., 2012].

Furthermore, the notion of vehicular fog computing (VFC) was introduced to complement VCC, particularly for latency-sensitive applications [Hou et al., 2016].

The majority of vehicular cloud computing (VCC) and vehicular fog computing (VFC) systems typically adopt a layered architecture, commonly consisting of three layers:

- The client layer is the end-user of the VCC/VFC application. The client layer can be a vehicle, a passenger in the vehicle, a mobile phone, or an access device.
- The communication layer is the interface between the end-user and the traditional cloud. The communication layer can be supported by a variety of technologies, including the Internet, a GPS private network, a 3G/ 4G network, or a Remote Service Provider (RSU).
- The cloud layer can be a traditional cloud composed of data centers, including the conventional cloud computing infrastructure, or a temporary cloud where the servers and data centers are deployed to meet customers' requirements.

1.5.3.1 Vehicular Cloud Computing

The Vehicular Cloud Computing [Whaiduzzaman et al., 2014] paradigm encompasses the utilization of cloud computing within VANETs. This concept stemmed from the increasing demand to advance VANETs by integrating diverse applications, catering to drivers' comfort and road safety. Given that these applications typically have moderate requirements for computing capacity and storage space, the idea was to harness cloud computing resources to meet the needs of all these applications for drivers efficiently.

VCC can be implemented through conventional cloud resources accessed via the Internet. Connected vehicles seeking support in terms of computing capacity or storage

to serve their applications and meet drivers' requirements utilize the traditional cloud to fulfill their needs. The cloud provides vehicles with the necessary resources for a specific duration, precisely when the vehicles require them. Furthermore, the concept of VCC extends to situations where vehicles can lease their own resources to other vehicles when they are not in use. Rather than letting their resources go to waste when parked, such as in a shopping center parking lot, vehicles can make these resources available to other vehicles or users for productive utilization.

1.5.3.2 Vehicular Fog Computing

Vehicular Fog Computing [Yousefpour et al., 2019] entails the application of fog computing within the vehicular context. It alleviates the burden on and reduces the data traffic directed toward cloud data centres by relocating data storage and computing capabilities to the network's edge. Additionally, Roadside Units (RSUs) and other network elements like traffic lights can serve as Fog Nodes (FNs) and promptly handle vehicle requests in real-time without overburdening the network. This approach is particularly well-suited for time-sensitive applications, such as road accident information, which necessitates immediate communication with nearby residents and authorities. The incorporation of fog computing in vehicular environments also proves advantageous in terms of bandwidth conservation, offering significant savings compared to conventional cloud usage. You can refer to Figure 1.5

for an illustration of the VFC architecture.

There is a lack of studies employing vehicular communication technology specifically for evacuation rerouting and shelter reallocation. While vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication have been studied for intelligent transportation applications, very little research has examined the potential of leveraging these technologies during emergency evacuations. Most evacuation routing and shelter management work relies on traditional systems and protocols with no real-time vehicular network data integration. More interdisciplinary work is needed to explore the feasibility and potential benefits of utilizing vehicular communication capabilities for evacuation rerouting and shelter allocation purposes.

1.6 Open problems

Realistic planning Current evacuation management plans lack realistic solutions. A truly comprehensive evacuation plan should go beyond optimal vehicle routing to include the designation of safe destinations for evacuees. Furthermore, since evacuations are rare and abnormal events, the resulting traffic flows cannot be accurately modelled using analytical models based on normal traffic conditions. The rigid assumptions of these analytical models make them unsuitable for formulating and solving complex evacuation planning problems. A more effective approach may be using simulation-based models that do not make oversimplified assumptions about traffic flow dynamics. Simulation models can better capture the uniqueness and inherent unpredictability of evacuation traffic. By leveraging simulation modelling rather than purely analytical techniques, more robust and adaptive evacuation plans could be developed to account for diverse scenarios. Overall, advancing evacuation planning requires transitioning from static analytical models toward dynamic simulation capabilities that can represent the realities of irregular evacuation events.

Limitations in simulation-based models There is a lack of studies that integrate both traffic assignment and destination location problems within a unified simulation-

based framework. Existing works have approached these problems separately. For example, the authors in [Gama et al., 2016] proposed a facility location model without considering dynamic traffic assignment, while in [Zhu et al., 2018], the authors used MATSim to solve a simulation-based dynamic traffic assignment model without integrating destination location decisions. However, evacuation planning requires simultaneously optimizing destination selection and routing of vehicles under realistic traffic conditions.

Real-time evacuation management Developing optimal evacuation plans to transport people from hazardous areas to safer destinations is crucial, yet many unpredictable events and challenges can arise during implementation. While pre-planned routes and protocols are important, effective real-time management and adaptation is also essential. Vehicular communication technology has the potential to enable safer and faster evacuation by providing capabilities to handle emergent and unforeseen circumstances. By allowing vehicles to exchange information during the evacuation, issues such as congestion, accidents, or changing conditions could be detected and mitigated dynamically. Vehicular networks could reroute vehicles based on real-time feedback, coordinate responses, and help guide evacuees through the volatile evacuation environment. While proper planning lays the groundwork, leveraging vehicular communication systems and intelligence could provide the flexibility to execute evacuations under chaotic real-world conditions. The focus should be on both optimizing pre-defined evacuation plans as well as integrating communication networks and technologies to facilitate adaptable real-time coordination and response management.

Scaling, securing, and standardizing cloud-vehicular integration The prevalent cloud-centric model, where connected vehicles send data to the cloud for processing and analysis, can introduce challenges. With numerous vehicles generating immense datasets, massive bandwidth is required to transmit this data to the cloud and return solutions to each device [Alippi et al., 2016]. Additionally, physically distant cloud data centres lead to security, latency, and reliability concerns, especially for time-critical vehicle applications [Chiang and Zhang, 2016]. The long transmission distances and heavy network loads strain the connectivity between vehicles and the cloud. Relying on external cloud infrastructure creates dependencies that impact system responsiveness in safety-sensitive vehicular scenarios. While clouds enable valuable analytics, their removal from the local context results in bottlenecks, delays, vulnerabilities, and single points of failure. An alternative approach may be distributing intelligence and processing to the network edge in proximity to data sources through solutions like multi-access fog computing. This could alleviate the issues of bandwidth strain, latency, and external dependency for time-sensitive and context-aware vehicular applications.

Compliance to online orders While online platforms allow rapid dissemination of evacuation orders, compliance varies across demographics. Internet access limitations, lack of tech literacy, distrust in institutions, and unclear threat perception inhibit universal adherence to online directives. This presents an open challenge.

Dynamic nature of the hazardous situation The evacuation creates a dynamically changing situation by the rapidly evolving state of risk that needs to be considered while planning for the process and also to be taken into account while exchanging information in real-time. This kind of dynamic situation can have a big impact on the evacuation operation's success.

1.6.1 The open problems considered in this dissertation

Dynamic population evacuation (DPE) optimizes evacuation operations to move people from hazardous zones swiftly. DPE situations involve high demand and congestion across transport networks. Considering evacuation operations' importance and potential to impede vehicle flow, researchers have modeled DPE as a planning dilemma. To reduce gridlock, some researchers have focused on traffic routing, while others have explored destination choices using shelter location-allocation models.

In this research, we propose a new simulation-based framework that accounts for the dynamic nature of evacuations and lessens congestion risk. Our approach couples traffic assignment and shelter allocation decisions to enhance DPE efficacy.

This research also examines the real-time management of evacuation operations to improve efficiency. Vehicular communication enables real-time coordination and is critical for enhancing many transportation domains, including object identification, congestion avoidance, accident detection, etc.

In the context of evacuation, vehicular communication has been applied to address challenges such as optimizing speed strategies and rerouting decisions. Additionally, rerouting and accurate reallocation decision-making present challenges due to the substantial information and computational requirements involved. However, recent advances in cloud computing and fog computing make addressing complex evacuation problems more viable for researchers. Leveraging these technologies, this dissertation proposes congestion prediction and avoidance techniques to mitigate risk by reducing vehicle presence in hazardous situations.

We examine these techniques implemented within both centralized and decentralized architectures. By accounting for large-scale information processing demands, our approach aims to optimize rerouting and destination allocation to minimize gridlock risks during time-critical evacuations.

1.6.2 Research questions

A considerable amount of research has examined dynamic population evacuation planning in various settings. However, current approaches appear to rely predominantly on analytical methods, while simulation-based techniques may be better suited for large-scale urban road networks.

Notable gaps exist in simulation-based evacuation planning:

1. Most solutions address destination choice or route choice separately rather than integrating both.
2. No studies have coupled evacuation planning with vehicular communication to improve the initial plan's execution. Incorporating vehicular communication could significantly enhance evacuation efficiency by allowing real-time adjustments. Incorporating the hazard's evolution and the network's changing state into the planning process could produce more adaptive evacuation plans. These potential improvements merit exploration.
3. In practice, many strong assumptions used in mathematical formulations are violated in real urban networks. For instance, cost functions, signalized intersections violating FIFO rules, and other common features break typical assumptions.

Interestingly, research rarely intersects evacuation planning and vehicular communication, as these problems fall under distinct emergency response and transportation research silos. A more integrated approach considering both planning and communication could

provide novel insights. This thesis aims to advance evacuation planning and execution methods by addressing key knowledge gaps. Specifically, we will investigate the following research questions to improve existing solutions and provide novel planning approaches for real-world evacuation scenarios. Furthermore, we will integrate planning and real-time decisions to develop new end-to-end solutions. The overarching goals of this thesis can be summarized by the following questions related to dynamic population evacuation:

- The disaster evacuation process involves determining the optimal allocation of evacuees to shelters (the shelter allocation problem or SAP) as well as modelling time-dependent traffic flow and congestion (the dynamic traffic assignment or DTA problem). Traditionally, these two problems have been solved separately, but some research has proposed combining them into a single model. This raises the question: Could coupling the SAP and DTA problems lead to increased overall efficiency of the evacuation process? Challenges include the added computational complexity of combining two NP-hard problems.
- Could connecting and coordinating vehicles via vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) networks improve the efficiency of the evacuation process? Online traffic management could impact efficiency gains. Factors like communication range and latency all may affect how well vehicles can share information and coordinate.
- How can we optimize vehicular network architecture and address vital remaining questions to maximize efficiency gains, determine suitable architecture, and provide systems-level insights through comparative analysis of VANET specifications and evacuation metrics that will guide efficient VANET design for emergency evacuation safety?
- Disaster evacuation planning and real-time management could potentially be improved by incorporating dynamic risk modelling. Traditional static plans and procedures may not account for the unpredictability and rapidly changing conditions often present during evacuations. This raises the question: Could adding dynamic risk factors to our modelling and solutions provide more beneficial results for both evacuation planning and real-time operational management?

1.7 Research objectives

The main objective of this dissertation is to propose a Simulation-based framework to plan and adjust real-time evacuation orders. The four following sub-objectives are considered towards achieving the main objective of this dissertation:

- First, a planning framework integrating both shelter assignment and traffic assignment models is proposed to generate optimal evacuation plans.
- Second, a real-time evacuation management system is developed to enable recalibrated rerouting and reallocation decisions.
- Third, centralized and decentralized VANET architectures for vehicular communication are compared and contrasted.
- Finally, incorporating dynamic hazard state information to better optimize the evacuation process is explored.

1.8 Thesis outline

The objective of this PhD thesis is to address the aforementioned research questions. The remaining of the thesis is structured as follows. Chapters 2, 3, 4, and 5 address research questions 1, 2, 3, and 4, respectively; and Chapter 6 concludes the thesis. Chapter 2 presents a simulation-based framework to model the dynamic evacuation of populations, coupling shelter allocation and traffic assignment. The proposed framework is implemented on a real road network to assess performance metrics, including clearance time, mean speed, and more. In Chapter 3, we further develop an online management service leveraging vehicular communication technology. Multiple scenarios are tested to evaluate the online framework across varying market penetration rates of connected vehicles. The simulation framework provides a novel approach to integrated modelling of key evacuation sub-problems. Meanwhile, the online service explores the potential of emerging vehicular networks to enable real-time coordination and adaptive management under dynamic conditions. Together, these contributions provide new modelling capabilities and reveal insights into improving future evacuation planning and operations. Chapter 4 investigates vehicular ad hoc network (VANET) architectures to enable reliable vehicular communication during emergencies. Multiple VANET designs are analyzed to identify the most suitable architecture based on transmission delay performance. The proposed framework is then demonstrated on real-world, large-scale scenarios to further evaluate the capabilities of the selected VANET architecture. This analysis provides important insights into designing vehicular networks specifically optimized for robust performance under emergency evacuation conditions. Chapter 5 incorporates dynamic modeling of hazard risk propagation over time into the proposed framework. This allows the evacuee simulations to account for the evolving disaster state. The model defines and integrates risk progression to assess impacts on evacuees as the threat spreads. It is implemented for real-world natural disaster scenarios to demonstrate adaptability to changing conditions. Finally, Chapter 6 summarises and concludes the work. An overview of the thesis outline is given in Figure 1.6



Figure 1.6: Visualisation of the thesis outline

Chapter 2

Evacuation Planning

Evacuating the population during crises to safe zones via optimal paths is vital. This chapter investigates the state of the art of population evacuation management to identify the gaps in providing an effective evacuation plan. Based on the review results, we highlight the research gap in coupling the two main challenges of evacuation problems, i.e., shelter allocation and traffic assignment. Thus, we design a framework that couples both shelter allocation and traffic assignment in a dynamic context to consider the traffic conditions.

We solve SAP following a linear formulation of the shelter allocation, considering the number of opened shelters and their capacity. In addition, we deploy the SUMO simulator to address the simulation-based DTA problem. We calculate multiple metrics to measure the quality of the framework and compare the methodology with existing models in the literature. We also establish multiple scenarios to look for the best optimization setting through sensitivity analysis. Finally, we apply the proposed model to the real test case of Luxembourg City.

This chapter is an updated version of the paper:

- H. Idoudi, M. Ameli, C. N. Van Phu, M. Zargayouna and A. Rachedi, "An Agent-Based Dynamic Framework for Population Evacuation Management," in *IEEE Access*, vol. 10, pp. 88606-88620, 2022, doi: 10.1109/ACCESS.2022.3199445.

2.1 Introduction and motivation

Natural disasters and catastrophes endanger the lives of people in devastated areas. Evacuating people from those areas to safe places or shelters is a feasible solution to decrease or avoid enormous losses [Yuan et al., 2019, Siyam et al., 2019]. Order and guidance are crucial and decisive to running this process effectively and safely managing the evacuation process [Jiang, 2019]. There are two main information pieces that each evacuee should have during the evacuation process: (i) the destination (shelter) and (ii) the route toward that shelter. Both information pieces are obtained by solving shelter allocation and traffic assignment, respectively. Each problem can follow different principles. We can categorize the models based on their principles into three groups [Bayram, 2015, Yuan et al., 2019]: the first addresses the problem of the evacuation process considering the user equilibrium (UE). The second models the evacuation as a system optimal (SO) problem. The third model uses the nearest allocation (NA) approach. These models differ mainly in their objective function. In the UE model, each traveler aims to minimize his benefit by minimizing his own cost. In other words, this principle assumes that the users are perfectly informed, rational and behave selfishly. The SO principle aims to optimize the total benefit of all evacuees. To this end, evacuees may not be assigned to shelters or routes that maximize their own benefits but shelters or routes that optimize the overall system benefit. This principle can be difficult to get people to accept, especially in evacuation situations. To minimize the total traveled distance, the NA approach assigns evacuees to the closest shelter in terms of traveling distance between origins (hazardous zones) and destinations (safe nodes). Such a model could not provide supportable results for both evacuees and system operators [Bayram et al., 2015].

Multiple indicators are applied in the literature to identify and quantify the solution provided by these models. Here, we mention the most common measures in developing evacuation models. Most studies aim to minimize the following indicators:

- Network clearance time: It is defined as the arrival time of the last evacuee to the shelter or safety zone [Bi et al., 2020, Hsu and Peeta, 2014, Lim et al., 2015].
- Total evacuation time: It denotes the sum of the evacuation time of all evacuees [Hajjem et al., 2017, Bayram and Yaman, 2018, Bayram et al., 2015].
- Total traveled distance: It is the sum of all trip lengths traveled by all evacuees during the evacuation [Sheu and Pan, 2014, Alçada-Almeida et al., 2009].

The UE or SO route choice approach is represented formally as a traffic assignment problem. The problem could be classified into two main categories: static and dynamic models. Static traffic assignment (STA) models determine the number of vehicles selecting each route between origins and destinations for the demand profile. However, solving the problem of traffic assignment in a static setting cannot capture the changes in the number of vehicles on routes over time. The dynamic traffic assignment (DTA) problem generalizes the static setting to determine at each time instant the flow on each route over the study period [Daskin, 1985]. Although static models are used for planning purposes, they cannot accurately describe congestion and do not model spillbacks [Ameli et al., 2018]. DTA aims to determine the relationship between routes, time, and network characteristics. It can produce stable and meaningful solutions, which are crucial for practical applications [Levin et al., 2015]. Traffic assignment models could also be seen as trip-based or flow-based models. Flow-based models aim at determining the vehicular flow on each route, while trip-based models' objective is to specify the number of travelers (particles) on each route, making the traffic assignment problem more challenging to solve because of the discrete setting [Alisoltani et al., 2023]. We conduct a comprehensive literature

review on all static and dynamic traffic assignment models used in evacuation problems, either flow-based or trip-based.

In this chapter, we investigate the state of the art of population evacuation management to identify the gaps in providing an effective evacuation plan. Based on the review results, we highlight the research gap in coupling the two main challenges of evacuation problems, i.e., shelter allocation and traffic assignment. Thus, we design a framework that couples both shelter allocation and traffic assignment in a dynamic context to consider the traffic conditions. We solve SAP following a linear formulation of the shelter allocation, considering the number of opened shelters and their capacity. In addition, we deploy the SUMO simulator [Lopez et al., 2018a] to address the simulation-based DTA problem. We calculate multiple metrics to measure the quality of the framework and compare the methodology with existing models in the literature. We also establish multiple scenarios to look for the best optimization setting through sensitivity analysis. Finally, we apply the proposed model to the real test case of Luxembourg City.

Regarding the objectives of the evacuation process, the ultimate goal is to evacuate all people from hazardous zones as fast as possible. In other words, we are looking for a minimal network clearance time, considering the evacuees' utilities. We consider the SO objective for the shelter allocation without considering any attraction or individual preferences to shelter as evacuees have no information about these shelters [Zhao et al., 2017]. We have also chosen Stochastic User Equilibrium (SUE) as the assignment principle to consider the heterogeneity in the users' decision-making process. In addition, UE is the special case of SUE in which users have no error in their decision-making process, i.e., users have a perfect knowledge of the network, which is not the case during an emergency period. Thus, we take into account this error with the SUE formulation. We consider two types of decisions that could be conflicting, SO for shelter allocation and SUE for traffic assignment. We compare the results of the proposed method with those of methods already used by multiple performance measures: mean evacuation time, network clearance time, and average travel delay. We also propose a new measure called *average evacuation travel delay*. It is noteworthy that our method considers a generic concept of risky areas following most of the models proposed in the literature, i.e., the model is independent of the hazard type [FEMA, 2010].

The rest of this chapter is organized as follows. The following section reviews the literature on network evacuation problems, focusing on shelter allocation and traffic assignment. Then, it highlights our contributions. Section 2.3 presents our framework and mathematical formulations. Section 2.6 presents the case studies, optimization scenarios, and numerical results. We discuss the results in subsection 2.6.3, and we perform a sensitivity analysis on both convergence metrics and planning and optimization intervals in subsection 2.6.5. Afterward, we apply the framework to a real case scenario (subsection 2.6.6) using the best setting resulting from sensitivity analysis. We discuss the results, and we provide concluding remarks in Section 2.7.

2.2 State of the Art

This section reviews the related works to the population evacuation problem in static and dynamic contexts. It reviews studies that use STA formulation for evacuation problems and then presents all studies in the dynamic context. Table 2.1 illustrates the results of the literature review. Here, we present the most advanced methodologies for the evacuation problem.

2.2.1 Static models

Many studies using STA models applied bi-level optimization to address SAP and traffic assignment problems with different objective functions [Idoudi et al., 2022b]. The upper level formulates the shelter location-allocation problem to optimize the system’s objectives, and the lower level represents the traffic assignment in a static setting following the evacuee’s interests. [Sherali et al., 1991] used a p-median model to solve the problem of shelter site selection with a traffic assignment model under the SO principle and deployed a heuristic algorithm. [Kongsomsaksakul et al., 2005] proposed a model to study the effect of shelter locations on evacuation management, taking into consideration the interest of system operators and evacuees. At the upper level, they defined the objective to minimize the total network evacuation time based on shelter allocation. The lower level represented the UE model that aims to minimize the individual travel time of each evacuee. The authors have solved the problem with a version of the genetic algorithm. [Ng et al., 2010] used the same formulation and solved the problem with a simulated annealing algorithm. [Li et al., 2012] presented a scenario-based model. The upper level is a two-stage model. In the first stage, they determine the shelter location, and in the second stage, they choose the selected shelters, considering the hurricane conditions. They solve the STA problem at the lower level using the Lagrangian relaxation algorithm. [Xu et al., 2018] proposed a hybrid model based on scenarios in the central area of Beijing. The upper level makes location-allocation decisions such that the total evacuation distance is minimized subject to capacity and distance constraints. The lower-level model minimized the individual evacuation distance. They have used a modified particle swarm optimization algorithm with simulated annealing heuristics.

The main drawback of STA models is that they cannot capture the evolving state of traffic conditions [Szeto and Wong, 2012]. In addition, the solution is calculated by heuristic methods due to the complexity of the bi-level formulation. Before reviewing the dynamic studies, we present recent studies that formulate the evacuation process as a single-level optimization problem. [Bayram et al., 2015] formulated the evacuation problem as a single-level non-linear mixed-integer program. They have proposed a scenario-based approach to minimize the total evacuation time. The decision variables considered are both shelter selection and route assignment variables. The authors propose an exact method based on second-order conic programming to solve the problem. They applied the methodology to a realistic Istanbul traffic network test case. In [Bayram and Yaman, 2018], they revised the formulation and solved it with Bender’s decomposition approach. Note that many other studies in the literature addressed only one of the problems, either STA or SAP, for the evacuation problem (see Table 2.1).

2.2.2 Dynamic models

Multiple time-dependent variables should be considered to formulate the evacuation problem dynamically, and consistent assumptions should be made. Due to this difficulty, many studies formulated population evacuation solving only one sub-problem in a dynamic context, either DTA or dynamic shelter allocation. For instance, [Hsu and Peeta, 2014] used DYNASMART simulator [Peeta and Mahmassani, 1995b] to address the traffic conditions in the evacuation process with a given risky zone and shelter allocation plan. [Gan et al., 2016] coupled simulation and optimization to create an evacuation plan. They considered multiple stages for the iWays simulator with arc capacity penalties to simulate vehicles in departure time intervals. The model aims to minimize the total evacuation time and the sum of the arcs penalties. Besides, [Zhang et al., 2015] came up with a multi-period optimization method including a status variable for the available network capacity, called productivity. They have used the TRANSIMS simulator to represent the evacuation process

and solve the network UE problem. However, [Jeihani, 2007] confirmed that TRANSIMS had not received good exposure, and its capabilities are unknown to many researchers in the transportation field. [Zhu et al., 2018] have used Matsim to solve simulation-based DTA considering UE conditions of the problem. Authors considered the city of north New Jersey and only one type of hazard (Hurricane). Note that all of the abovementioned research studies used given shelter allocation and performed only traffic assignment or solved DTA and SAP separately. we aim to fill this research gap by combining and solving both simulation-based DTA and SAP.

Table 2.1 presents the characteristics of the evacuation planning method of 36 studies. We define seven categories to classify the papers. Some papers formulated the problem of shelter allocation as a facility location model by deciding how to allocate evacuees to shelters. Some other studies considered the traffic assignment problem only or with a given shelter allocation plan to decide the path distribution toward the destinations (shelters). When considering the traffic assignment sub-problem, we should also decide on multiple other factors, such as the static or dynamic setting of the problem and the analytical or simulation-based nature of the solving. In addition, we should decide on whether to assume the super sink principal or not. A *super sink* is an artificial node connected to all destination nodes through artificial links with infinite capacity. The objective function definition is also crucial in the mathematical model. Therefore, we present different objectives of the evacuation problem in the literature. Finally, we show the setting of our study compared to the state of the art. As shown in Table 2.1, the evacuation process is tackled as a complex problem that is composed of different sub-problems. In each paper, the authors try to solve a sensitive and decisive part of the evacuation process.

Unlike the existing solutions, we propose a novel model to couple the SAP and the DTA problem in this chapter. This model offers for the first time to formulate a fully simulation-based dynamic evacuation problem that integrates the decision of system operators to choose the best allocation of evacuees to shelters and evacuees' interests while choosing their routes to these shelters. Besides, we investigate the impact of the dynamic shelter allocation on network evacuation problems using agent-based simulations. Our framework considers the dynamic location-allocation model distinguished from most literature models that solve the problem in a static setting. The proposed model is multi-period and combines system operators and user needs. We also consider the problem with a realistic network of Luxembourg City without any assumption of super origin or sink. Afterward, we propose an iterative procedure to solve the problem for every time interval of the evacuation horizon. In the next section, we formulate both problems and present our methodology.

2.3 Coupling Traffic Assignment and Shelter Allocation

In this section, we first present the proposed methodological framework for the population evacuation problem. Second, the mathematical problem formulation embedded in the framework is presented and discussed. Finally, two quality metrics named the *average travel delay* (ATD), and *average evacuation travel delay* (AETD) used to evaluate the performance of the framework are presented.

Table 2.1: The sample of different studies on multi-class traffic assignment in the Literature.

Research	Problem		Objectives				Traffic Assignment				Research approach			Level of optimization		Super Sink
	Traffic assignment	Shelter allocation	Traffic assignment		Shelter allocation		Dynamic	Static	Trip based	Flow based	Analytical based	Simulation based	Single	Multilevel		
			UE or SUE	System optimum	Evacuees optimum	System optimum										
Lu et al., 2005 [Lu et al., 2005]	x		x			x				x			x			
Sbayti et al., 2006 [Sbayti and Mahmassani, 2006]	x			x		x					x		x			
Balakrishna et al., 2008 [Balakrishna et al., 2008]	x		x			x					x		x			
Yao et al., 2009 [Yao et al., 2009]	x			x		x								x		
Xie et al., 2009 [Xie and Turnquist, 2009]	x			x		x										
Kalafatas et al., 2009 [Kalafatas and Peeta, 2009]	x			x		x										
Xie et al., 2010 [Xie et al., 2010]	x			x												
Ng et al., 2010, [Ng et al., 2010]	x	x														
Ben-Tal et al., 2011 [Ben-Tal et al., 2011]	x			x		x										
Bretschneider et al., 2011 [Bretschneider and Kimms, 2011]	x			x		x										
Li et al., 2011 [Li et al., 2011a]	x															
Karoonsontawong et al., 2011 [Karoonsontawong and Lin, 2011]	x															
Lim et al., 2012 [Lim et al., 2012]	x															
Liu et al., 2012 [Liu and Luo, 2012]	x															
Duanmu et al., 2012 [Duanmu et al., 2012]	x															
Continho-Rodrigues et al., 2012 [Continho-Rodrigues et al., 2012]	x															
Wang et al., 2012 [Wang et al., 2012]	x															
Li et al., 2012 [Li et al., 2012]	x															
Goerigk et al., 2014 [Goerigk et al., 2014]	x	x														
Kaleci et al., 2015 [Kaleci et al., 2015]	x	x														
Lim et al., 2015 [Lim et al., 2015]	x															
Bayram et al., 2015 [Bayram et al., 2015]	x															
Zhang et al., 2015 [Zhang et al., 2015]	x															
Wang et al., 2016 [Wang et al., 2016a]	x															
Heßler et al., 2016 [Heßler and Hamacher, 2016]	x															
Liu et al., 2016 [Liu and Lim, 2016]	x															
Shahparvari et al., 2016 [Shahparvari et al., 2016]	x															
Gama et al., 2016 [Gama et al., 2016]	x															
Zhao et al., 2017 [Zhao et al., 2017]	x															
Bayram et al., 2018 [Bayram and Yaman, 2018]	x															
Shimamoto et al., 2018 [Shimamoto et al., 2018]	x															
Zhu et al., 2018 [Zhu et al., 2018]	x															
Yuan et al., 2019 [Yuan et al., 2019]	x															
Escribano-Macias et al., 2020 [Escribano-Macias et al., 2020]	x															
Tanaka et al., 2021 [Tanaka et al., 2021]	x	x														
This study	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x

2.3.1 Assumptions

To facilitate the presentation of the essential ideas without loss of generality, the following basic assumptions are made in this chapter:

- Users do not have perfect knowledge of prevailing and future traffic conditions.
- Users have no information about the locations and capacity of the shelters, so they do not have preferences.
- Users have experiences with the network, and so they could choose their path by C-logit mechanism (under SUE principle) at the beginning of the evacuation.
- Users departure times are preplanned and given.

2.3.2 Problem formulation

Table 2.2: Notations used in this chapter

O	Set of origin nodes, subset of set of nodes, $O \subset N$.
S	Set of destination nodes, subset of set of nodes, $S \subset N$.
T	Set of small time intervals.
H	Total duration considered.
o	Index of origin node, $o \in O$.
s	Index of destination node, $s \in S$.
α	Time interval index.
y_s	Binary variable; it is set to 1 if shelter s is selected; 0 otherwise.
x_{os}	Number of evacuees allocated to the pair having origin o and destination s .
w_o	Amount of demand from origin o .
c_s^α	Capacity of shelter s , limit number of evacuee allocated to shelter s in time interval α .
P	Maximum number of open shelters.
π_{os}	Set of all paths between origin o and destination s .
π	Index of path, $\pi \in \pi_{os}$.
Tr_{os}^α	List of trips which travel between origin o and destination s in departure time interval. α .
Tr_π^α	List of trips which travel between o and s on path π in departure time interval α , $Tr_\pi^\alpha \subset Tr_{os}^\alpha$.
tr	Index of trip, $tr \in Tr_{os}^\alpha$.
$t_{tr,\pi}^\alpha$	Experienced travel time of trip tr on path π in departure time α .
$t_{os}^{\alpha*}$	Minimum experienced travel time form origin o and destination s in departure time α .
t_{os}^*	Global minimum experienced travel time form origin o and destination s ; $t_{os}^* = \min\{t_{os}^{\alpha*}\}, \forall \alpha \in T$.
$\hat{t}_{tr,\pi}^\alpha$	Perceived travel time of trip tr on path π in departure time α .
$\xi_{tr,\pi}^\alpha$	Random error term for trip tr on path on π in departure time α , and $E(\xi_{tr,\pi}^\alpha) = 0$.
pr_π	Path choice probability for path π in the C-logit model.
$n(A)$	Cardinality of set A .

Mathematically, two decision variables should be determined for each evacuee sequentially: (i) shelter choice that determines the destination, and (ii) route choice toward that

destination. The first choice problem is the SAP and the second one is the DTA problem. We aim to formulate the SAP to minimize the total evacuation time. However, we formulate the DTA problem to find the SUE solution. Recall that the global objective of our framework is to evacuate the risky nodes (origins) as fast as possible, i.e., minimizing the network clearance time. In a sense, this scenario is equivalent to a real-world scenario wherein vehicles are guided by the system to choose their shelter (destination) as they do not have any information about the shelter conditions and capacities. Afterwards, they choose their path rationally and selfishly to reach the shelter with minimum travel time.

Let us define the evacuation problem on a directed graph representing a traffic network $G = (N, A)$, where N is the set of nodes, A is the set of edges (links). We define O as the set of origin nodes that determines the risky zone to evacuate and S as the destination nodes representing safe locations, i.e., shelter sites. Without loss of generality, we assume that O and S are disjoint subsets of N ($O, S \subset N$; $O \cap S = \emptyset$). We denote by w_o the amount of demand of each origin o ($o \in O$). This demand represents the number of vehicles that should evacuate. We note x_{os} the integer decision variable that determines the number of evacuees allocated from origin o to destination s in the current time interval. y_s is a binary variable for the shelter selection. $y_s = 1$ if a shelter is selected ($x_{os} > 0$), otherwise $y_s = 0$. $t_{os}^{\alpha*}$ denotes the minimum travel time between origin o and destination s in time interval α . Table 2.2 presents this chapter's full list of important notations.

A large number of studies in evacuation planning calculate travel time based on the STA using a convex travel time function, e. g., BPR function [Bayram, 2016]. Here, we use a dynamic simulator to provide real-time information for the travel time. We used that information to solve SAP and DTA sub-problems sequentially (cf. Figure 2.1).

The finite period of interest is the planning horizon H defined as the total duration considered. This total duration is discretized into a set of small intervals of time, indexed by α ($\alpha \in T = \{\alpha_0, \alpha_0 + \eta, \alpha_0 + 2\eta, \dots, \alpha_0 + M\eta\}$ and $\alpha_0 + M\eta = H$). η is the duration of the time intervals. At each evacuation time step α , we need to solve SAP for a given evacuation demand profile. In other words, we separate each two SAP problems by the index of the time interval (α). Then we solve the simulation-based DTA based on the results of SAP. Therefore, $t_{os}^{\alpha*}$ is defined as a time-dependent variable in this problem. At each time interval α , $t_{os}^{\alpha*}$ calculated by the simulator and replaced as a fixed value in Equation 2.1. This assumption transforms the model into a linear form. Thus, we can formulate it with linear integer programming. We define c_s^α as the capacity of shelter s in time interval α and P as the maximum allowable number of opened shelters. For simplicity, we do not use the time interval index for parameters and variables that are not updated by the dynamic simulator, e. g., x_{os} and w_o . First, we propose to solve SAP for each time interval α . The goal is to allocate evacuees to shelters for the minimum total evacuation time (TET) based on the currently observed travel times (from risky nodes to shelters). The p-median model is the most common approach to represent the shelter location-allocation problem under different types of hazards [Ma et al., 2019]. The model prioritizes efficiency and fairness over users' preferences by minimizing the overall evacuation time, equivalent to the SO optimization. We formulate the SAP based on the p-median model proposed by [Hakimi, 1964]. In the following formulation, the α is fixed to the current time interval when we are at Step 3 of the framework (cf. Figure 2.1).

$$\min \sum_{o \in O} \sum_{s \in S} t_{os}^{\alpha *} x_{os} \quad (2.1)$$

$$s.t. \sum_{s \in S} x_{os} = w_o; \quad \forall o \in O, \quad (2.2)$$

$$\sum_{o \in O} x_{os} \leq c_s^{\alpha} y_s; \quad \forall s \in S, \quad (2.3)$$

$$\sum_{s \in S} y_s \leq P, \quad (2.4)$$

$$x_{os} \leq w_o y_s; \quad \forall o \in O, \forall s \in S, \quad (2.5)$$

$$x_{os} \geq 0; \quad \forall o \in O, \forall s \in S, \quad (2.6)$$

$$y_s \in \{0, 1\}; \quad \forall s \in S. \quad (2.7)$$

The number P is a predetermined parameter that restricts the number of shelter sites that can open due to budgetary and management issues [Bayram, 2015]. In Objective function (1), we minimize the total travel time of evacuees from all origins to all chosen shelters. Constraint (2) ensures that all the demand from origin o is evacuated. Constraint (3) forbids assigning evacuees to shelters exceeding the capacity of the shelter (c_s^{α}), taking into account the used capacity in the previous time interval $\alpha - 1$ [Shimamoto et al., 2018]. Constraint (4) specifies a fixed number of open shelters. Constraint (5) forbids assigning evacuees to non-opened shelters. Constraints (6) and (7) represent logical variable restrictions. For each time interval, we are solving the above linear formulation where we use a fixed capacity term that changes over time intervals. The residual shelter capacity denotes the effect of the arrival of users on shelters. This capacity is updated after the arrival of evacuees, and it is used afterwards in the next time interval based on the following formula $\forall s \in S$:

$$\begin{cases} c_s^{\alpha} = c_s^{\alpha-1} - \sum_{o \in O} x_{os} & \alpha \geq 1 \\ c_s^1 = c_s^0 - \sum_{o \in O} x_{os} \end{cases} \quad (2.8)$$

where c^0 is the initial capacity that shelters have at the beginning of the process. The presented model is an NP-hard problem [Sherali and Nordai, 1988]. The result of the SAP is the demand from each origin o to each shelter s , i.e., the OD matrix needed for the DTA model.

In the DTA model, we formulate the network equilibrium based on agent-based simulation. While we solve the SAP at a given time, the DTA problem has to be solved time-dependently. For example, in time interval α , travel times and traffic conditions are fixed based on the dynamic simulator for the SAP. Note that each evacuee's departure time is given in this study.

The SUE model is deployed to represent the network equilibrium. Because the UE principle, [Wardrop, 1952], always supposes that all users have perfect knowledge of the network information and consistently choose paths to minimize their travel costs. The assumption is so rigorous for users that it cannot hold on to a realistic scenario. The principle of SUE can further relax the assumption and be stated that all travelers cannot improve their perceived travel cost by unilaterally changing paths [Daganzo and Sheffi, 1977, Idoudi et al., 2021]. Based on the SUE principle, the perceived travel cost can be expressed by the actual travel cost and a random error for each traveler as follows:

$$\hat{t}_{tr,\pi}^{\alpha} = t_{tr,\pi}^{\alpha} + \xi_{tr,\pi}^{\alpha}, \quad \forall \pi \in \pi_{os}, \alpha \in T, tr \in Tr_{\pi}^{\alpha} \quad (2.9)$$

The C-logit SUE condition on the road network is expressed as follows for each departure time interval (α) [Daganzo and Sheffi, 1977]:

$$Tr_{\pi} = x_{os}pr_{\pi}, \quad \forall \pi \in \pi_{os} \quad (2.10)$$

Note that x_{os} is the number of evacuees allocated to the pair having origin o and destination s . x_{os} denotes the solution of SAP. pr_{π} corresponds to the path choice probability of the employed route choice model.

In the simulation-based DTA, we tend to attain the SUE state at each departure time interval so that each vehicle could not reduce their trip travel time by changing the chosen route. To achieve this condition, we iteratively run both phases, optimization, and simulation. The optimization determines the route choice of vehicles, while in the simulation part, we simulate the trajectories on paths by executing a dynamic simulation of vehicles taking specified routes. The model used to assign users to the route is the C-logit mechanism [Cascetta et al., 1996].

The C-logit model is based on the logit model [Cascetta et al., 1996] with the assumption that all route alternatives' travel times are identically and independently distributed Gumbel variates [Daskin, 1985]. C-logit presents a probability pr_{π} for selecting path π . The formula is shown below:

$$pr_{\pi} = \frac{\exp[\theta \cdot (t_{\pi} - CF_{\pi})]}{\sum_{h \in \pi_{os}} \exp[\theta \cdot (t_h - CF_h)]} \quad \forall \pi \in \pi_{os} \quad (2.11)$$

where θ denotes the dispersion parameter of the travel time perception among vehicles. t_{π} represents the travel time on path π . The set $\pi_{os,\alpha}$ is the path set for the OD pair. CF_{π} is the ‘‘commonality factor’’ of the route π that determines the degree of overlap between the current path and all alternative routes. This commonality factor is calculated using the following formula:

$$CF_{\pi} = \beta_0 \ln \sum_{h \in \pi_{os}} \left[\frac{ID_{h\pi}}{t_h^{0.5} \cdot t_{\pi}^{0.5}} \right]^{\gamma} \quad (2.12)$$

where $ID_{h\pi}$ represents an identical part between path h and path π . The respective unit can be travel time or other measures. t_h and t_{π} denote the travel time of Path h and π respectively. β_0 and γ are parameters of the model. With the path probability and a network loading model, the general DTA calculation consists of the following steps:

- **Step 1:** Calculate the shortest paths for each OD pair.
- **Step 2:** Load vehicles onto the network for a defined time interval based on the path probabilities calculated based on the chosen route choice model.
- **Step 3:** Recalculate the shortest paths considering the updated link travel times.
- **Step 4:** Go to step 2.

2.3.3 Optimization framework

The process of solving population evacuation planning comprises three main parts: the SAP problem, the DTA problem, and the traffic simulation. Here, we propose a new scheme for the sequence of execution of each step. We solve these steps in a time-dependent manner. In each period, we optimize all of these parts iteratively based on the data provided by the dynamic simulation until all the demand is satisfied. Recall that, according to state of the art, these steps are solved together using static traffic assignment

models as a single-level optimization [Bayram et al., 2015, Bayram and Yaman, 2018], or bi-level programming problem originally proposed by [Von Stackelberg, 1934] (see, e.g., [Ng et al., 2010, Li et al., 2011b, Kongsomsaksakul et al., 2005, Xu et al., 2018]).

In the dynamic setting, [Hsu and Peeta, 2014] proposed a dynamic evacuation framework with multiple time intervals wherein they considered the evolution of the network. They do consider the problem of risk assessment based on risk estimation; however, they do not address the SAP, i.e., the shelters are predetermined in their methodology. Their methodology is equivalent to solving the DTA under SO in multiple time intervals. Here, we also address the SAP in addition to the DTA using a simulation-based approach. Figure 2.1 presents the proposed methodology in this chapter.

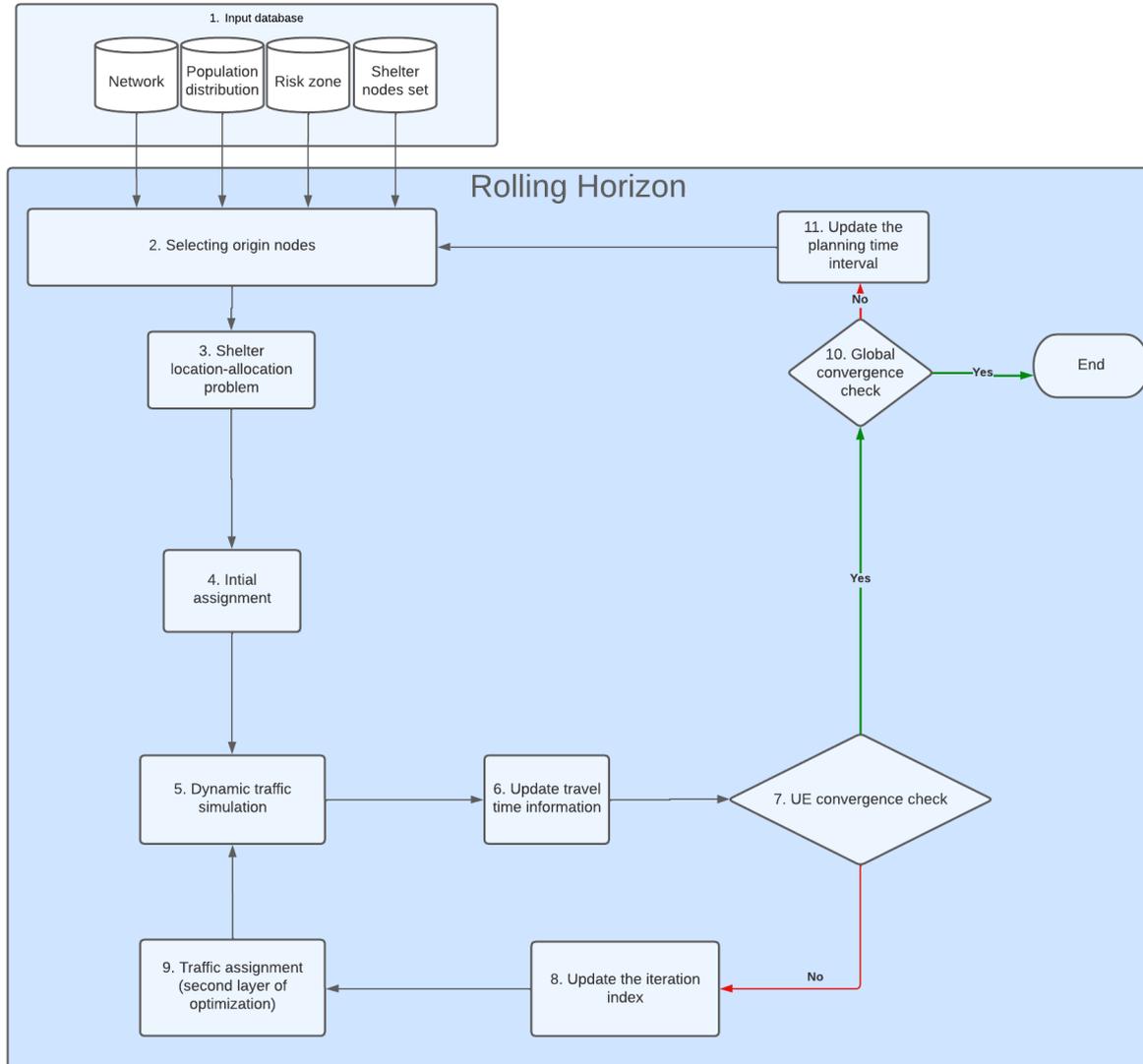


Figure 2.1: Flowchart of the process of solving the evacuation problem

The proposed framework consists of two loops that combine all three mentioned parts. The first loop, called the outer loop, represents the SAP under SO. The loop updates the network information needed by the SAP at each time interval. The second loop inside the outer loop addresses the simulation-based DTA. The solution method starts with initialization and solves the SAP for the first departure time interval. The results of the SAP are used as the input of the inner loop. The DTA calculation under SUE is started by the all-or-nothing assignment. Then the dynamic simulation is executed, and all users' travel times are updated. Afterward, we check the convergence test for the SUE

conditions (presented in the following subsection). If we do not converge, we reassign the users to the new paths based on a DTA optimization method and rerun the simulation.

Regarding the outer loop convergence, we stop when we found the solution from the SAP and inner loop for all evacuees. Otherwise, we go to the next time interval. Afterward, we solve the SAP again, considering the updated network dynamics provided by the simulation until the current departure time interval. The main advantage of this process is to capture and consider the traffic state while we are solving the SAP for each time interval. It means that we first solve dynamic SAP, and then for the OD matrix resulting from the SAP, we solve the DTA problem. The steps of the framework are detailed as follows:

2.4 Solution quality indicators

In this section, we define the metrics that we use to evaluate the optimality of our solution and monitor the network performance. The first metric we use to compare the quality of solutions is the network clearance time. We define the clearance time as the arrival time of the last evacuee to his shelter. This metric gives us information about the total duration of the evacuation process. Note that the best solution method provides the minimum clearance time. The second metric we use is the mean evacuation time, defined as the average travel time of all evacuees. The third metric we consider is the mean waiting time calculated for each vehicle, defined as the amount of time the vehicle speed was less or equal to 0.1 m/s. The fourth metric we consider is the network speed, which is the mean speed of the network on all simulation time steps, to quantify the network usage [Vickrey, 1994].

To evaluate the quality of the DTA solution, we define the average travel delay (ATD), which is the mean amount of delay compared to the best evacuee of each OD pair [Ameli, 2019].

$$ATD = \frac{\sum_{\alpha \in T} \sum_{o \in O} \sum_{s \in S} \sum_{\pi \in \pi_{os}^\alpha} \sum_{tr \in Tr_\pi^\alpha} t_{tr,\pi}^\alpha - t_{os}^*}{\sum_{o \in O} w_o} \quad (2.13)$$

where t_{os}^* denotes the global minimum experienced travel time from origin o and destination s ; $t_{os}^* = \min\{t_{os}^{\alpha,*}\}, \forall \alpha \in T$; w_o denotes the total demand that depart from origin o in hole time horizon. We have calculated this measure to compare the effectiveness of the SUE assignment. In other words, the minimum value of this measure shows that all users of the OD pair have almost the same travel time.

We also calculate a practical indicator called the *average evacuation travel delay* (AETD), representing the mean amount of delay over the best evacuee of each origin. This indicator is meaningful in the context of evacuation problems because the ultimate goal of each evacuee is to reach any shelter as soon as possible.

$$AETD = \frac{\sum_{\alpha \in T} \sum_{o \in O} \sum_{s \in S} \sum_{\pi \in \pi_{os}^\alpha} \sum_{tr \in Tr_\pi^\alpha} t_{tr,\pi}^\alpha - t_o^*}{\sum_{o \in O} w_o} \quad (2.14)$$

where t_o^* denotes the minimum travel time of the evacuation trip from origin o . Note that both ATD and AETD are not time-dependent, and at the pure SUE state, ATD and AETD are equal to zero; however, with the trip-based setting and network dynamics, it is not trivial to find the pure SUE solution.

Steps	Description
Step 1.	<p>Input database:</p> <ul style="list-style-type: none"> a. Population distribution: the number of people that should be evacuated from each node. b. Network map: the city map is represented as a graph via a network file. c. Risky zone: the set of all origins that will be considered. d. Destination nodes set: the set of shelters. nodes.
Step 2.	<p>Selecting origin nodes: This step corresponds to selecting nodes of the current time period, beginning with the highly risky nodes. This step offers us the possibility to have dynamic origin node adding. In fact, as hazards progress, we can add new origin nodes that are unknown at the beginning of the evacuation.</p>
Step 3.	<p>Shelter location-allocation problem: This is the first optimization problem following the SO principle and solving the SAP. The objective of this layer is to assign users to the right destination. The output of this step is the demand profile defining the origin-destination pair with the number of users of each pair (OD matrix).</p>
Step 4.	<p>Initial assignment: This step consists of the All-or-Nothing assignment and the initialization of the iteration index.</p>
Step 5.	<p>Dynamic traffic simulation: In this step, we simulate each vehicle from their origin to the planned shelter by Step 3 based on the path that is determined from Step 4 or Step 9. Note that any trip-based dynamic simulator can be used in this step.</p>
Step 6.	<p>Updating travel time information: This step is for updating the users travel time and path travel time based on the result of the simulator. Moreover, we calculate all metrics for the solution quality and network performance.</p>
Step 7.	<p>SUE convergence check: Check if the quality of the SUE solution (ATD) is below a threshold or not. OR Is the maximum number of iterations is reached or not. The second condition is designed to skip the infinite loop problem when arriving at the equilibrium. If we converge, we go to Step 10; otherwise, we go to the next step.</p>
Step 8.	<p>Update the iteration index: This step is for calculating the new iteration number.</p>
Step 9.	<p>Traffic assignment (second layer of optimization): The reassignment procedure follows the C-logit mechanism to generate routes to be simulated.</p>
Step 10.	<p>Global convergence check: This step checks if all the demand is evacuated or not. If that is true, we had to end the all process. Otherwise, we go to the next step.</p>
Step 11.	<p>Update the planning time interval In this step, we change the planning time interval and move to the next departure time interval ($\alpha + 1$).</p>

2.5 Tools and framework implementation

In the strategic formulation of crisis response plans for hazardous events that have the potential to induce public panic, it is imperative to incorporate a comprehensive set of key components. A multifaceted approach involves the integration of analytical location planning techniques, which play a pivotal role in optimizing the positioning of critical facilities geared towards effectively serving the affected populations.

2.5.1 SUMO Simulator

The Simulation of Urban MObility (SUMO), developed by the German Aerospace Center (DLR), is a pivotal open-source microscopic traffic simulator. It is instrumental in modeling and analyzing urban transportation systems. SUMO’s microscopic approach facilitates real-time simulations of individual vehicles, offering critical insights into traffic dynamics and congestion patterns, which are essential in planning effective evacuation strategies.

SUMO’s selection is underpinned by its versatility and realism. It provides a detailed representation of traffic flows and individual vehicle behaviors, enabling accurate simulations of complex urban traffic systems. This level of detail is vital for simulating evacuation scenarios and understanding the impacts of various management strategies.

SUMO’s customizability allows for the adaptation of simulations to specific evacuation scenarios or urban contexts. It can model diverse road networks, traffic patterns, and emergencies, enhancing its practical applicability. Moreover, its scalability is a significant advantage, enabling the simulation of large-scale evacuations involving thousands of vehicles.

The tool’s interoperability is also crucial for evacuation management. Its compatibility with various programming languages and external applications through its TraCI API allows for integrating additional data and models, aiding in developing comprehensive evacuation plans.

Additionally, SUMO benefits from a robust community of users and developers, providing a wealth of shared knowledge and resources. This is invaluable for both novice and experienced researchers working on evacuation management.

The use of SUMO in our study is driven by its capability to create a realistic, customizable, and detailed simulation environment. This is essential for effectively planning and analyzing population evacuation strategies in urban areas, ensuring that the research findings are relevant and applicable to real-world challenges. The comprehensive overviews by [Behrisch et al., 2011] and [Krajzewicz et al., 2012] further underscore SUMO’s capabilities in this domain.

2.5.2 Implementation of the optimization framework

Analytical methodologies, such as traffic assignment with due consideration to stochastic elements and p-median facility location modeling, offer robust frameworks for pinpointing optimal facility sites. These techniques consider various factors, including the distribution of demand and the intricacies of transportation networks. Planners can rigorously test and refine location plans in simulated disaster scenarios by leveraging advanced tools like transportation simulators —such as SUMO— in tandem with optimization solvers like CPLEX.

The synergistic application of SUMO and CPLEX facilitates meticulous evaluation of proposed facility sites, considering their accessibility during crises. This evaluative process is essential for ensuring the resilience and efficiency of crisis response systems. Figure 2.2

visually represents the intricate interplay between analytical location planning techniques and simulation-based testing, offering a comprehensive overview of the strategic considerations involved in optimizing facility locations for crisis response. This integrated approach not only enhances the preparedness of response systems but also contributes to a more effective and adaptive response to hazardous events, ultimately mitigating the potential for public panic.

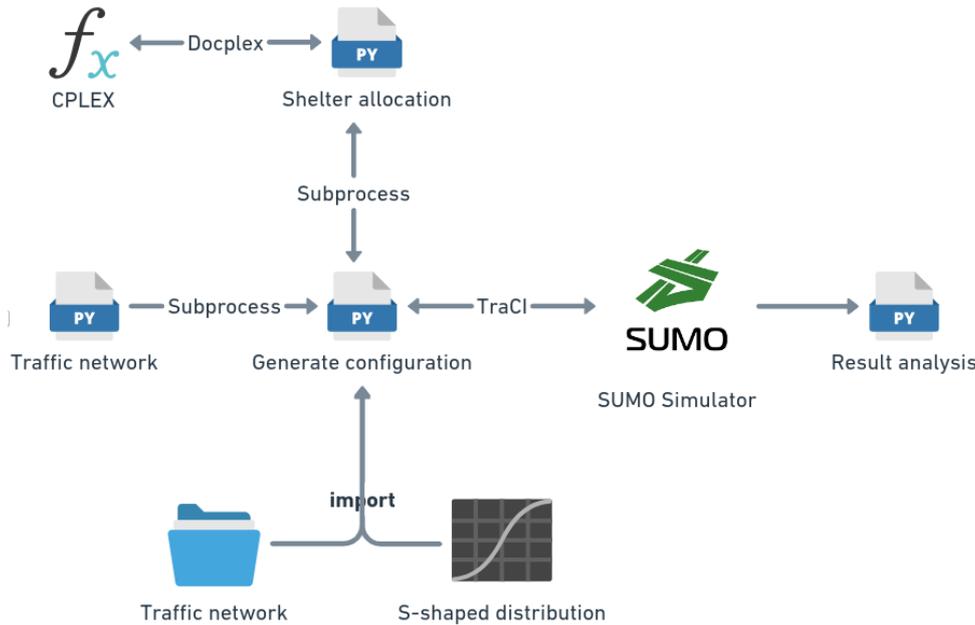


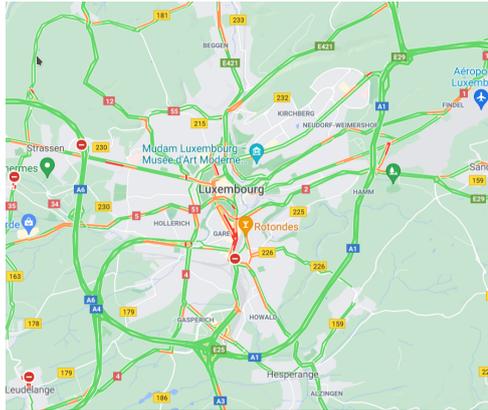
Figure 2.2: Proactive plan creation for evacuation.

2.6 Application

2.6.1 Case study

We implement our framework for the scenario [Codeca et al., 2015], representing the city of Luxembourg (cf. Figure 2.3). We base the demand profile on synthetic data of the evacuation scenario. To include the simulator in the optimization process, we implement the rolling horizon approach [Peeta and Mahmassani, 1995a]. To solve the simulation-based DTA problem, we use the SUMO simulator with its C-logit optimization function [Lopez et al., 2018a]. We set the simulation time step to 1 second. In addition, to tackle the shelter location allocation problem, we employ ILOG CPLEX version 12.9. We performed all simulations on a personal computer with 1.7 GHz and 16 GB of RAM.

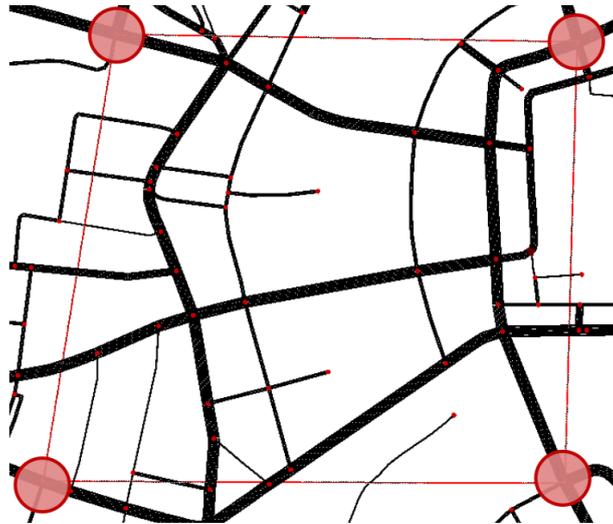
Figure 2.3 presents the network of Luxembourg with the size of 155.95 km² and the traffic network graph considered by SUMO for dynamic simulation. We examine a hypothetical threat in the center zone affecting people of the region colored in red (cf. Figure 2.3(b)). While the origin nodes are in the same area, we do not assume a super origin (source) node. We consider multiple origin nodes as evacuation sources in the risky zone, as described in Figure 2.3(c). Vehicles carrying people should be evacuated to the shelters, colored in green in Figure 2.3(b), located at the network’s periphery. In this evacuation context and without a loss of generality, the S-shape response curve model is employed based on [Na and Banerjee, 2019] with its parameter $\alpha = -0.005$ and $\beta = 15$ for the departure time of each evacuee. We have set each departure time interval (λ) to 5 minutes for the simulation. The demand at each node is 200 vehicles at each period. We consider four origin nodes selected and four shelters, each with the capacity of holding



(a) Luxembourg mapping data ©Google 2022



(b) Luxembourg sumo city network



(c) Luxembourg sumo city network hazard nodes

Figure 2.3: Evacuation network map

Table 2.3: Performance metrics

Metrics	Dynamic shelter allocation	Fixed shelter allocation
Network clearance time(s)	1,946.00	2,850.00
Mean evacuation time(s)	1,107.71	1,517.22
Mean waiting time(s)	27.37	133.38
Average travel delay (ATD)	267.18	441.90
Average evacuation travel delay (AETD)	332.50	455.48

1,500 evacuees. Therefore, the total demand is 600 vehicles per origin for the planning horizon H .

2.6.2 Scenario Definition

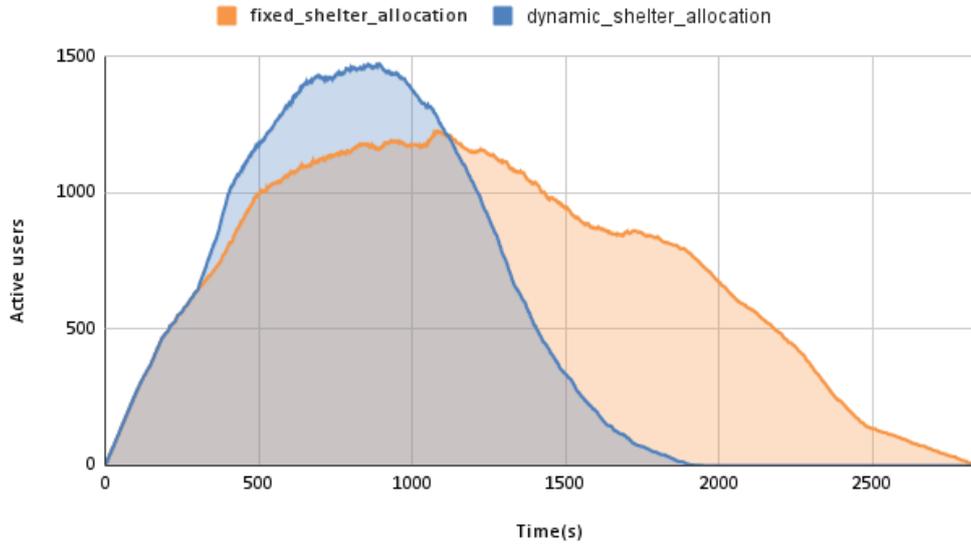
In this chapter, we consider the following scenarios to investigate the impact of the dynamic SAP on the evacuation planning problem. The scenarios are detailed below:

- **Dynamic shelter allocation:** This scenario includes our proposed framework (illustrated in Figure 2.1). It sequentially solves the shelter allocation and the traffic assignment coupled in a loop at multiple time intervals.
- **Fixed shelter allocation:** This scenario represents one of the advanced existing approaches to address the evacuation problem in the literature via DTA (proposed by [Hsu and Peeta, 2014]). In each departure time interval, the DTA problem is solved without modifying the choice of shelters. Note that several studies choose the shelters based on Euclidean distance or network distance, which is not realistic compared to this setting as they do not consider the network’s characteristics, e.g., road capacities.

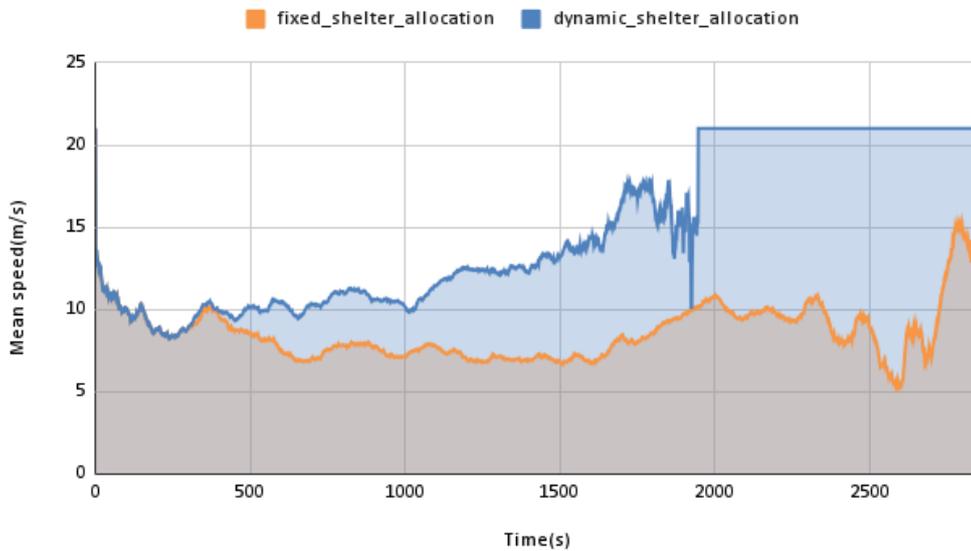
2.6.3 Comparison of Scenarios

This section presents the results for the two scenarios mentioned above—both scenarios run with the same evacuation demand profile, source nodes, and shelter set. We measure multiple performance indicators to evaluate the efficiency of the solution method in each scenario. We use the metrics defined in the subsection 2.4. Table 2.3 presents indicator values for the two scenarios. The results show a significant improvement in the quality of the final solution obtained by our model compared to the fixed shelter allocation scenario. For instance, we reduced the network clearance time by 15 minutes (31%). It means that the dynamic allocation of evacuees to shelters, considering the network congestion, improves the evacuation process. The high congestion level around shelters during the evacuation could explain this difference. With the fixed shelter plan in all time intervals, we observe a higher congestion level in paths leading to these shelters. However, solving the dynamic allocation problem ensures that we assign evacuees to the shelters based on the time-dependent shortest path and not the closest shelters by distance or free-flow travel time.

Moreover, the reduction of mean evacuation time in Table 2.3 confirms that the dynamic allocation improves the evacuation planning solution. In addition, it also provides better AETD for evacuees. The improvement amount is even higher for ATD, 39%, which shows that the DTA solution of our method is closer to the SUE solution.



(a) Number of active users in the network variation



(b) Network mean speed variation

Figure 2.4: Performance measures variation

Figure 2.4 illustrates the results graphically, comparing the two scenarios in terms of active users in the network (Figure 2.4(a)) and network mean speed variation (Figure 2.4(b)).

Figure 2.4(a) presents the evolution of the number of vehicles evacuating in the network. The network is initially empty; thus, we have the same solution for the SAP for both scenarios for the first time interval. Then the two curves are separated because we have different shelter allocation approaches. In addition, the curve representing our method arrives at the final state of zero running vehicle before the second curve, proving that the network clearance time is decreased compared to the other method.

Figure 2.4(b) presents the evolution of the mean speed in the evacuation process. The network's maximum speed is equivalent to the mean free-flow speed (75.6 km/h). At the beginning of the evacuation, the speed curve is the same because the two scenarios had the same solution in the first time interval. After that, the speed increases considering dynamic shelter allocation and stays higher than fixed shelter allocation until the end. It means that the dynamic shelter allocation scenario uses the network's capacity better than fixed shelter allocation and finishes the evacuation process faster. The network speed for the dynamic allocation scenario (blue curve in Figure 2.4(b)) varies a lot at the end

of the evacuation process. The multiple queues formed at the entrance of the shelters but rapidly cleared explain this variation.

We illustrate in Figure 2.5 the variation of ATD and $AETD$ measures and the number of arrived vehicles over time intervals to capture the differences between the two scenarios. Most studies use ATD to characterize the found solution of DTA under SUE principles. ATD could be seen as the mean distance between the travel time of users and the minimum travel time of that OD pair [Moghaddam et al., 2022]. Figure 2.5(a) illustrates the evolution of this measure over time intervals. The difference in ATD between the scenarios becomes more significant in the second time period, indicating that having flexible shelter allocation offers evacuees the possibility to reduce their travel time by changing their choice of destination.

Figure 2.5(a) presents $AETD$ variation over time intervals. Recall that the main difference compared to ATD is that the user evacuation delay is calculated w.r.t minimum evacuation time of all users from the same origin. In other words, we compute the average difference between the travel time of each user and the shortest travel time having the same origin node. Similar to Figure 2.5(a), $AETD$ has the same shape as ATD . This proves that our method is better than the second method, even for the destination-free measure.

Figure 2.5(c) compares the number of evacuees that arrived at shelters at each time interval. Our method evacuates vehicles faster than the second scenario by using the remaining capacity of the network. That is why, in dynamic shelter allocation, more evacuees finish their travel in the second interval.

Moreover, we measure the computation time for each optimization scenario (see Table 2.4). The results show no significant difference between the two scenarios, so the dynamic shelter allocation optimizer does not require a long calculation time. Note that the shelter location-allocation is a simple linear formulation solved with the branch and bound technique. In Table 2.4, the computation time of the shelter allocation is defined only for the first scenario because the second scenario does not consider it. Note that a small difference in the DTA calculation is due to the probabilistic nature of the C-logit model. The computation time needed for DTA calculation in the second stage is lower because the SAP generates a less computationally expensive allocation for the DTA simulation.

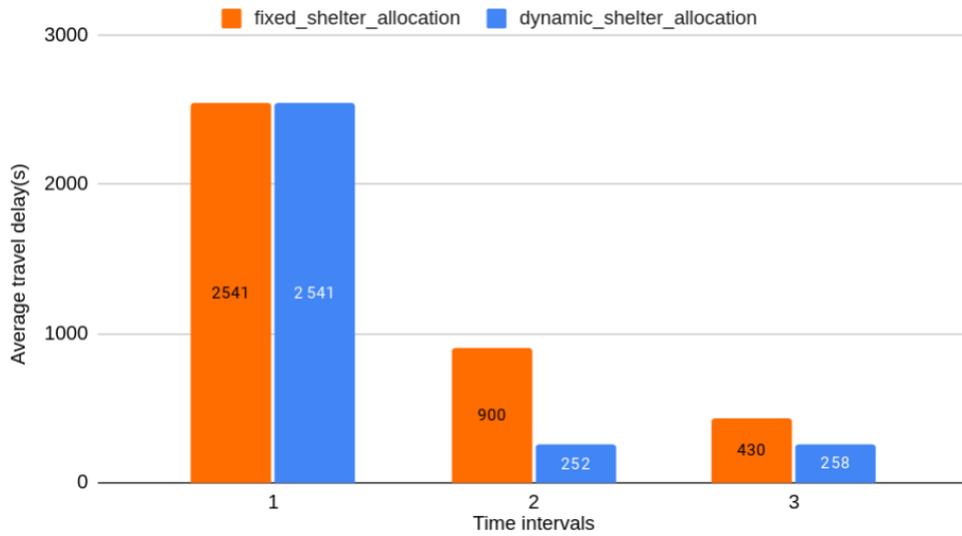
As shown in Table 2.4, the major part of the computation time is the DTA calculation. Therefore, it is worth performing a sensitivity analysis on DTA iterations because the number of iterations directly impacts the computation time.

Table 2.4: Computation time of the solution methods

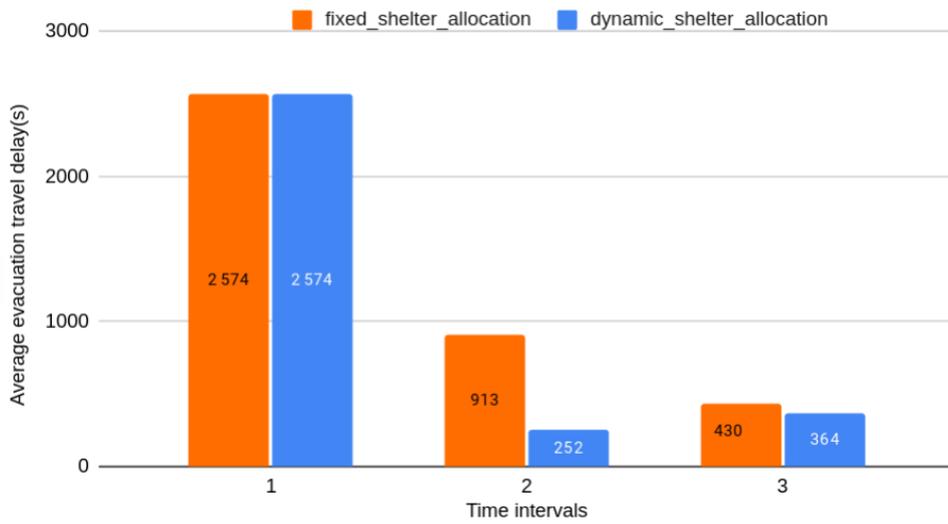
α	Computation time [s]	Dynamic shelter allocation	Fixed shelter allocation
1	Shelter location allocation	0.09	-
	DTA Calculation	687.08	690.03
2	Shelter location allocation	0.09	-
	DTA Calculation	632.54	698.31
3	Shelter location allocation	0.09	-
	DTA Calculation	789.53	624.21

2.6.4 Convergence analysis

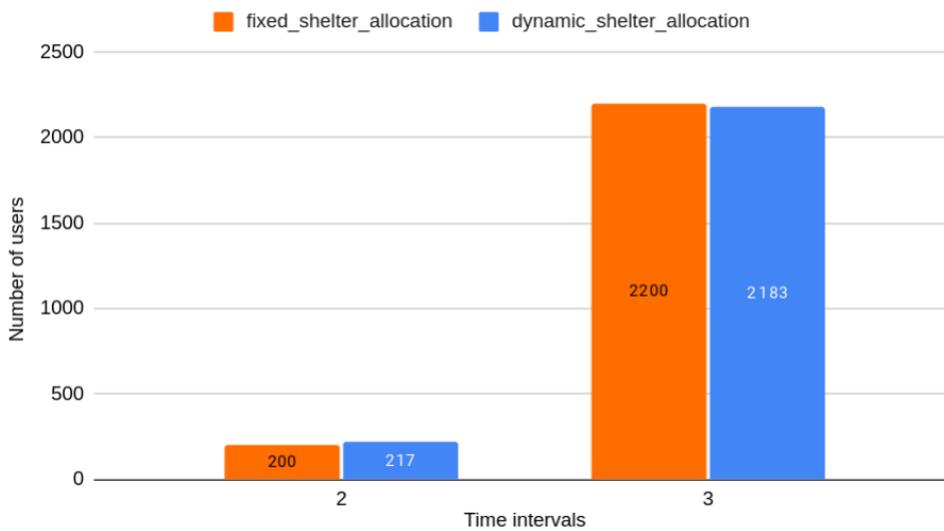
This section analyzes the effect of the convergence test threshold, i.e., the impact of changing the maximum number of iterations in the DTA calculation on the final solution.



(a) Average travel delay variation



(b) Average evacuation travel delay variation



(c) Number of evacuees arrived to shelters in time periods.

Figure 2.5: Delay and number of arrival measures variation

We conduct our comparison based on performance measures used in subsection 2.6.4. Table 2.5 presents the results. As expected, the ATD is minimized in addition to the AETD and the mean evacuation time. However, the network clearance time oscillates in the value of measures for many iterations (20 or 30). We expected this oscillation because the optimizer aims to achieve the SUE, not the SO. Therefore, our algorithm minimizes the individual travel time, which may affect the whole system’s performance. Table 2.5 shows that by increasing the number of iterations to search for the optimal solution for the SUE, we decrease the network production factors. From these results, we can conclude that if we fix the number of iterations to 20, we could have a good evacuation plan for this test case from both points of view: users and the system.

SUMO uses a measure of convergence to test whether the simulation is in a state of equilibrium or not. In Appendix 6.1, we report a sensitivity analysis performed on this measure. The results prove the consistency of the final solutions provided by the SUMO DTA calculator.

Table 2.5: The impact of the number of DTA iterations on the final solution.

Number of iterations	10	20	30
Network clearance time [s]	2,050.00	1,946.00	2,207.00
Mean evacuation time [s]	1,137.77	1,107.71	1,104.35
ATD [s]	303.27	267.18	246.00
AETD [s]	346.24	332.50	315.24

2.6.5 Sensitivity analysis on the rolling horizon approach

In our methodology, we use a rolling horizon approach for DTA solving. The idea behind this approach is to use currently available information and near-term forecasts with some degree of reliability to solve the assignment problem [Peeta and Mahmassani, 1995a]. We consider simulation time intervals responsible for acquiring the near-term forecast of traffic evolution and optimization time intervals for optimizing the current assignment problem. This section evaluates the influence of the simulation duration and the optimization time intervals on our optimization framework. First, we capture the impact of simulation time intervals on the effectiveness of the population evacuation process while we fix the optimization time interval. Second, we illustrate the influence of optimization time interval variation on the efficiency of the process. Third, we highlight the most reasonable values for the duration of time intervals for the rolling horizon configuration.

We rerun the optimization process using simulation time intervals ranging from 10 minutes to 30 minutes. We set the maximum iteration threshold to 20 for calculating the DTA solution at each time interval in addition to the fixed 5 minutes interval for optimization in all scenarios. To identify the differences found between each experiment, we plot the figure presenting the dynamics of the evolution of active users (running vehicles) over time (cf. Figure 2.6).

Having a long simulation period (e.g., 30 minutes time intervals) is inefficient in terms of needed computational resources when considering people under evacuation conditions. On the other hand, short simulation time is not beneficial either since it does not give the vehicles of the current stage enough information about future events to optimize their trips. Therefore, finding the appropriate duration for the simulation time interval is crucial. Figure 2.6 illustrates the impact of simulation time interval on the evacuation duration and network usage. It presents three curves for three different values of the simulation time interval 30 (blue), 20 (orange), and 10 (green). Figure 2.6 specifies that there is a remarkable effect, especially on clearance time measure. There is an increase in

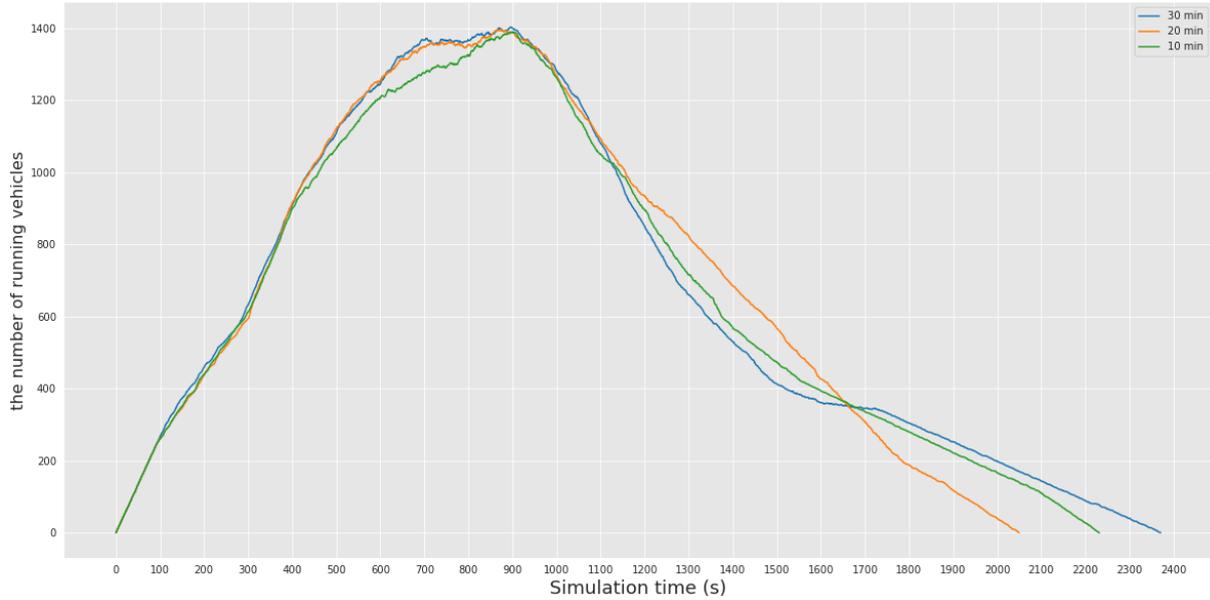


Figure 2.6: Active users for multiple simulation time intervals

network clearance of more than 5 minutes between the blue and the orange curve. This figure also demonstrates that it is not beneficial for evacuation to take long simulation time intervals. The network clearance time, our global objective, is higher when simulating 30 minutes than 20 minutes. In Figure 2.6, in the range between 1200 sec and 1700 sec, the scenario with 20 min (orange curve) benefits from the network’s capacity compared to other scenarios, and it leads to better results in terms of clearance time.

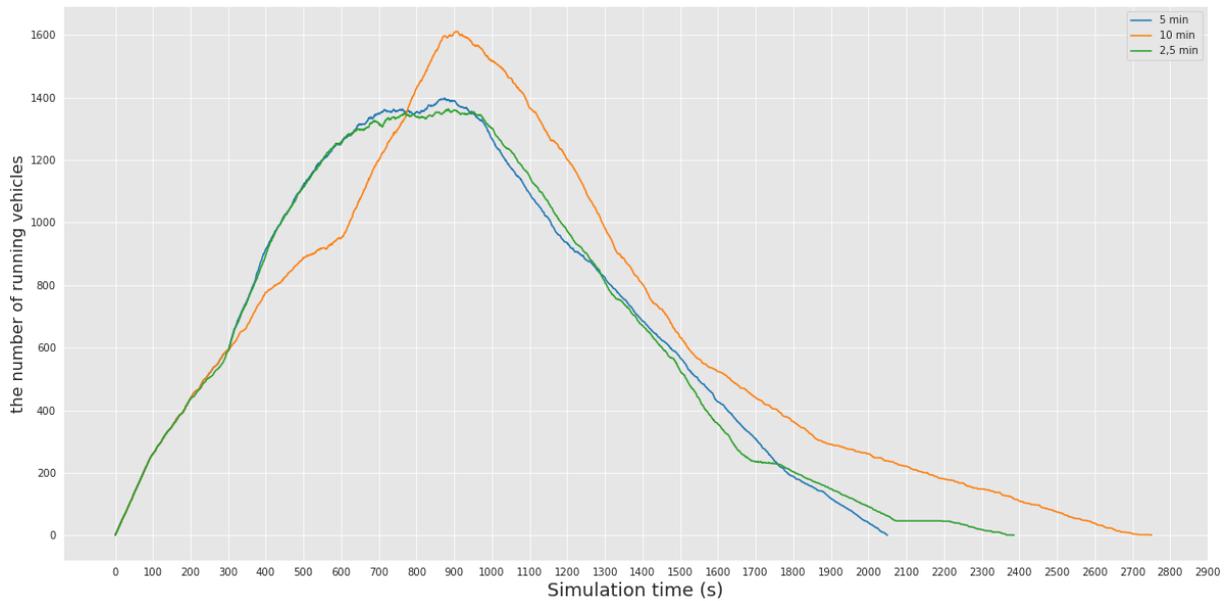


Figure 2.7: Active users for multiple optimization time intervals

For the second part of the analysis, we conduct multiple simulations, varying the optimization time interval and fixing 20 minutes for the simulation and 5 minutes for the departure time. Figure 2.7 depicts the effect of the optimization time interval variation on the number of active users in the network and the impact on the clearance time measure. The figure points out that fixing the optimization interval to 5 minutes provides the minimum clearance time compared to the other curves. Indeed, having a short optimization time, such as 2.5 minutes, needs more computation resources. It also prioritizes

Table 2.6: Real case performance metrics

Metrics	Dynamic shelter allocation	Fixed shelter allocation
Network clearance time(s)	40,565.00	74,929.00
Mean evacuation time(s)	15,991.98	31,433.40
Mean waiting time(s)	8,396.12	15,853.25
Mean speed(m/s)	4.74	6.83

users from the first and second departure time intervals to optimize their utilities. On the other hand, the users in the third time interval cannot achieve a comparable value for their objectives compared to the other users. Because after the two first intervals, the evacuees experience a long ending queue (after 1500 sec).

In addition, the long optimization interval (10 minutes) leads to having a longer clearance time than 5 minutes interval. We expected this effect because if users are not assigned well due to the network dynamics in the previous time interval, we must wait for another 10 minutes to revise the optimization solution. Figure 2.7 highlights this point between 300 sec and 800 sec, where the two other curves are above the orange curve. We conclude that the best simulation time interval for this test case is 20 minutes and the best optimization interval is 5 minutes.

2.6.6 Real case study

The proposed framework is applied to a more extensive demand profile to address a realistic population of Luxembourg City. We conducted the simulation with the best parameters of the optimization framework specified in the previous subsections. We consider 60,000 vehicles, which represent 70% of the actual population of Luxembourg City (125,000 inhabitants [RTL, 2021]). Note that a vehicle carries a maximum of three individuals to evacuate [Eurostat and Commission, 2019].

Increasing the evacuation demand level significantly affects the simulation duration. We consider the fixed shelter allocation methodology to benchmark our solution method in the real test case. Table 2.6 shows that solving shelter allocation dynamically improves the efficiency of evacuation planning. Table 2.6 illustrates a reduction of more than 9 hours in network clearance time, and the mean evacuation time decreases by 49% between the two methods of solving the problem. In addition, mean waiting time and mean speed are two measures that allow us to monitor the speed of the evacuation process. Lower values of these measures mean that solving SAP in each time interval provides a better solution. The comparison between the final solutions shows that around 15% of the evacuees (more than 10,000) have different destinations. It means our framework switches the evacuees' destination to another rapidly reachable shelter (less congestion in paths leading to new shelters). Thus, the shelter allocation allows us to revise the current shelter allocation plan for a new one that considers the evolving state of the network.

2.7 Discussion

This chapter focused on evacuation planning of people from risky zones to safe areas is one of the urgent tasks that should be done to avoid life losses caused by these disasters. Each evacuee must determine the destination (shelter) and evacuation path from hazardous areas as quickly as possible. This chapter focuses on solving the population evacuation problem to determine these two pieces of information. In this chapter, we performed a

literature review and analyzed the different approaches and models used in the research field to address the shelter choice and the route choice of evacuees. The first choice problem is usually represented as a facility location problem. The second choice model is formally known as traffic assignment, and it has two types of models: STA and DTA models. Many studies have considered the static formulation of the population evacuation problem, including a shelter allocation model, while few studies about the evacuation problem in the dynamic context for traffic routing and shelter allocation. We proposed a new planning framework to solve the dynamic population evacuation problem, including both SAP and simulation-based DTA.

To solve the evacuation problem dynamically, we have considered multiple departure time intervals by allocating shelters under the SO principle and assigning routes in the SUE manner. To couple the two problems, we consider the network dynamics in solving the SAP. We determine actual vehicle evacuation time using a trip-based dynamic simulator that provides travel information every timestep. We apply our methodology to the network of Luxembourg City and compare it with a model using a fixed shelter allocation plan. The results show that the proposed model outperforms the model with the fixed shelter plan by more than 31% reduction in network clearance time. We conclude that using dynamic allocation improves the evacuation process because it provides the optimal evacuation plan considering the dynamics of the network. Besides, the analysis of the computation time shows that solving the SAP in each time interval needs tiny computational resources, while it significantly reduces the duration of the evacuation process. The second main finding is that we can benefit from the capacity of the traffic network by using dynamic shelter allocation (Figure 2.4).

Moreover, we have conducted a sensitivity analysis on optimization parameters used in the framework, such as the maximum number of iterations, the simulation time interval, and the optimization time interval. Afterward, we applied the best setting resulting from the sensitivity analysis to a real case of Luxembourg City considering realistic demand. The results show that the proposed framework can address a real test case with feasible computation time.

Chapter 3

Real-time Evacuation Operation

Based on the investigation in the previous chapter, we notice that most existing formulation of the DPE problem does not include any online measures to improve the efficiency of the original plan and provide readjustments during evacuation. Considering vehicular communication can improve safety and situational awareness for evacuating vehicles by providing up-to-date information about hazards or risks along the route. More specifically, the goal of this chapter is to overcome the drawbacks of only planning for solving the DPE problem.

In this chapter, first, we conclude our review of the drawbacks and advantages of existing models designed to deal with emergency events in the literature. Second, a new framework for online rerouting and shelter reallocation is proposed. Third, a list of scenarios is designed to compare and assess the impact of vehicular communication. scenarios are applied a realistic and large-scale networks. Finally, the best solution scenario is highlighted.

This chapter is an updated version of the paper:

- H. Idoudi, M. Ameli, C. N. Van Phu, M. Zargayouna and A. Rachedi. Smart Dynamic Evacuation Planning and Online Management Using Cloud Computing for Population Evacuation. *Computer-Aided Civil and Infrastructure Engineering*, (accepted to be published)

3.1 Literature review on online and offline DPE

This section provides a comprehensive review of the literature on evacuation models and classifies them into two main groups: (1) models that focus on minimizing costs for both users and the system by addressing shelter allocation and traffic assignment issues and (2) models that concentrate on vehicular communication techniques and protocols to manage DPE. The research gaps are highlighted in these two groups and discuss the bi-level problem formulation used in many studies to address the complexity of DTA and SAP [Bayram, 2016]. Specifically, the upper level deals with shelter location allocation from the system operator’s perspective, while the lower level focuses on routing and evacuee route choice behavior [Li et al., 2012].

In the following, the studies employing a bi-level programming approach to address these challenges are discussed. [Kongsomsaksakul et al., 2005] proposed a planning model to study the effects of shelter locations on the evacuation process. They considered the interests of system operators and evacuees at the same time. However, they address the problem with a static formulation that does not consider traffic congestion evolution. [Ng et al., 2010] used a hybrid model to tackle the problem of evacuation planning. The upper level was dedicated to sheltering site selection in an SO fashion, and the lower level was for static traffic assignment in a UE manner. The presented model was solved by employing a simulated annealing heuristic, and for calculating the arc’s congestion level, they used the Bureau of Public Roads (BPR) static function [Davazdah Emami and Khani, 2023].

[Li et al., 2012] presented a scenario-based model. The upper level is a two-stage model. In the first stage, the shelter location is determined, and in the second stage, the selected shelters are chosen, considering the hurricane conditions. Then the lower level is for traffic assignment between origins and destinations selected by the upper one. They solved the problem using the Lagrangian relaxation algorithm. For calculating each edge’s travel time, they used the BPR function.

[Xu et al., 2018] proposed a hybrid model based on scenarios in the central area of Beijing. They formulated the problem based on distance measures to choose the nearest shelters and shortest path. In their solving method, they used a modified particle swarm optimization algorithm with a simulated annealing heuristic.

Few studies considered both SAP and traffic assignment in the dynamic context. [Hsu and Peeta, 2014] considered the evacuation planning process, including the DTA problem with a fixed shelter allocation schema. The previous study of the authors [Idoudi et al., 2022a] tackled both dynamic problems sequentially, minimizing the total travel time in SAP, and calculating UE for DTA. However, this work did not consider telecommunication networks. To the best of our knowledge, no study in the literature addresses the population evacuation problem considering both the planning phase (optimization methodology for SAP and DTA) and the online management phase (taking into account vehicle communication).

However, the DPE problem is addressed with telecommunication technologies in the literature, independently of the planning phase.

Indeed, many studies focus on evacuation models with vehicular communication capacity. They consider evacuation in different aspects using different communication architectures, protocols, and types of emergency messages. Here, the related works to the DPE problem are reviewed.

Some studies focused on network architectures used for emergency situations. They aim to collect data rapidly and use it to ensure a successful evacuation process. For instance, [Rego et al., 2018] used a Software Defined Network (SDN) to manage emergencies. The control part of the SDN collects the data from the different Internet of Things

(IoT) networks formed by traffic lights, traffic surveillance cameras, etc. It combines them to obtain the best and fastest evacuation routes and access roads to the emergency services units. In addition, the authors used the delay measure to quantify the quality of their solution. However, this study did not propose any rerouting process. Other studies target evacuation by proposing different and less redundant emergency message exchange schema. For example, [Liu et al., 2018] focused on only highway scenarios and proposed a novel safety-related message exchange protocol based on the Non-Redundant Communication Range (NRCCR).

[Alazawi et al., 2014] applied and evaluated an evacuation strategy called Speed Strategy (SS) to quantify driver response to emergency evacuation pre-plans. To implement this strategy, the authors deployed the VCC architecture. However, this chapter only considered the responsiveness of evacuees to SS orders and did not propose any replanning orders to evacuees to change their routes or destinations. This study considers the VCC architecture for rerouting and includes the bi-level programming in the initial planning phase.

Our study offers two significant contributions. First, it investigates the impact of VANET on the success of solving the DPE problem by leveraging an initial plan determined through solving the SAP and DTA. Second, it develops a novel planning model that integrates vehicular cloud computing, SAP, and DTA to optimize the simulation-based framework for the DPE problem while considering online orders, system operators' decisions, and evacuees' interests. The proposed methodology considers various factors, such as vehicle travel time, VCC delays in telecommunication exchanges, and network characteristics, to enable effective replanning. Furthermore, the methodology is applied to the realistic network of Luxembourg City and a real evacuation scenario of Mill Valley City to validate and evaluate its performance.

3.2 Problem formulation

Table 3.1: **Specific notations in this chapter**

Symbol	Definition
$t_{n_i s}$	Estimated Travel time from node n_i to node s , $n_i \in N \setminus S$ and $s \in S$.
t_n	Average of the travel time of incoming edges to node n , $n \in N$
D_i	Distance separating vehicle i to the center of the hazard.
D_{max}	Maximal distance separating vehicle i to the center of the hazard.
N_i	Number of vehicles in the following edge that evacuee i approach to.
N_{max}^i	Maximum amount of vehicles in the following edge that evacuee i approach to.
λ	Safety threshold for rerouting vehicles.
$ A $	Cardinality of set A .

Efficient evacuation operations are critical in emergencies and require a systematic approach to minimize evacuation time. The proposed approach consists of two phases: an offline phase to generate an initial evacuation plan and address the SAP and DTA problems and an online phase that considers vehicular communication within the cloud computing paradigm. In the decision-making process, each evacuee must determine the shelter they wish to reach and the optimal route to get there. The initial decision problem involves the SAP, followed by the DTA problem. To optimize the evacuation process, the

SAP is formulated to minimize evacuation time, which aligns with the system operators' interests. The DTA problem is formulated to address the Stochastic User Equilibrium (SUE), taking into account the tendency of evacuees to prioritize their perceived minimum travel time when selecting their path to their chosen shelter.

The DPE problem is defined on a directed graph $G = (N, A)$ that represents a traffic network, where N is the set of nodes and A is the set of edges (links). Let us assume that $O \subset N$ and $S \subset N$ are disjoint subsets of nodes representing the hazardous zone to be evacuated and safe shelter sites, respectively. The demand of each origin $o \in O$ is denoted by w_o , which represents the number of users to be evacuated. x_{os} is defined as the integer decision variable that determines the number of evacuees allocated to the origin-destination pair os and y_s as the binary decision variable for shelter selection. The minimum travel time between origin o and destination s is denoted by t_{os}^* . Let us assume that the shelter capacity c_s^α in time interval α and the maximum allowable number of opened shelters are denoted by P .

Previous literature has typically used a static formulation of the traffic assignment problem to calculate travel time with an analytical travel time function [Bayram, 2016]. However, a dynamic simulator is used to provide updated travel time for each edge in the network at each time step. The important notations used in this chapter are presented in Table 3.1.

The objective of the SAP is to minimize the total evacuation time and achieve the desired outcome for the system operator. This involves assigning evacuees to shelters, considering the travel time from hazardous nodes to the shelters. The objective function for the SAP problem is presented in Equation 3.1.

$$\min \sum_{o \in O} \sum_{s \in S} t_{os}^* x_{os} \quad (3.1)$$

To solve the shelter location-allocation problem under a generic type of hazard, the p-median model is deployed [Hakimi, 1964], a commonly used approach. The p-median model involves selecting a set of p shelters from a list of candidates and assigning evacuees to the selected shelters to minimize the total travel time. Equation 3.2 ensures that all the demands are served, meaning that all evacuees exit the hazardous zone and enter a shelter.

$$\sum_{s \in S} x_{os} = w_o; \quad \forall o \in O. \quad (3.2)$$

Our model accounts for the limited capacity of shelters and does not assume infinite capacity. Thus, users must be assigned to shelters while respecting the capacity limitations that change over time, concerning the assignment in the previous time interval, as shown in Equation 3.3.

$$\sum_{o \in O} x_{os} \leq c_s^\alpha y_s; \quad \forall s \in S. \quad (3.3)$$

Finally, a limited number of opened shelters (P) is considered in the studied network:

$$\sum_{s \in S} y_s \leq P. \quad (3.4)$$

It is worth noting that the model presented in this chapter is classified as an NP-hard problem [Sherali and Nordai, 1988]. Finding an optimal solution for SAP is computationally challenging and requires sophisticated algorithms and techniques. Once the SAP is solved, it provides the origin-destination (OD) matrix for the DTA model, which indicates the demand from each origin o to each shelter s .

The UE principle assumes that all users have perfect knowledge of network information and consistently choose paths to minimize travel costs. However, this assumption is unrealistic in emergency scenarios, where users may not have perfect knowledge or make biased decisions based on various factors. To address this issue, the Stochastic User Equilibrium (SUE) model is deployed in the DTA phase of the model. The SUE model relaxes the UE assumption and ensures that all travelers cannot improve their perceived travel cost by unilaterally changing paths [Daganzo and Sheffi, 1977].

In the proposed model, the departure time of evacuees is given in emergencies unless the system forces them to evacuate, and the shortest path is defined as the path with the minimum travel time. To generate the initial predictive evacuation plan, a trip-based simulator is deployed.

In the following, the two main parts of the model are presented: planning, which considers both DTA and SAP (cf. section 3.2.1), and online management (cf. section 3.2.2).

3.2.1 Predictive evacuation plan

The SUE model is used in the DTA phase of the model to represent the network equilibrium. The SUE model incorporates a probabilistic route choice process, which is more realistic than the deterministic approach used in the UE model. Specifically, in the SUE model, the route choice model is derived by assuming a random component associated with the travel cost [Daganzo and Sheffi, 1977].

$$\hat{t}_{tr,\pi}^\alpha = t_{tr,\pi}^\alpha + \xi_{tr,\pi}^\alpha, \quad \forall \pi \in \pi_{os}, \alpha \in T, tr \in Tr_\pi^\alpha \quad (3.5)$$

where $\hat{t}_{tr,\pi}^\alpha$ is the perceived travel cost on route π . $\xi_{tr,\pi}^\alpha$ is a random term with $E(\xi_{tr,\pi}^\alpha) = 0$ that represents the traveler's perception error. Using the perceived travel cost concept, the SUE conditions can be characterized by the following equation [Daskin, 1985]:

$$Tr_\pi^\alpha = x_{os} pr_\pi^\alpha, \quad \forall \pi \in \pi_{os} \quad (3.6)$$

where pr_π^α is the probability that travelers choose route π of os . In this case, the equilibrium model depends on the congestion and stochastic effects, which are associated with the random terms' distribution. An equivalent unconstrained optimization formulation for the SUE problem was provided by [Daganzo, 1982] under a general distribution assumption of random terms. During the simulation-based DTA process, the goal is to reach the SUE state where vehicles cannot reduce their perceived travel time by altering their selected route. To achieve this, an iterative approach is used to involve both optimization and simulation phases. The optimization phase determines the most suitable route choice for the vehicles. In contrast, the simulation phase involves simulating the vehicles along their designated routes, which are determined by the output of the optimization process. The model used to assign users to the route is the C-logit mechanism [Idoudi et al., 2022a] that satisfied the SUE conditions at the convergence. All the models mentioned above are defined in the planning phase and used to create the initial plan for evacuees. The next model corresponds to online evacuation management, representing the evacuation process over time.

3.2.2 Online management (reactive planning)

The proposed framework for online management aims to respond to unexpected events and dynamically modify the initial evacuation plan during the evacuation by leveraging vehicular communication capabilities. The communication capabilities enable evacuees to receive and send new information and update their routes, improving the efficiency and safety of the evacuation process.

Our online evacuation guidance system comprises three components, as depicted in Figure 3.1: The first component is a centralized traffic monitoring and rerouting service, representing the cloud server (which can be physically distributed across multiple servers). The second component is the Road-Side Units (RSUs) set, representing the network infrastructure required to facilitate communication between the cloud server and vehicles. The third layer is represented by vehicles or any transportation mode equipped with OnBoard Units (OBUs), which allow vehicles to communicate with each other and with infrastructure (Vehicle-to-Everything or V2X). The vehicles are considered end communication nodes that periodically send and receive data (e.g., current position, speed, and direction) via the OBUs, as shown by arrows in Figure 3.1.

3.2.2.1 Rerouting

Online rerouting of vehicles based on vehicular communication is a cutting-edge transportation management system that leverages advanced technology to enhance traffic flow and reduce road congestion. The system relies on a network of communication devices embedded in vehicles to collect real-time data about the surrounding traffic, such as speed, location, and direction. This data is transmitted to a central server, which uses it to analyze the current traffic conditions and identify areas of congestion.

The proposed cloud-based evacuation guidance system implements a rerouting method to evacuate hazardous zones as quickly and safely as possible. To achieve this goal, the congestion level of each vehicle's route is estimated by measuring vehicular road density. The evolving risk is also considered by measuring the distance between the vehicle and the hazardous zone, as shown in Equation 3.7.

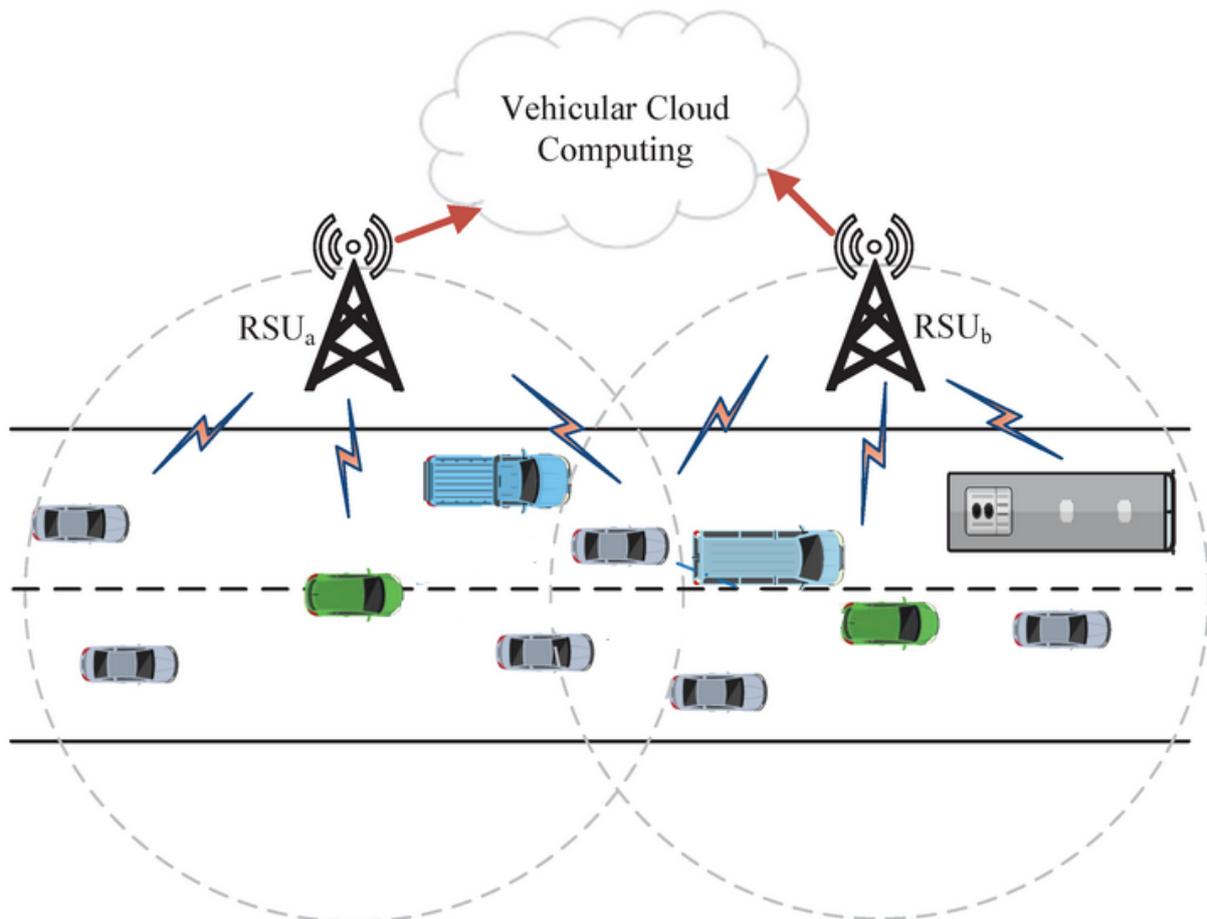


Figure 3.1: Vehicular cloud computing.

$$(1 - \Delta_t^i) \left(\frac{N_i}{N_{\max}^i} \right) \left(\frac{D_{\max}}{D_i + \epsilon} \right) - \lambda < 0, \quad \forall i \in M \quad (3.7)$$

To determine whether vehicle i should be rerouted at time t , the binary variable Δ_t^i is introduced, which equals to 1 if the vehicle is rerouted and to 0 otherwise. Equation 3.7 uses various normalized fractions to calculate Δ_t^i . Specifically, $\frac{N_i}{N_{\max}^i}$ represents the density of vehicles in the next edge of vehicle i , which measures the congestion level that should be avoided during evacuation. To prioritize vehicles close to the hazard, a normalization function is applied to the distance between the current location of each vehicle and the hazard by the maximum distance covered by the hazard, as shown by $\frac{D_{\max}}{D_i + \epsilon}$. Combining these factors allows us to determine whether rerouting is necessary and identify the safest and most efficient route for each vehicle.

To ensure that the rerouting decision always prioritizes safety, a safety threshold λ is defined, which limits the acceptable level of risk. In addition, several conditions must be met for Equation 3.7 to be valid. Specifically, the distance D_i must be positive and fall within the hazard zone, i.e., $0 \leq D_i \leq D_{\max}$. Additionally, for ϵ , a small positive value is set to avoid dividing by zero, such that $0 < \epsilon \leq 1$. Considering these conditions, the system can effectively reroute vehicles to avoid congestion and prioritize safety during evacuation.

3.2.2.2 Shelter reallocation

Online shelter allocation of vehicles based on vehicular communication also uses the network of communication devices embedded in vehicles, but to collect real-time data about the surrounding shelters, such as their location, capacity, and availability. This data is transmitted to a central server, which uses it, this time, to analyze the current shelter situation and identify the most suitable ones for evacuees. The system can dynamically allocate shelters to vehicles in real time, suggesting the most convenient and appropriate ones for each evacuee. The allocation is based on various factors, such as the shelter's proximity to the vehicle's current location, its capacity, and the driver's original destination.

In some cases, vehicles may need to change their destination because the shelter they are heading to is too far away or otherwise unsuitable. To address this issue, the shelter reallocation concept is introduced, allowing the system to dynamically assign new destinations to evacuees when necessary.

$$(1 - \Psi_t^i) \frac{t_{n_i s}}{t_{n_i j}} - \alpha < 0, \quad \forall i \in M, \forall s \in S, j \in S \setminus \{s\} \quad (3.8)$$

To determine whether a vehicle needs to be reallocated, the binary variable Ψ_t^i is defined, which equals 1 if vehicle i needs to be reallocated at time t and 0 otherwise. Equation 3.8 uses the fraction $\frac{t_{n_i s}}{t_{n_i j}}$ to determine whether a new destination j is closer to the vehicle's current location than the initially planned shelter s . Specifically, this fraction measures the gain between the time needed for vehicle i to travel from its current node n_i to the new shelter j and the time needed to arrive at the initially planned shelter s . To be considered for reallocation, the gain must exceed a predetermined threshold α , which ensures that the reallocation is beneficial in terms of time saved.

This section presented the formulation for both the initial planning and the online guidance to revise the solution to the DPE problem. However, finding an optimal solution for the DPE problem is challenging and time-consuming. Therefore, multiple indicators are required to measure the distance between the obtained solutions and the optimal solution for evacuees without delay. Additionally, the evolution of the network during the

evacuation should be analyzed to investigate the impact of the online guidance on the entire network.

3.2.3 Solution quality indicators

This section will define the performance metrics utilized to evaluate the optimality of the solution and track the network’s performance. To compare the quality of solutions obtained using different methods, the network clearance time is calculated. It is determined as the point at which the final evacuee arrives at their designated shelter. This measure provides insight into the speed of the evacuation operation, and the optimal solution method should result in the shortest possible clearance time. In addition to the network clearance time, the mean evacuation time is defined as the average travel time for all evacuees. This metric allows us to assess the overall efficiency of the evacuation process. Furthermore, the average network speed is measured to evaluate the network usage rate [Vickrey, 1994]. A higher network speed indicates a more efficient network use, which can result in faster and more reliable evacuations.

To successfully evaluate the DPE problem, multiple indicators are required to measure the performance of the online management phase. The metric used in to evaluate the performance is the Packet Delivery Ratio (PDR), defined as the percentage of data packets successfully delivered to their intended destination [Fabian et al., 2021]. However, some factors, such as disconnections of nodes or bad radio transmission conditions, can cause a decrease in the PDR due to increased retransmissions. Therefore, it is essential to investigate other metrics, such as the delay, to comprehensively evaluate the system’s performance.

To evaluate the performance of the online management phase, many papers rely on the transmission delay as a key metric [Sommer and Dressler, 2014]. This metric is relevant to safety-critical and latency-sensitive applications, as it measures the time it takes for a message to be transmitted from the source to the destination. The delay is usually measured in seconds (s) or milliseconds (ms). Here, an interesting measure could be the end-to-end delay, i.e., the time from creating a message until the destination node finally receives it. Note that this measure depends on the quality of the radio conditions, and many retransmissions will increase the PDR and delay. Generally, the best performance is achieved when the PDR is high and the delay is low.

3.3 Methodology

The proposed methodology in this chapter follows a sequential process, consisting of two main phases: the initial planning phase and the online evacuation management phase. The initial planning phase adopts the methodology used in the previous chapter to provide the initial plan. However, the planning model is modified for SUE instead of a pure UE solution. In the online evacuation management phase, a network layer is added for vehicular communication to capture the congestion of the network. This communication network allows us to re-plan the evacuation route and shelter during the evacuation process and provide them with instructions in real-time. A cloud computing scheme is used to achieve this, as it has a low implementation cost compared to fog or edge architectures, which require a large implementation budget [Gaouar and Lehsaini, 2021]. The proposed methodology is presented in the Plan-Do-Check-Act (PDCA) diagram format in Figure 3.2 [Realyvásquez-Vargas et al., 2018].

The steps of the framework for online management of the evacuation process are detailed in Table 3.2. The online management of the evacuation process provides several advantages over just planning. Real-time access to data allows for quick identification and response

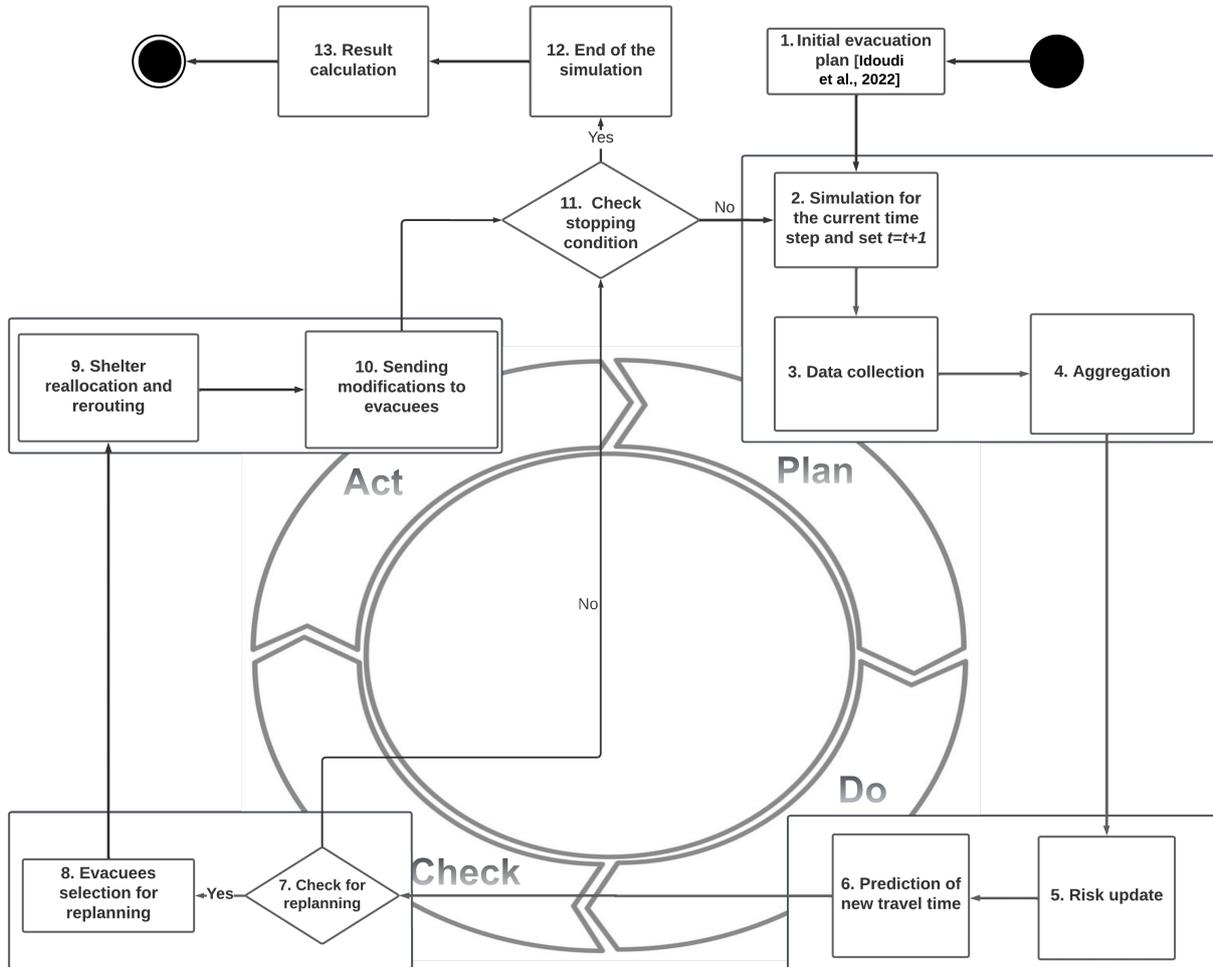


Figure 3.2: flowchart of the solving the DPE problem

to emerging issues, which is particularly important in fast-paced environments such as the emergency situation where delays in decision-making can have significant consequences. Real-time data and analytics can also identify trends and patterns that may not have been apparent during the planning stage, enabling faster and more effective decision-making.

To address this issue, the PDCA cycle is proposed for online problem-solving, which allows us to leverage data and analytics to make decisions based on the real-time data sent by evacuees [Isniah et al., 2020]. The planning unit can quickly identify patterns and trends using this real-time data and analytics, enabling informed decisions on rerouting and shelter reallocation, improving response times, and ensuring that network capacity is used effectively.

The "Plan" phase includes all the steps related to collecting and aggregating the data needed for the process. The "Do" phase updates risk and travel times based on the aggregated data and new updates. The "Check" phase determines whether a replanning is needed based on the aggregated data and new updates. Finally, the "Act" phase involves sending new decisions to each evacuee. The execution of each phase of the PDCA cycle is iterating until all demand is evacuated.

3.4 Vehicular communication tools and framework implementation

The necessity of an online information technology (IT) structure for instantaneous data collection, analysis, and communication cannot be overstated. Utilizing network simula-

Table 3.2: The steps of the methodological process described in Figure 3.2

Initiating:	
Step 1.	Initial evacuation plan: This step corresponds to solving the multi-level DTA and SAP to generate an evacuation plan. The SAP is going for SO, and the DTA is formulated under SUE detailed in [Idoudi et al., 2022a].
Plan:	
Step 2.	Simulation for the current time step and set $t=t+1$: This step corresponds to simulating the evacuation process that could be the same as proposed by the plan, or new events could occur due to several decisions made by evacuees in the previous time step. In addition, it is necessary to increase the simulation time index. It should be noted that any dynamic simulator that is based on trips can be utilized for this purpose.
Step 3.	Data collection: This is the first part of the cloud computing architecture wherein each vehicle (node) broadcasts data messages, using their OBU, to RSUs that send it to the cloud server.
Step 4.	Aggregation: This step aggregates messages from different RSUs. an evacuee could be connected to more than one RSU and broadcast his message to all RSUs in his range of communication.
Do:	
Step 5.	Risk update: This step updates the risk based on data from step 3. The considered risk consists of two main components: the vehicle's distance from a hazardous area and the congestion levels of the vehicle's location used in equations.
Step 6.	Prediction of new travel times: In this step, the travel time of edges might change according to the risk and congestion evolving by Step 4. This step uses a prediction model to predict new travel times. Here a classical prediction model is deployed which is embedded in the simulator.
Check:	
Step 7.	Check for replanning: This step is for deciding whether a user i is concerned by the rerouting process or not. For user i , the edge density is estimated, including the road speed and traffic density based on the Greenshield model [Pan et al., 2016]. The user i is considered to be in congestion if his current edge density is above a certain threshold 3.7.
Step 8.	Evacuees selection for replanning: This step corresponds to selecting vehicles that to go to another safe destination or have to be rerouted before getting inside a congested edge (road). The shelter reallocation process selects vehicles if there is congestion in front of their original destinations, and the server asks them to go to a less congested destination 3.8. For rerouting, all users with the congested edge in the set of the next planned edges of their journey are selected.
Act:	
Step 9.	Shelter reallocation and rerouting: This step prepares a message to the targeted users to ask them to reroute to the path with the current shortest travel time having their newly planned shelter as a safe destination.
Step 10.	Sending notification to evacuees: This step represents the second essential part of the cloud computing scheme where the cloud server sends its decisions to the nearest RSU that forward the results to vehicles to react accordingly.
Finishing simulation:	
Step 11.	Check the stopping condition: This step checks if all the demand is evacuated, go to 12 otherwise, go to 2.
Step 12.	End of the simulation: This step ends the simulation of the evacuation process,
Step 13.	Result calculation : After ending the simulation, all results, including all performance metrics (presented in Section 3.2.3) are calculated.

tors such as OMNeT++ in conjunction with vehicular communication models like Veins enables the simulation of automated and connected vehicles and infrastructure performance in crisis situations. This facilitates the evaluation of system capabilities in coordinating responses among responders, officials, and the public as unfolding events are tested.

3.4.1 OMNeT++ simulator and Veins project

The combination of the OMNeT++ simulation framework with the Veins project has matured into a powerful and frequently used instrument in the field of vehicular communication systems research. Since its 2008 introduction by [Varga and Hornig, 2010] OMNeT++ which is distinguished by its architecture that is both modular and extensible—has established itself as a flexible discrete event simulation framework. Meanwhile, Veins, an extension to OMNeT++, has been designed with the express purpose of tackling the complexities involved in modeling communication protocols and vehicular networks. The Veins project smoothly expands OMNeT++ to include realistic vehicle motion models and communication protocols. The Veins project and OMNeT++ work together to improve simulation capabilities for researchers studying vehicle ad hoc networks (VANETs). The Veins project offers a specialized framework for modeling realistically vehicular scenarios, taking into account network protocols, vehicle motion, and communication range. [Sommer et al., 2010] made a significant contribution to the literature by investigating bidirectionally connected network and road traffic simulation in Veins to enhance the understanding of inter-vehicle communication (IVC). This integrated approach has become a standard choice for researchers seeking to simulate and evaluate the effectiveness of communication strategies in dynamic vehicular environments. The open-source nature of both OMNeT++ and the Veins project, coupled with an active research community, ensures continuous development of vehicular communication systems research.

3.4.2 Implementation of the optimization framework

Having an online IT architecture for real-time data gathering, analysis, and communication is essential. Network simulators like OMNeT++ coupled with vehicular communication models like Veins can simulate the performance of automated and connected vehicles and infrastructure during a crisis. This allows testing of how well systems can enable coordination between responders, officials, and the public as events unfold.

The flowchart of Figure 3.3 consists of three main components: SUMO, TraCI, and OMNeT++ Simulator. The SUMO Server is the central component that connects to TraCI, which in turn interacts with both the SUMO Client and Launcher. The SUMO Client generates mobility results in XML format, while the Launcher is associated with result analysis in PY format and network results in CSV format generated by OMNeT++ Simulator. The simulator includes car nodes, RSUs, and a cloud server written in C++. The flowchart provides a visual representation of the subprocesses and interfaces involved in the integration of SUMO with OMNeT++ Simulator. It is a useful tool for understanding the interaction between these two simulators.

3.5 Numerical experiments

This section applies the methodology and framework described in the preceding section to a real-world network to validate the proposed solution. It begins by selecting a test case and then discussing the experimental design.

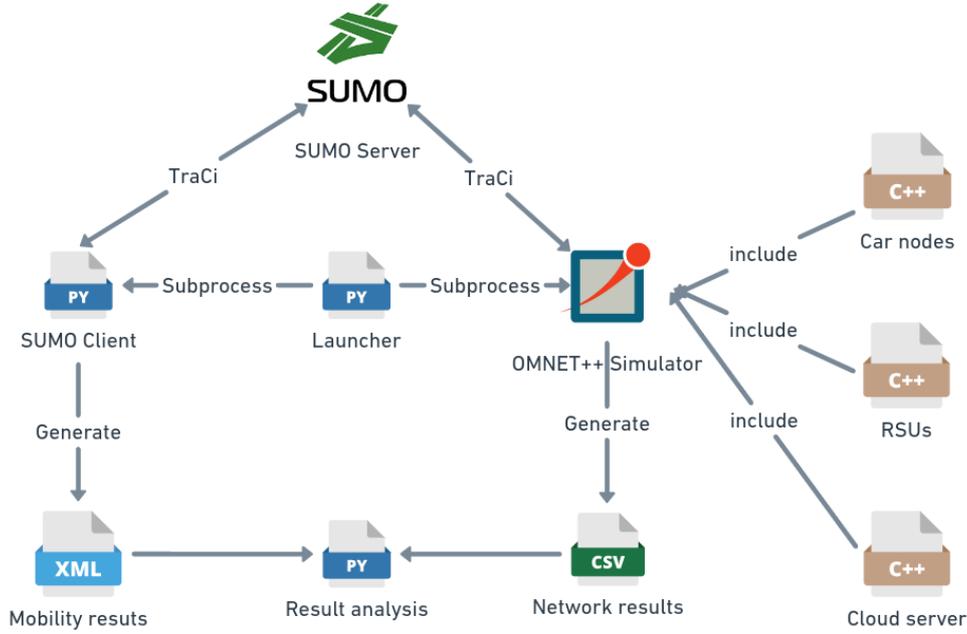


Figure 3.3: Vehicular communication for reactive evacuation management.

3.5.1 Case study

This section discusses the hardware and software used to implement the proposed solution and conduct the experiments. The experiments were performed on two different networks, namely, the LuST scenario representing Luxembourg city [Codeca et al., 2015] and the network of Mill Valley city in California. A laptop with 1.7 GHz and 16 GB of RAM was used to generate all the results. A simulation-based dynamic traffic assignment (DTA) method was used to implement the solution, and all simulations were performed using the SUMO simulator. SUMO calculated the C-logit model and travel time prediction. The SAP model was implemented using ILOG CPLEX version 12.9 and solved to optimize the planning phase. To simulate the vehicular communication aspect, the Veins/Omnet++ simulator was used in conjunction with a cloud computing architecture based on previous works [Wang et al., 2020].

3.5.1.1 Luxembourg city

Figure 3.4 depicts the evacuation network map of two cities, Luxembourg City and Mill Valley, which are used for the simulation. The traffic network graph used for the dynamic simulation is shown in Figure 3.4(a). This graph represents the Luxembourg network, which covers an area of 155.95 km². To assess the impact of a hypothetical threat, the affected population in the central region is considered. This population is highlighted in Figure 3.4(b). Note that there are no super source (risky) nodes. Four origin nodes were considered evacuation sources in the risk zone (see Figure 2.3). The vehicles carrying people needed to be evacuated to safe destinations (shelters) located on the border as shown in Figure 3.4(b) and were located at the network’s border. Given the network’s size, each planning departure time interval (η) is set to 20 minutes for the simulation. For the planning horizon (H), a demand of 200 vehicles at each node is considered for every period. There are four origin nodes and three shelters, each accommodating 1500 evacuees. Thus, the total demand per origin was 600 vehicles. For the purpose of this evacuation scenario, the S-shape response curve model is used (described in [Na and Banerjee, 2019]) with a parameter value of $\alpha = -0.005$ and $\beta = 15$ to determine the departure time of each evacuee. The departure time intervals for the simulation have been set at 5 minutes.

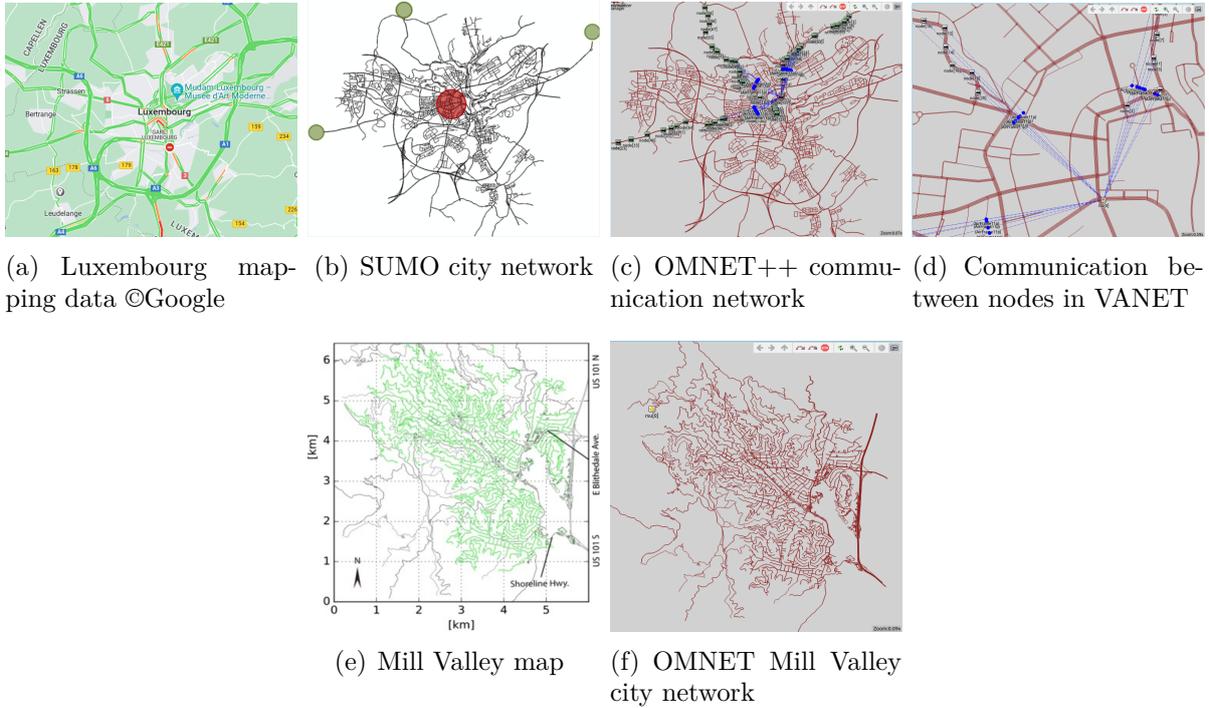


Figure 3.4: Vehicular communication maps

There are four shelters in this test case, each with a capacity of accommodating up to 1500 evacuees. Figure 3.4(c) shows the vehicular communication network in the OMNET++ simulator, and the message exchange process between vehicles and the network infrastructure is illustrated in Figure 3.4(d). The radius of RSU coverage is 4 km in the model, and the value for λ is set to 0.2 due to the small penetration rate values. It is assumed that the maximal radius of the risk scenario R_{max} is 4km.

3.5.1.2 Mill Valley city

We apply the proposed framework to plan and manage the DPE problem in Mill Valley in California (cf. Figure 3.4(e)). The state has determined that a large part of the city is in an area of very high fire hazard [Chen et al., 2020]. The Mill Valley network’s total length of residential roads is 337 km. To add the vehicular communication layer to the traffic network graph, the Veins project of [Sommer et al., 2019] is deployed. The evacuees depart their trip from their houses, with 6000 households on the Mill Valley map. For shelter allocation, no super or artificial nodes, such as super source or super destination nodes (risky or safety nodes) are considered. Only vehicles were considered as a mode of transportation in this study. The safe destination is reaching roads to the highway to escape the hazardous situation. The departure time distribution is defined by the scenario, with an average demand of 2 vehicles for each household. Figure 3.4(f) illustrates the vehicular communication network in the OMNET++ simulator.

3.5.2 Experiment design

In this chapter, we design four scenarios to investigate the impact of planning and online orders on the DPE problem. The scenarios are detailed below:

- **Scenario P+C: Scenario with both planning and vehicular communication:** This scenario follows the proposed framework (demonstrated in Figure 3.2).The approach involves creating an initial plan for optimal shelter allocation

and traffic assignment across several time intervals. Additionally, it utilizes vehicular cloud computing to provide updated instructions to vehicles, enabling them to shorten their routes and reach safety quicker.

- **Scenario P: Scenario with the initial plan only:** This scenario illustrates the case of just planning for evacuation without any communication between vehicles or vehicles to RSUs. It means that evacuees are not rerouted during the evacuation process; they just follow the initial plan.
- **Scenario C: Scenario with vehicular communication only:** This scenario is the same as Figure 3.2 except in step 1 where evacuees consider the nearest shelter and choose their routes following the SUE. This scenario describes a situation where system operators do not have an optimal plan in place prior to starting the evacuation process. Instead, they assign evacuees to the nearest shelter based solely on distance without considering traffic optimization. Despite this, the scenario provides an opportunity for system operators to receive new instructions for their evacuation plans through vehicular cloud technology.
- **Scenario N: Naive scenario without any optimal plan and vehicular communication:** This scenario represents the case where the system operators do not provide guidelines for evacuees. It means that the evacuees choose the nearest shelter and choose their routes following the SUE without rerouting.

3.6 Results

The four mentioned scenarios were executed on the same evacuation demand profile. The evaluation metrics presented in 3.2.3 measure the solution quality provided by the methodology. Section 3.6.1 highlights the results of our model applied to the Luxembourg medium-scale test case. Section 3.6.1.1 analyzes the effect of different penetration rate values of connected vehicles to VANET. Section 3.6.2 is dedicated to validating the model on a large scale and real-world case of Mill Valley City.

3.6.1 Results for the Luxembourg case

The outcomes of the four scenarios are summarized in Table 3.3. The results indicate a considerable advancement in the final solution quality obtained by the P+C scenario that employed both planning and online guidance models. For instance, the network clearance time was reduced by over 18 minutes (39%) compared to the naive scenario. Additionally, there was an improvement of more than 2 minutes (10%) compared to the P scenario. The findings reveal that the P scenario is the second-best solution. Comparing P+C and P scenarios demonstrates that handling new orders resulting from unexpected events during the evacuation planning process results in a more successful evacuation operation.

Besides, scenario C provides a better solution than scenario N, meaning that using the telecommunication network can improve the evacuation solution, even without any planning phase. This observation could prove the effectiveness of online communication and highlights the importance of giving new orders to evacuees to revise their route choice during the evacuation process. Inspecting the result for scenario P and scenario C illustrates that planning contributes more than telecommunication during the evacuation operation. One of the reasons behind this observation is that in scenario C, the shelter allocation was done without considering the congestion level. Scenario C can provide a better view and understand more of the effect of online evacuation guidance. It shows that allocating all users to the same nearest shelters in all evacuation operation generate

congestion that cannot be escaped even by using online vehicle rerouting. That is why different shelters, like in scenario P in each state, will ensure the assignment of evacuees to the closest destinations in terms of time-dependent shortest path and not distance measure.

Table 3.3: Performance metrics

Metrics / Scenario	P+C	P	C	N
Network clearance time(s)	1775	1980	2765	2835
Mean evacuation time(s)	1071.54	1093.70	1407.92	1447.61
Average travel delay (ATD)	205.47	220.62	341.63	349.78
Average evacuation delay (AED)	241.32	366.65	366.65	392.12

The decrease in mean evacuation time in Table 3.3 shows that the online DPE improves the evacuation solution. The proposed model used in scenario P+C generates better ATD for evacuees with more than 6% of reduction compared to the second best. The improvement is remarkable for AED (34%). Recall that including telecommunication network provides us with some errors and delays in sending and receiving messages. Both cases, P+C and C, have around 205.30 ms for the end-to-end delay and PDR around 74%, which is acceptable in this kind of latency-sensitive application with many network users [Noor-A-Rahim et al., 2020].

Figure 3.5(a) presents four scenarios' distribution accumulation over time. The accumulation at each time is the number of users traveling in the network. The figure shows that the two scenarios with an initial evacuation plan outperform the others. The clearance time and network capacity usage in scenario P+C are better than in scenario P. There is a significant difference between scenarios P+C and scenarios N and C with different penetration rates. Note that the gain of around 60 seconds in clearance time between scenarios C and N is remarkable in the test case which includes only 2400 evacuees. It is expected that a better result by increasing the number of evacuees and deploying larger networks. Figure 3.5(b) shows the evaluation of network mean speed during the evacuation process. This figure followed the results of the distribution of accumulation Scenario P+C outperforms other scenarios meaning that the blue curve representing scenario P+C stands upper than the other curves in most cases. A dramatic decrease can be observed in the speed before the end of evacuation because of queues formed in front of shelter sites.

3.6.1.1 Sensitivity analysis on penetration rate

This section performs sensitivity analysis on simulation parameters to identify the best in terms of results achieved and computation feasibility. First, a sensitivity analysis is carried out on the penetration rate performing value variation of this parameter. The sensitivity analysis on the penetration rate is performed on the Luxembourg City map. Assuming that 100% of the evacuees are using connected vehicles is unrealistic but can be reachable in the future. That is why multiple penetration rate values are considered. Note that the connected vehicles are selected with a random distribution in the case of x% of penetration rate. Only this x% is sending positioning information and receiving online orders. Thus, the cloud server monitors and guides only this x% of the vehicles. The proposed evacuation framework is executed for five values of penetration rate, and the results are illustrated in Table 3.4.

There is no communication in the case of a 0% penetration rate, so the end-to-end packet delay or the packet delivery ratio cannot be measured. Therefore, "-" means that there is no possible value. The DPE problem is solved in the proposed framework for all

penetration rates. Table 3.4 presents the different values of the performance measures used for multiple penetration values. The table clearly shows that the case of a 100% of penetration rate is the best scenario. Table 3.4 also illustrates acceptable values of PDR measure for 70%, 50%, and 30% scenarios. This PDR level means that around 75% generated packets are received correctly in the range of network infrastructure and without the need for retransmission. Also, the delay measure is crucial, especially in this case dealing with population evacuation. The average end-to-end delay of packets considering the vehicular cloud computing architecture employed is around 203 ms which is the same in the literature with this number of nodes [Al Ridhawi et al., 2018]. In addition, each scenario’s values of network clearance time show that communication positively impacts the evacuation process by decreasing the clearance time. Table 3.4 shows fewer values for ATD when having a bigger penetration rate. This demonstrates that increasing the number of connected vehicles could enhance the traffic assignment by ordering evacuees to choose the route that minimizes their travel time going more to the pure UE state. Figure 3.5(c) illustrates the change in the number of vehicles evacuating in the network for five different scenarios. The curves shown in this figure represent different penetration rate values.

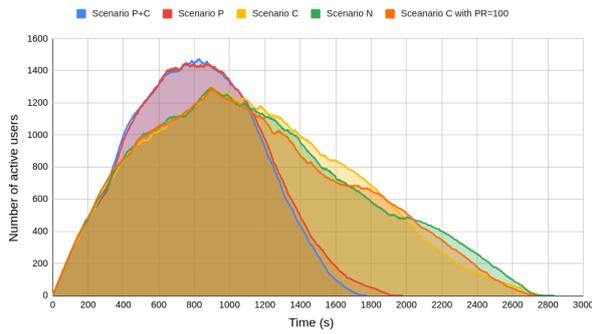
Table 3.4: Different penetration rate performance measures

Metrics	PR 100%	PR 70%	PR 50%	PR 30%	PR 0%
Network clearance time(s)	1775.00	1833.00	1846.00	1873.00	1980.00
Mean evacuation time(s)	1071.54	1081.17	1084.90	1081.17	1093.70
Average travel delay (ATD)	205.47	220.24	219.68	228.88	220.62
Average evacuation delay (AED)	229.04	243.58	243.58	252.49	241.32
End-to-end delay (ms)	205.30	203.75	202.77	201.17	-
Packet Delivery Ratio	74.20%	75.80	76.24	75.50	-

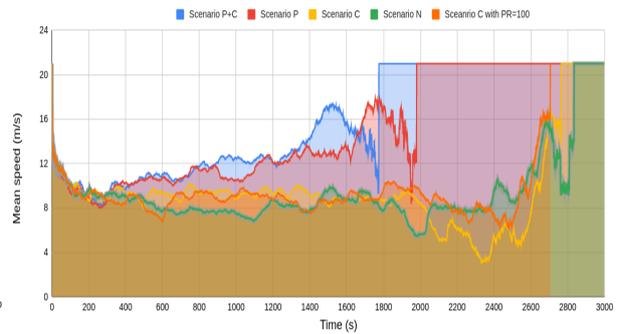
In addition, Figure 3.5(d) depicts the evolution of the mean speed in the evacuation operation. The maximum network speed limit is the free-flow speed (21 m/s) attained when the network does not have any vehicles. This value is proposed by [Dixit and Wolshon, 2014]. The network speed illustrated by Figure 3.5(d) shows that having a 100% penetration rate is the fastest curve by arriving at the free-flow speed in the shortest time. Also, the figure presents the result of the mean speed variation of other penetration rates showing that there is no considerable difference between 70% and 30% penetration rate on network clearance time (the arrival to the free-flow speed). Figure 3.5(d) shows that adding the communication layer, even with different penetration rates, positively affects evacuation. It means that the online solving of DPE uses the network’s capacity better than just planning. Based on the results presented, the conclusion is that using 30% of the penetration rate is more realistic, and its results are comparable to having 100%.

3.6.2 Results for the Mill Valley case

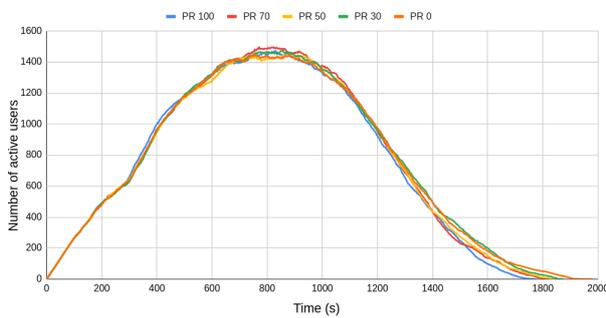
Based on the results of the Luxembourg case and sensitivity analysis on penetration rate, the proposed model is implemented in the evacuation operation of the large-scale case of Mill Valley City. Here just three scenarios (P+C, P, N) are considered as it was concluded previously that there is not much difference between scenarios N and C. A vehicular communication layer was included with a 30% adoption rate of vehicles in Mill Valley to evaluate the effects of online vehicular management and accurately simulate real-world scenarios. Figure 3.5(e) shows the cumulative percentage variation over the three considered scenarios. In Figure 3.5(e), it can be observed that there is a substantial improvement in the P+C scenario compared to the naive scenario. The results clearly indicate that the



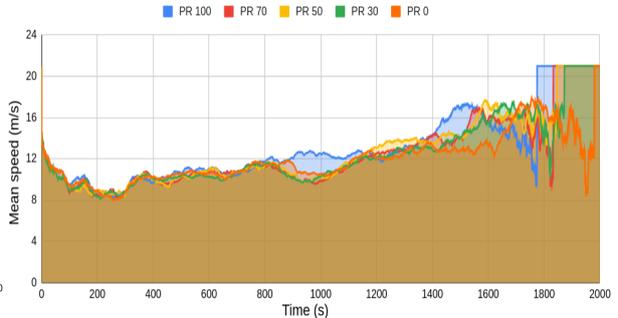
(a) Variations in the number of active users in the Luxembourg city network



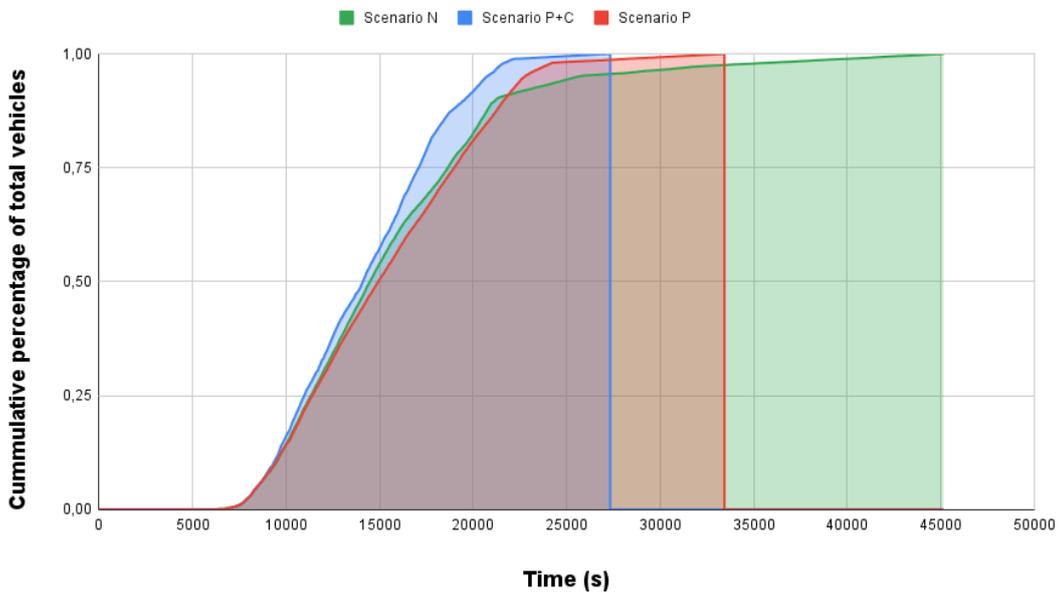
(b) Variation in the mean speed of the Luxembourg city network



(c) Variations in the number of active users in the Luxembourg city network over different PR values



(d) Variation in the mean speed of the Luxembourg city network over different PR values



(e) Cumulative percentage of evacuees variation in the network of Mill Valley city

Figure 3.5: Numerical results variation over the two networks

difference between the two scenarios is significant, especially when subjected to greater and more realistic demand. In other words, the figure provides evidence that the P+C scenario effectively addresses the challenges posed by real-world demand situations. According to the figure, an evacuation operation conducted with online communication yields significantly faster results compared to the scenario P evacuation approach. Specifically, the graph displays a clearance time reduction of over 20% for the online communication scenario, indicating a much quicker and more efficient evacuation process. In contrast, relying solely on planning for the evacuation results in a longer clearance time, which can potentially hinder the safe and timely evacuation of individuals in emergency situations. Also, The figure demonstrates a significant contrast in the effectiveness of reducing congestion between the three scenarios. This is evident in the graph's steep decline in the "P+C" scenario compared to the prolonged queue formed in the "N" scenario. This indicates that the combination of measures implemented in the "P+C" scenario substantially impacts mitigating congestion, leading to a more efficient and streamlined evacuation process. On the other hand, the lack of such measures in the "N" scenario results in a slower and less effective reduction of congestion, leading to longer wait times and potentially compromising the safety and well-being of the evacuees.

3.7 Discussion

During a disaster, efficient and quick evacuation of the affected population is crucial to minimize the loss of life and reduce overall costs. This chapter addresses the dynamic population evacuation (DPE) problem, which involves modeling and optimizing the evacuation process to save as many lives as possible faster and more efficiently. We provided a comprehensive literature review and analysis of multiple models used in evacuation planning and VANET creation and execution in the context of an evacuation. Based on the findings from the literature, the evacuation problem can be divided into two fundamental parts. The first is creating an evacuation plan considering dynamic shelter allocation and traffic assignment. The second involves considering new orders for the online guiding system.

For the first part, evacuation planning, several models are described in the literature, such as bi-level models. Many of these models utilize static traffic assignment and shelter allocation formulation to address the network evacuation problem. Despite resolving both planning problems of SAP and traffic assignment in a static setting, few consider the DPE in a dynamic case for both shelter allocation and routing.

For the second part, researchers made different proposals to improve evacuation operations by considering it from different sides of using architectures of a vehicular ad-hoc network (VANET), modifying the emergency message routing techniques, considering different types of messages, and transferring data between nodes. We proposed a framework to solve the DPE problem, creating an initial optimal plan and giving online orders considering unpredicted events not considered by the plan. To solve the DPE problem, the PDCA diagram is proposed to structure the framework. The framework uses a traffic simulator to capture the dynamics of the evacuation process. A planning process is achieved to determine shelters in the SO manner and routes in the SUE setting. Afterward, an online management procedure is performed during the evacuation. To this end, vehicles can send and receive data to update their route accordingly. To add this networking layer, a cloud computing architecture is deployed, which is composed of vehicles representing final nodes, RSU representing the network infrastructure, and a distant, powerful computer representing the cloud server.

In the implementation of the methodology, a trip-based dynamic simulator is utilized to provide travel information at each time step. Additionally, a network simulator is incor-

porated to enable vehicular cloud computing communication. The proposed methodology is applied to the network of the city of Luxembourg and the large-scale and real evacuation scenario of Mill Valley. The proposed model exceeds the model with only evacuation planning by more than a 10% decrease in network clearance time in the medium-scale network of Luxembourg City and more than 20% in the large-scale of Mill Valley city. This means that using vehicular communication for giving new orders improves the evacuation operation because it considers new events and emerging congestion not initially determined by the plan. Moreover, an analysis of the penetration rate of connected vehicles is carried out. The results show that solving the online DPE, even with a low penetration rate, could improve the quality of the proposed solution and use more of the network capacity.

Chapter 4

VANET Architectures

Online DPE allows evacuees to revise shelter and path choices during evacuation by communicating and getting updates. This is practical if vehicles connect to a vehicular ad hoc network (VANET). Vehicular Cloud/Fog Computing concepts support drivers, ensure comfort and safety, and increase VANET resources. In this chapter, we design a generic framework for DPE that will enable the evaluation of various telecommunication network architectures in terms of their performance. The focus will be on examining objective functions that are most effective for DPE planning, particularly in large-scale scenarios. Additionally, the research will investigate the optimal Penetration Rate of connected vehicles within a cloud computing setting, aiming to identify the ideal level of vehicle connectivity for efficient evacuation processes. Furthermore, a comprehensive benchmark will be conducted to compare and assess the performance of two commonly used telecommunication network architectures. By evaluating and optimizing telecommunication systems for population evacuation, this chapter aims not only to enhance the scientific understanding in this area but also to provide practical insights that could contribute to improving public safety during emergencies. The results may help inform the design and implementation of evacuation strategies, guide policy-making, and serve as a foundation for future research in this area.

This chapter is an updated version of the paper:

- Idoudi, H., Ameli, M., van Phu, C. N., Zargayouna, M., & Rachedi, A. (2023) Streamlining Disaster Response: A Benchmark Study on Population Evacuation Planning with Telecommunication Network. International Conference on Intelligent Transportation Systems (ITSC). IEEE.

4.1 Literature review on different architecture

The planning phase in disaster scenarios is crucial as it determines evacuation instructions such as the shelter destination and the path taken to reach it [Supian and Mamat, 2022]. Traditional offline planning methods involve pre-determining these factors by solving the Shelter Allocation Problem (SAP) and using Dynamic Traffic Assignment (DTA). Solving SAP involves identifying the most suitable shelters for different groups of people, such as families with children or individuals with special needs. While DTA is a traffic management strategy that considers real-time traffic conditions to determine path flow distribution. Several studies have investigated the use of traffic assignment and shelter allocation problems for offline evacuation planning. For example, a study by [Kongsomsaksakul et al., 2005] proposed a multi-objective DTA model for evacuation planning that considers both evacuation time and congestion. In [Idoudi et al., 2022a], we presented a comprehensive literature review on offline Dynamic Population Evacuation (DPE) planning methods and proposed a dynamic framework to solve SAP and DTA together using a simulation-based approach. However, offline planning alone may not be sufficient to handle the dynamic nature of an evacuation.

In this context, online DPE is defined as a process of revising the evacuees' shelter and path choices during the evacuation process. It means evacuees can communicate during the evacuation and receive new information to revise their decisions. From a practical point of view, this process can be feasible if vehicles are equipped to connect to a vehicular ad hoc network (VANET). Generally, the concept of Vehicular Cloud Computing (VCC) and Vehicular Fog Computing (VFC) have emerged in order to support and serve all drivers' needs, ensure their comfort and safety, and increase VANET resources [Mekki et al., 2017]. VCC uses connected vehicles and cloud computing to reroute vehicles and dynamically allocate shelters during an evacuation. Therefore, online solving of the evacuation problem using VCC for rerouting vehicles and shelter reallocation may further optimize the evacuation process. Several studies have investigated the use of VCC for evacuation planning. For example, [Liu et al., 2018] proposed a safety-related message exchange protocol for highway scenarios. However, their work does not revise the SAP and DTA problems. In a study by [Alazawi et al., 2014], an evacuation strategy called speed strategy was applied and evaluated using the VCC architecture. We quantified driver responses to evacuation pre-plans in emergencies. However, the authors did not propose any replanning orders to change their routes or destinations, a critical element we introduced in [Idoudi et al., 2022d] and aim to address in this chapter. Regarding VFC, most studies in the literature only mention the potential of this architecture for emergency situation and do not apply it to the DPE process.

Another question to be addressed is which indicator should be optimized for the DPE problem [Bayram, 2016]. In the literature, multiple studies have explored various key performance indicators (KPIs) used to optimize and evaluate evacuation planning. Evacuation orders serve several primary goals, which have been extensively studied by [Bayram, 2016]. Combined KPIs that take into account multiple factors like total evacuation time, network clearance time, and total traveled distance are also proposed in the literature [Alçada-Almeida et al., 2009]. The combination of these KPIs for optimization is mainly defined by the weighted sum function. However, there is no proof in the literature that shows optimizing one single KPI provides the optimal evacuation plan. These varied objectives highlight the complexity of the DPE problem and the need for nuanced, multi-faceted solutions. We seek to further investigate the effectiveness of single versus combined KPIs in optimizing the DPE process, thereby contributing to the ongoing discussion in the field.

In addition to the KPIs, another crucial aspect that warrants attention is the telecom-

munication network architecture within evacuation scenarios. In the literature applying to non-emergency travel, multiple studies were made to assess the impact of various telecommunication architectures on transportation systems. [Gaouar and Lehsaini, 2021] studied the impact of different vehicular communication architectures, such as cloud computing and fog/edge computing. They presented several applications of these architectures, excluding evacuation. [Jeong et al., 2021] presented a comprehensive summary and analysis of the latest research in smart transportation systems, focusing on standardization activities, protocols, applications, and security. In addition, [Behravan et al., 2023] describes the essential parts of a fog computing architecture and focuses on different applications, architectures, and significant performance metrics using fog computing in vehicular networks. All the aforementioned studies addressed normal conditions. However, understanding how these architectures perform during emergencies like population evacuation is crucial, as these scenarios present unique challenges that may impact system performance. Despite this, to the best of our knowledge, there is no previous study that examines the performance of these telecommunication architectures in a population evacuation context. In this chapter, we aim to fill this knowledge gap.

4.2 Framework for different architecture

Efficient evacuation operations are critical in emergencies and require a systematic approach to minimize evacuation time. The proposed approach consists of two phases: the initial evacuation plan (solving the SAP and DTA problems) and the online management process that considers vehicular communication. For the initial phase, we follow the methodology developed in Chapter 2. In SAP, we minimize the overall evacuation time, which aligns with the interests of system operators who prioritize efficiency in the evacuation process. Subsequently, the DTA problem addresses the concept of Stochastic User Equilibrium (SUE), considering the tendency of evacuees to prioritize their perceived minimum travel time when choosing their path to their selected shelter. By formulating and optimizing these decision problems, the evacuation process can be effectively streamlined, considering both the priorities of system operators and the preferences of individual evacuees.

The proposed online management framework aims to address unforeseen events and adapt the initial evacuation plan in real time by utilizing the communication capabilities of vehicles. This framework leverages the power of vehicular communication to enable evacuees to receive and transmit information, allowing them to update their routes as needed. This dynamic modification of ways based on real-time information significantly enhances the efficiency and safety of the evacuation process, ensuring that evacuees can respond effectively to changing circumstances and navigate the most optimal paths to their destinations. To use VANET, a network layer is introduced to incorporate vehicular communication, enabling network congestion monitoring. This communication network is crucial in re-planning evacuation routes and shelter allocation in real-time throughout the evacuation process.

The proposed methodology is structured following Deming’s Plan-Do-Check-Act (PDCA) cycle [Realyvásquez-Vargas et al., 2018], illustrated in Figure 4.1. This visual representation provides a systematic approach for continuously improving the evacuation plan and offers an overview of the proposed methodological framework’s key steps. We first detail the flowchart and subsequently, highlight the differences between VCC and VFC.

In the initial planning phase, Step 1 focuses on generating the initial evacuation plan. This stage involves solving the multi-level DTA and SAP, thereby creating an evacuation plan as described in [Idoudi et al., 2022a]. The objective function of SAP will be modified in the next section for our benchmark.

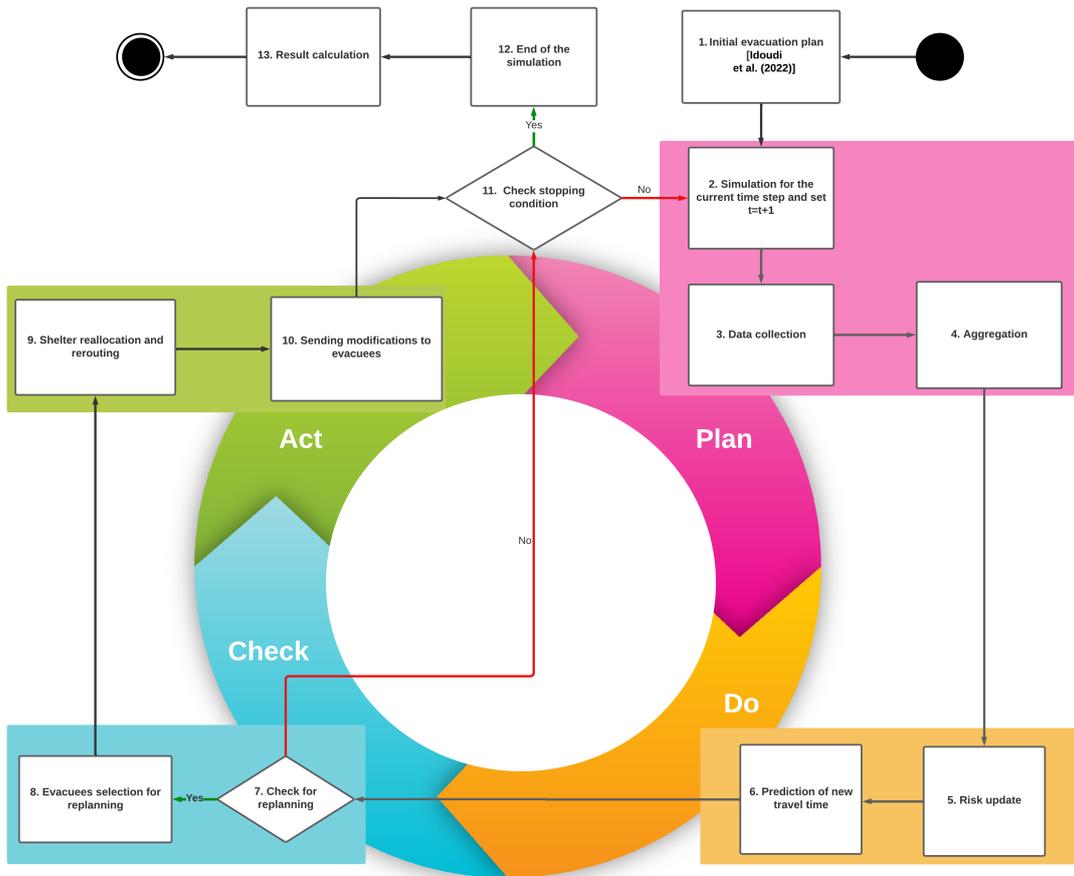


Figure 4.1: Flowchart of the proposed methodological framework to address the online DPE problem using the PDCA Cycle.

The PDCA cycle begins with the "Plan" phase, which simulates the evacuation process for the current time step and increments the simulation time index ($t=t+1$) in Step 2. The simulation considers the proposed plan and any new events that have occurred due to decisions made by evacuees in the previous time step. A trip-based or agent-based dynamic simulator can be used for this purpose. Step 3 focuses on data collection as part of the VCC architecture. Each vehicle (node) broadcasts data messages using its On-Board Unit (OBU) to Roadside Units (RSUs), which transmit the data to the cloud server. In step 4, the server has to aggregate the data sent from RSUs. This data could have a lot of redundant and replicated data due to vehicles that connect to multiple RSUs at the same time. The process of aggregation is achieved by unifying messages from the same vehicle. In the "Do" phase, the risk measure is updated based on the data collected in Step 3. The risk calculation in Step 4 considers the vehicle's distance from a hazardous area and the congestion levels at the vehicle's location. Afterward, new travel times are predicted in Step 5, taking into account the evolving risk and congestion.

The "Check" phase verifies the need for replanning. Step 7 determines whether a vehicle should be included in the replanning process. It estimates edge density, including road speed and traffic density, based on the Greenshield model [Pan et al., 2016]. Vehicles with current edge density exceeding a certain threshold are considered to be in congestion and are thus subject to rerouting. The shelter reallocation process selects vehicles when congestion is detected in front of their original destinations. In Step 8, prioritization is given to vehicles within a risky zone with a radius of 4 km, particularly focusing on those closest to the center of the risky zone.

In the "Act" phase of the PDCA cycle, two important steps are performed. Step 9 involves shelter reallocation and rerouting, where the content of a message is prepared to be sent to targeted users, asking them to reroute their vehicles to the path with the current shortest travel time, considering their possible newly planned shelter. This step aims to optimize the evacuation routes for efficiency and safety. Step 10 focuses on sending notifications to evacuees. In this step, the cloud server communicates its decisions to the nearest RSU, which then forwards the results to the vehicles. The vehicles receive these notifications and can react accordingly based on the instructions provided. This communication process ensures effective coordination and timely response during the evacuation, leveraging cloud computing and communication capabilities to improve the overall evacuation process. Lastly, Step 11 verifies whether all evacuees have reached the shelters. If not, the PDCA cycle restarts at Step 2, ensuring continuous improvements to the evacuation process.

The aforementioned description outlines the communication process within a cloud computing architecture, which bears a resemblance to that of a fog computing architecture. However, a pivotal distinction resides in the decision-making locus. While the cloud architecture consolidates decisions at the cloud server level, the fog architecture delegates decision-making to the RSU level. This decentralization fosters prompt decision-making and diminishes dependency on the cloud server, thereby bolstering the responsiveness of the evacuation system. Moreover, another divergence between the two architectures lies in the message aggregation process. In the cloud architecture, message aggregation is centralized at the cloud server level, while in the fog architecture, it occurs closer to the edge at the RSUs. These disparities underscore how fog computing brings decision-making and data processing closer to the network's edge, thus enhancing system agility while maintaining the overall communication framework established in the cloud computing architecture.

This methodology outlines a comprehensive approach for dynamic population evacuation using vehicular communication and different network architectures. By integrating planning, real-time adjustments, and dynamic decision-making, the framework ensures an

efficient evacuation process. Next, two city-scale case studies will be presented, applying this framework to demonstrate the potential of the methodology under different configurations, allowing a comprehensive cross-comparison of different optimization and VANET configurations by evaluating their effectiveness.

4.3 Case Study

This section provides an overview of the hardware and software components deployed in implementing the proposed solution and conducting the experiments. Two distinct networks were utilized for the experiments: the LuST scenario, which represents Luxembourg City, and the network of Mill Valley City in California. The experiments were conducted on a laptop with a processing speed of 1.7 GHz and 16 GB of RAM, which facilitated the generation of all the results. The solution was implemented using a simulation-based DTA method, employing the SUMO simulator [Lopez et al., 2018a]. SUMO facilitated the calculation of the C-logit model and travel time prediction. The planning phase was optimized using the SAP model implemented with ILOG CPLEX version 12.9. To simulate vehicular communication, the Veins/Omnet++ simulator was utilized to implement the fog and cloud computing architectures, which were based on previous works [Wang et al., 2020].

Figure 4.2 illustrates the evacuation network maps of Luxembourg City (covering an

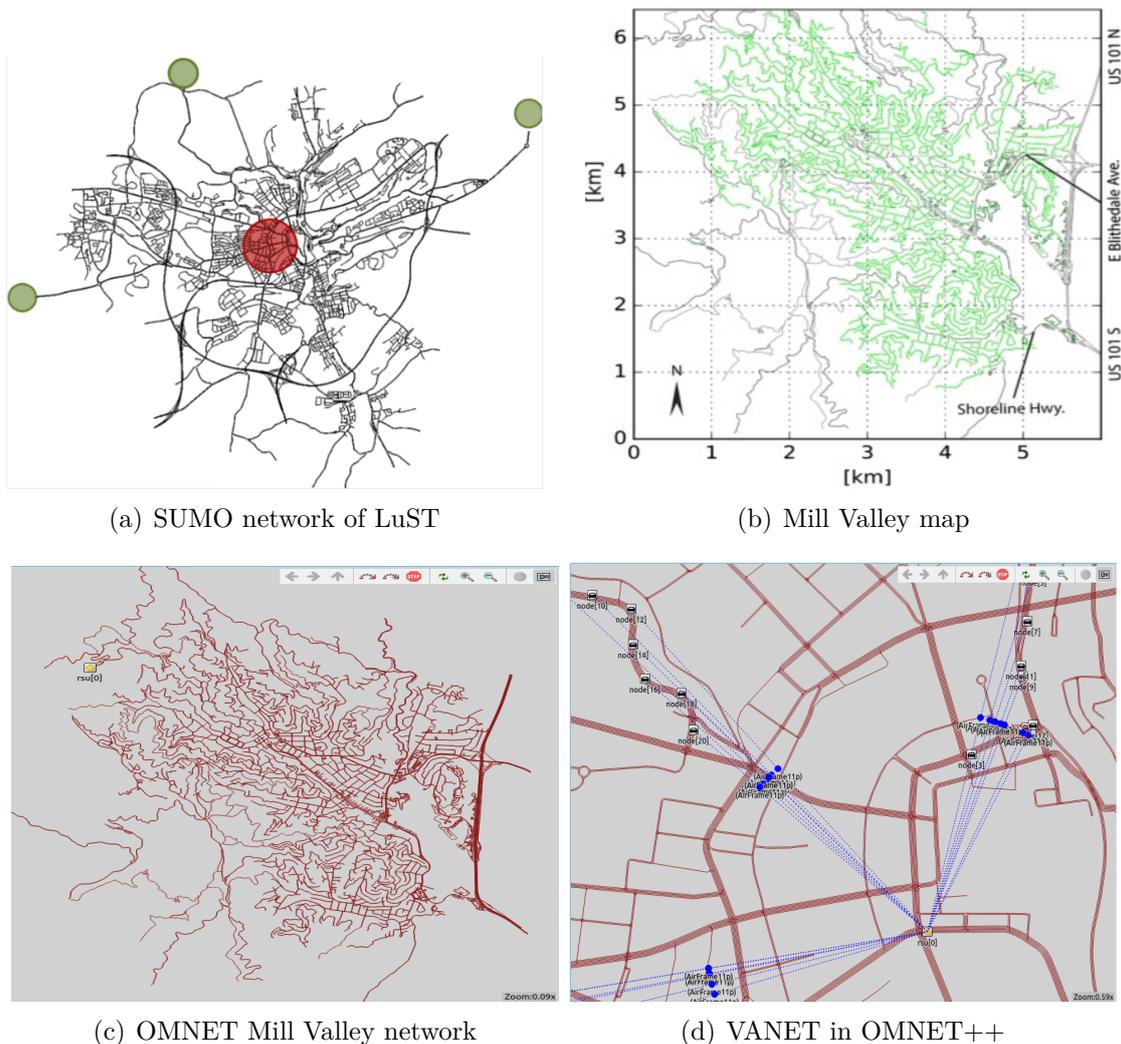


Figure 4.2: VANET maps of Luxembourg and Mill Valley network

area of 155.95 km²) and Mill Valley City (encompassed a total length of residential roads spanning 337 km), serving as the simulation environments. In the LuST scenario, we focus on the affected population in the central region, as shown in Figure 4.2(a). Similarly, the real evacuation scenario of Mill Valley (Figure 4.2(b)) is detailed in [Chen et al., 2020]. The Veins project was integrated to incorporate the vehicular communication layer into the traffic network graph. The vehicular communication network in the OMNET++ simulator is depicted in Figures 4.2(c) and 4.2(d).

4.4 Numerical Results

The proposed methodology is applied to both case studies using the scenario of Luxembourg city and the large-scale scenario of Mill Valley city. In this section, we begin by examining the influence of SAP’s objective on the effectiveness of evacuation planning. Subsequently, we conduct a sensitivity analysis to determine the optimal penetration rate of connected vehicles. Finally, we compare the VCC and VFC architectures to determine the most appropriate vehicular communication architecture for this specific application.

4.4.1 SAP Objectives

In the previous chapter, we determined the effect of telecommunication compared to just planning on the success of the evacuation process, and we noted that planning also contributed a lot to this success. Hence, here we modify our planning methodology, especially the model adopted in formulating the SAP. Recall that most studies that are discussed in Section 4.1 are using the formulation of the p-median problem proposed in [Hakimi, 1964]. The p-median problem aims to minimize the total evacuation time. However, there is a similar formulation, known as the p-center model aims to determine the optimal location for shelters, such that the maximum travel time between any demand point and shelters is minimized. In other words, it minimizes the network clearance time [Hsu and Peeta, 2014] which represents the most valuable quality indicator in the evacuation process success. The research question is which objective function is more suitable for the DPE problem considering other steps of DTA and real-time management of the evacuation. Note that both models are known to be NP-hard [Bayram, 2016].

Initially, we address the SAP by utilizing the p-median problem in Chapter 2. Here, a weighted sum operator is defined for the objective function, and we are progressively transitioning toward the p-center problem in order to minimize the time required for clearance. Hence, we define the following objective function for the SAP:

$$\min \quad z = w_{ct} \cdot \max_{\forall os} \{t_{os}^{\alpha} * a_{os}\} + w_{tt} \frac{\sum_{o \in O} \sum_{s \in S} t_{os}^{\alpha} * a_{os}}{|M|} \quad (4.1)$$

This formulation allows us to capture both the p-median and the p-center problem. If we set the weight $w_{tt} = 0$, the problem becomes a p-center problem, whereas if we set the weight $w_{ct} = 0$, it turns into a p-median problem, subject to the condition $w_{tt} + w_{ct} = 1$. In Equation 4.1, M represents the set of all evacuees. α denotes the time interval index, $\alpha \in T$. Furthermore, a_{os} denotes the number of evacuees allocated to a particular origin-destination pair os , and t_{os}^{α} stands for the minimum experienced travel time for the os pair within the time interval α . It is important to note that we have refrained from introducing any modifications to the DTA model deployed for directing evacuees toward their specified destinations, as determined by the shelter allocation solution. It means the congestion evolution will impact our results. For example, the pure clearance time optimization for SAP does not necessarily result in minimum clearance time for our test

cases after DTA calculation and dynamic simulation. This fact emphasizes the complexity of the problem and the impact of dynamic traffic conditions.

We conducted a sensitivity analysis on the network of Luxembourg City and the Mill Valley network, where we systematically adjusted both the w_{tt} and w_{ct} variables to observe their impact on clearance time and mean speed of the network during the evacuation planning phase.

Figure 4.3 displays the variation in clearance time across different scenarios with varying objective functions for Luxembourg City. The figure highlights that employing a pure p-median formulation with $w_{tt} = 1.0$ and $w_{ct} = 0.0$ yields the most favorable results in terms of clearance time. Furthermore, the figure demonstrates that the simulations having total travel time weights ranging from 0.2 to 0.8 have the same clearance time, which can be explained by the fact that these weights generate the same solution to the SAP problem, which could be expected for the medium-scale problem. In Figure 4.3, the mean speed of the network is depicted. A higher value of mean speed indicates better performance in terms of the efficiency of the evacuation process. The graph reveals a combination of the two objectives with weights ranging from 0.2 to 0.8 that result in more efficient use of the network.

The results for the Mill Valley network are presented in Figure 4.4. This figure shows that going for a mixed p-center and p-median formulation with $w_{tt} = 0.1$ and $w_{ct} = 0.9$ gives the best output in terms of clearance time. Regarding the mean speed of the network, the results show optimizing clearance time provides less mean speed for the network. Note that higher mean speed does not provide minimum clearance time as the departure time distribution of evacuees is not uniform. In addition, Figure 4.4 shows that there is no correlation between mean speed and clearance time, as all scenarios have different values for clearance time measures.

The two optimization approaches, namely minimizing total evacuation time and minimizing clearance time, both play a significant role in the SAP formulation to address the DPE problem. However, the effectiveness of these approaches can vary greatly depending on the specific scenario or test case.

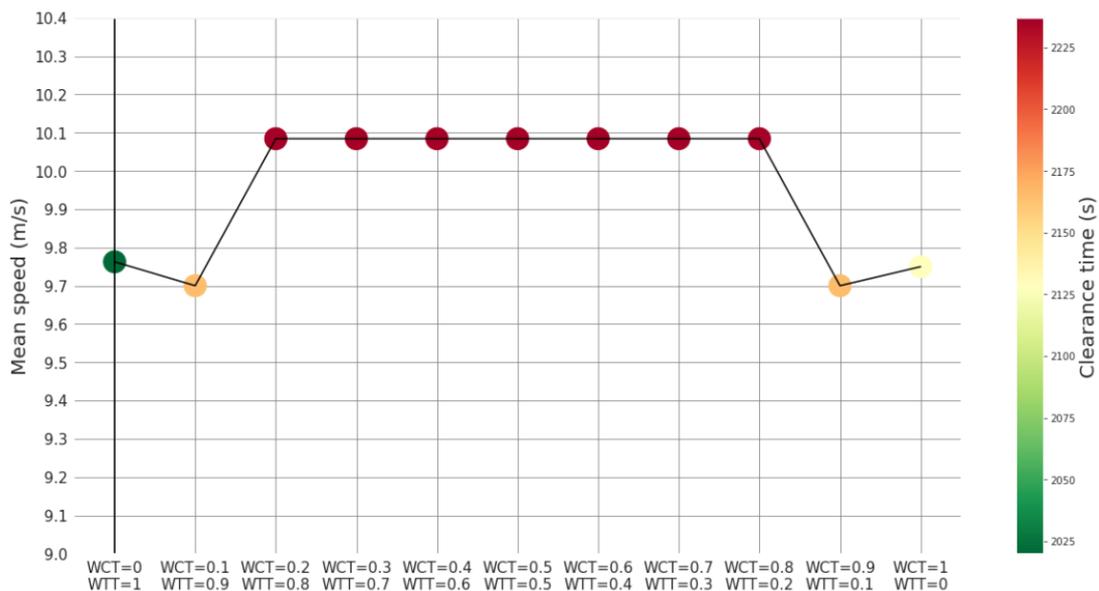


Figure 4.3: Network mean speed and clearance time variation over different objectives of SAP of Luxembourg City.

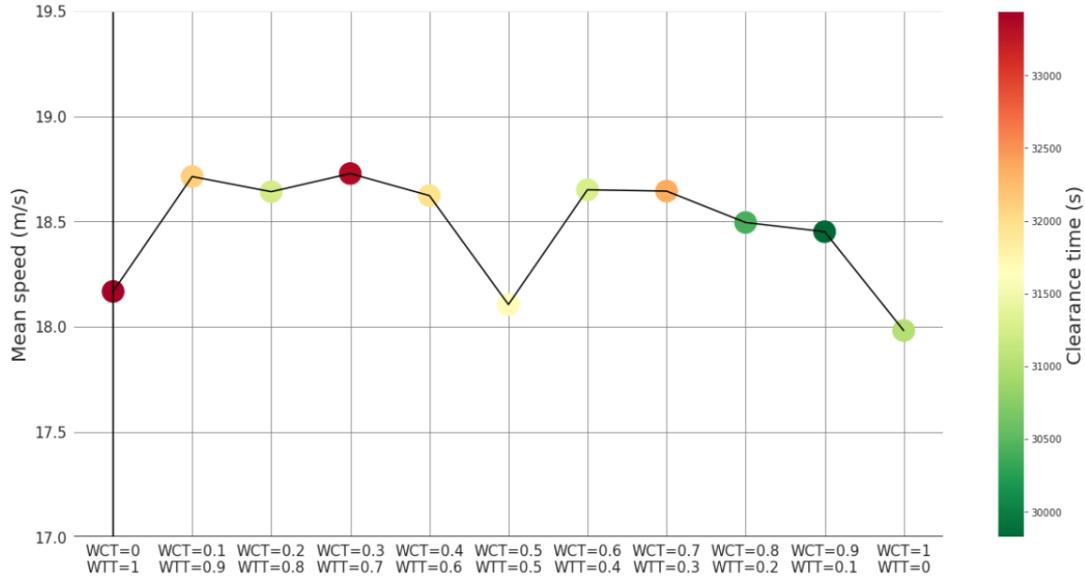


Figure 4.4: Network mean speed and clearance time variation over different objectives of SAP of Mill Valley City

4.4.2 Penetration rate sensitivity analysis

While assuming that 100% of evacuees use connected vehicles may be unrealistic at present, it is a potentially attainable scenario in the future. Hence, multiple penetration rate values for connected vehicles are considered for both test cases. Note that, This sensitivity analysis is applied to scenarios with the best weights for each case determined in the previous section. The connected vehicles are chosen randomly when considering a certain percentage of penetration rate. Only this specific percentage is responsible for transmitting positioning information and receiving online orders. Consequently, the cloud server exclusively monitors and guides this subset of vehicles. The proposed evacuation framework is executed for five penetration rate values, and the results are presented in Tables 4.1 and 4.2 for the LuST and Mill Valley scenarios, respectively.

Table 4.1 presents the different values of the performance measures used for multiple penetration values. The table clearly shows that the case of a 100% of penetration rate is the best scenario in the LuST network. Table 4.1 also illustrates acceptable values of Packet Delivery Ratio (PDR) measure for 70%, 50%, 30%, and 10% scenarios. This PDR level means that around 75% generated packets are received correctly in the range of network infrastructure and without the need for retransmission. Also, the delay measure is crucial, especially in this case dealing with population evacuation. The average end-to-end delay of packets considering the VCC architecture employed is around 203 ms.

Table 4.1: Different penetration rate performance measures

Metrics	PR 100%	PR 70%	PR 50%	PR 30%	PR 10%
Network clearance time(s)	1775	1833	1846	1873	1923
Mean evacuation time(s)	1071.54	1081.17	1084.90	1081.17	1102.28
Average travel delay (ATD)	205.47	220.24	219.68	228.88	234.47
Average evacuation delay (AED)	229.04	243.58	243.58	252.49	254.34
End-to-end delay (ms)	205.30	203.75	202.77	201.17	200.25
Packet Delivery Ratio	74.20%	75.80%	76.24%	75.50%	76.44%

Table 4.2 shows multiple values of the penetration rate of vehicles in the large-scale scenario of Mill Valley City. The large network and the high demand considered put limitations on simulating penetration rate high values. In this Table 4.2, we compare scenarios with 0%, 10%, 20%, 30%, and 40%. Results demonstrate that the evacuation process is optimized using vehicular communication, with a difference of more than 2 hours in terms of clearance time between scenarios with PR=0% and PR=40%.

Table 4.2: Different penetration rate performance measures

Metrics	PR 40%	PR 30%	PR 10%	PR 00%
Network clearance time(s)	23311	23387	23683	29826
Mean evacuation time(s)	14502.9	14570.34	14572.84	14719.26
Average travel delay (ATD)	520.29	511.37	363.99	449.57
Average evacuation delay (AED)	1204.16	1075.49	1004.29	942.92
End-to-end delay (ms)	405.30	403.75	401.17	-
Packet Delivery Ratio	70.20%	71.80	72.50	-

The outcomes presented in Table 4.1 and 4.2 demonstrate a noteworthy enhancement in the quality of the final solution achieved through the scenario with only PR=30%, where both planning and online guidance models are utilized. The results concerning End-to-End delay and PDR indicate that with a 30% penetration rate, we achieve a latency-sensitive application that exhibits limited delay and a high PDR value, thereby meeting acceptable standards as the higher value than 30% for the PR does not improve the results significantly.

4.4.3 Vehicular communication architectures

In this section, we use the results of the previous sensitivity analysis sections about SAP’s best objective and a realistic penetration rate value of PR=30%. Our focus lies in modifying the vehicular communication architecture and investigating its impact on the success of evacuation operations. Therefore, we conduct a comparative analysis between two well-known architectures, namely Vehicular Fog Computing (VFC) and Vehicular Cloud Computing (VCC), to assess the effects of this alteration. By examining these architectures, we aim to understand how changes in the communication infrastructure can influence the overall efficiency and effectiveness of evacuation operations. VFC and VCC are two distinct architectures for vehicular communication, each offering unique characteristics and advantages. Due to its proximity to vehicles, VFC offers lower latency and faster response times for real-time applications. Fog nodes in VFC can process and analyze data locally, reducing the need for data transmission to remote cloud servers. In contrast, VCC introduces higher latency as data has to travel to distant cloud data centers for processing and storage.

As expected, Table 4.3 reveals an increase in network clearance time, 3.9% for medium scale and 0.4% for the large scale, when deploying the fog computing architecture. However, it also demonstrates a significant decrease in the end-to-end delay. We can conclude that fog computing can achieve comparable results to cloud computing in terms of transportation performance while offering the advantage of reduced latency. This finding highlights the potential of fog computing in delivering efficient and timely communication in transportation systems, bridging the gap between local processing capabilities and the need for real-time data analysis and decision-making.

Table 4.3: Different architectures performance measures

Scenarios Metrics / Telecom. architecture	Luxembourg City		Mill Valley City	
	VCC	VFC	VCC	VFC
Network clearance time (s)	1873.00	1948.00	23387.00	23488.00
Mean evacuation time (s)	1081.17	1110.53	14570.34	14541.81
Average travel delay (ATD)	228.88	221.11	511.37	431.70
Average evacuation delay (AED)	252.49	265.28	1199.52	1108.12
End-to-end delay (ms)	201.17	0.24	403.75	0.24
Packet Delivery Ratio	75.50%	65.01%	75.80%	49.88%

4.5 Discussion

We made an attempt to address the dynamic population evacuation (DPE) problem by introducing a comprehensive framework incorporating both strategic planning and online management via VANET. An analysis of various models used in evacuation planning and VANET creation and execution in the context of evacuations is presented. We propose a generic framework following the PDCA improvement cycle for the DPE problem. The model is implemented for city networks, namely Luxembourg City and Mill Valley, and a complete analysis is conducted to find the best configuration of the model for real applications. Our sensitivity analysis suggests that the choice of the objective function for the DPE problem can have significant implications for evacuation efficiency. The results recommend that the pure p-median approach for minimizing total evacuation time is suitable for medium-scale scenarios, and a weighted objective showing better performance for large-scale evacuations. Another noteworthy finding is that even a low penetration rate (e.g., 30%) of connected vehicles can provide substantial benefits in managing the online DPE, leading to better utilization of network capacity. In our analysis of vehicular communication architectures, we found that the Vehicular Fog Computing (VFC) implementation results in lower message transmission delay, with clearance time outcomes comparable to a centralized architecture deploying Vehicular Cloud Computing (VCC).

Chapter 5

Spatio-temporal Risk Evolution in the Evacuation Process

The chapter proposes an integrated framework for wildfire evacuation combining fire modeling, traffic simulation, optimization techniques, and vehicular communication networks. Evacuation planning involves solving optimization models for shelter allocation and route assignment. Real-time adjustments are enabled through a cloud architecture where vehicles communicate to receive updates on routes and shelters. Experiments apply the framework to evacuation scenarios based on the 2017 Tubbs Fire. Results show the integrated approach reduces network clearance time, vehicles exposed to fire risk, and congestion compared to models without real-time communication. The findings demonstrate the value of combining evacuation planning with dynamic adjustments facilitated by vehicular networks for more effective evacuation during wildfires. The framework provides a novel methodology [Idoudi et al., 2023a] integrating emerging technologies like optimization, simulation, and networking to enhance evacuation management.

5.1 Introduction

Wildfires have been a significant threat to US communities living in the wildfire-urban interface (WUI) areas [Nauslar et al., 2018]. According to [Wong et al., 2020], from 2017 to 2019, a series of devastating wildfires affecting WUI regions led to the evacuations of over one million people only in California. Moving a large proportion of residents to safety points in a timely manner requires advanced emergency planning. Therefore, evacuation modeling and simulation tools with real-time information are critical for such a process.

With the expansion of urban and suburban areas, the increase of WUI regions poses wildfire threats to more communities [Kuligowski et al., 2022]. With unexpected factors such as winds or fire fuels in the region, wildfire would expand to the city level, as in the 2017 Tubbs Fire, the 2018 Paradise Fire, and the 2019 Kincade Fire. With this in mind, one could not neglect that when evacuating residents towards the urban region is one of the viable planning measures, regular urban traffic would bear large pressure [Soga et al., 2021].

Previous work has studied evacuation simulation using different methodological setups. Simulating phased evacuation combined with fire modeling has been studied by [Beloglazov et al., 2016]. Integrating traffic simulation into evacuation has been developed by [Soga et al., 2021], [Melendez et al., 2021], and [Grajdura et al., 2022], as further discussed in the next section. While these works explore different aspects of a wildfire evacuation, more emerging technologies such as smart transportation, optimization, and real-time communication systems could be integrated into an evacuation in planning for disaster management. Such technology could inform transportation planning and shelter establishments when policymakers try to prepare for a large-scale evacuation. To our knowledge, there has been no research that combines fire data with emerging technology, such as real-time mobility and communication, with disaster evacuations.

In the study, we proposed a framework that combines traffic simulation with daily mobility, optimization systems, and cloud communication systems to represent and implement wildfire evacuation scenarios. We used fire data directly derived from the 2017 Tubbs Fire in Calistoga, California. The focus of our study is to examine the potential impact of integrating smart infrastructure and transportation planning on the evacuation results of a region, specifically during extreme fire incidents when all inhabitants opt to evacuate the area.

The remainder of this chapter is organized as follows. The next section discusses relevant literature on fire risk management, transportation network optimization with shelter allocation and dynamic traffic assignment, and communication systems. Section "Problem Formulation" formulates the network optimization problem detailing problem variable inputs and optimization constraints. Planning and online phases are presented in this section. Section "Methodological Framework" illustrates the architectural system design to capture and manage the evacuation process. Sections "Test case" and "Results" cover our experiment setup, and results and discuss findings, respectively, before concluding remarks in the "Conclusion" section.

5.2 Literature review

Research in wildfire evacuation takes from both quantitative and qualitative perspectives. Qualitative studies focus on understanding the factors behind the evacuation choices of residents living in fire-prone regions. Meanwhile, quantitative research combines wildfire modeling and transportation simulation to understand transportation network resilience and the total travel time of a community to evacuate people to safe places.

In their review of wildfires between 2017 and 2019 in California, [Wong et al., 2020]

conducted a survey to study evacuation choices of evacuees to offer a descriptive picture of evacuees' behaviors including choices of destination and route. Researchers in the study recommended that public shelters should be maintained across stakeholders to increase evacuation efficiency. [Kuligowski et al., 2022] modeled behavior choices from survey results of households that were involved in the 2019 Kincade Fire in the Sonoma County of California. The survey found that pre-fire perception of safety proves to be one of the factors impacting residents' decision on whether to evacuate. Leaving your property behind for a safe place is a significant decision for residents. For those who decide to leave, many factors could affect their trips, such as departure time and destination choices. [Beloglazov et al., 2016] developed a comprehensive dynamic factors-based simulation model in contrast with traditional static models to study evacuation performance. [Soga et al., 2021] combined wildfire modeling, transportation planning, and telecommunication modeling to study the evacuation of three communities in California and proposed tailored strategies for stakeholders in each community in wildfire planning. [Grajdura et al., 2022] developed an agent-based model which combined survey data and transportation modeling with running evacuation scenarios of the 2018 Camp Fire in Paradise, California. Differed from [Soga et al., 2021], which assumes two nearby towns, Chico and Oroville, of the Camp Fire as destinations for evacuees, [Grajdura et al., 2022] modeled public shelters as destinations in their simulations. While previous works studied wildfire evacuation with various transportation planning models and explored dynamic factors that could affect evacuation outcomes, they have not explored the interaction dynamics of evacuation planners and evacuees making use of communications between the two ends during the process.

Combining mobility data with evacuation modeling has been emerging since the development of using cellular data to model traffic. [Melendez et al., 2021] used cell phone data to predict vehicle densities of traffic during the 2017 Lilac Fire in San Diego County in California. [Wu et al., 2022] shows the GPS data collected from mobile devices during the 2019 Kincade Fire is a valuable addition to existing methods and provides new insights into evacuation studies. To our knowledge, no research has combined daily mobility from phone data, vehicular communication, and fire evolution for tackling the evacuation problem. This work is distinguishable from the previous work by taking into account the impact of the dynamic evolution of the hazard on both the planning level and vehicular communication level.

The literature addresses the Dynamic Population Evacuation (DPE) problem from a telecommunication perspective by utilizing vehicular ad-hoc networks (VANETs) specifically designed for emergency situations. Various telecommunication technologies have been explored in the literature, regardless of the planning phase. Numerous studies extensively explore evacuation models incorporating vehicular communication capabilities. These studies comprehensively cover various aspects of evacuation, employing different communication architectures, protocols, and types of emergency messages.

[Alazawi et al., 2014] have presented a tool designed to examine ITS Services such as VANET under a cloud computing architecture. The primary objective of this tool is to enhance transportation evacuation speed strategies, thereby contributing to the preservation of human lives during road disasters and facilitating efficient day-to-day transport management and emergency response operations. Some studies have focused on network architectures used for emergency situations, aiming to collect data rapidly and ensure a successful evacuation process. For instance, [Nobre et al., 2019] used Software Defined Network (SDN) to manage emergencies. The authors examined fog-enabled Vehicular Software Defined Networking (VSDN) design principles, encompassing systems, networking, and services. The evaluation was conducted using real data on a traffic management system for fast accident rescue. A discussion of research challenges and opportunities

for integrated fog-enabled VSDN was also included. Other studies target evacuation by proposing different and less redundant emergency message exchange protocols. For example, [Siddiqua et al., 2019] proposed an integrated Content-Centric Network (CCN), iCAFE, for intelligent Congestion Avoidance and Fast Emergency services in smart cities. It introduces a novel content-centric VANET-based protocol, efficient traffic control algorithm, and unique packet headers. iCAFE achieves high packet delivery and minimal rescue delay. [Khalid et al., 2016] highlighted the need for emergency evacuation preparation. They developed a cloud-based service that provides real-time route suggestions, prioritizing rescue vehicles. Experimental evaluation of simulated traffic demonstrated the service’s potential to improve traffic operations during evacuations. Efficient real-time data management was a key advantage. The mentioned studies focused on the quality of communication during the evacuation process. However, the content of the communication which supports the decision of evacuees is also crucial. [Idoudi et al., 2022d] also included vehicular communication using VANET under a cloud-based architecture to add rerouting capabilities in order to reduce evacuation time. However, this study does not take into account the dynamic nature and evolving state of the hazard in their framework.

Here a brief literature review on evacuation planning and risk assessment models is presented. The evacuation problem can be defined as an optimization problem to determine the optimal decisions for the destination and route of all evacuees. From applied mathematics points of view, both decisions can be formulated separately by Shelter Allocation Problem (SAP) and Dynamic Traffic Assignment (DTA) following the bi-level structure of the problem [Wang et al., 2016b]. Hence the complexity of SAP and DTA is often tackled in many studies using a bi-level problem formulation, as discussed in Chapter 2. In this formulation, the upper-level perspective revolves around the allocation of shelter locations by the system operator. In contrast, the lower level is dedicated to exploring routing strategies and the behavior of evacuee route choice, as highlighted in [Ma et al., 2019].

In the dynamic context, only a few studies have considered both SAP and DTA simultaneously. [Hsu and Peeta, 2014] examined the evacuation planning process, incorporating the DTA problem with a fixed shelter allocation scheme. In a previous study by the same authors, in [Idoudi et al., 2022a], both dynamic problems were addressed sequentially, aiming to minimize the total travel time in SAP and calculating Stochastic User Equilibrium (SUE) for DTA. However, these works did not take into account telecommunication networks or the evolving nature of the hazard. In [Idoudi et al., 2022d], a VANET architecture is implemented for the DPE problem to revise the route choice during the evacuation process; while the shelter assignment was static. Besides, the nature and evolution of the hazard were not considered in that study. To the best of our knowledge, no existing literature has addressed the population evacuation problem considering the evolving hazard, constructing an optimization plan to solve both SAP and DTA, along with the online management phase that incorporates vehicle communication.

5.3 Problem formulation

Evacuation operations have to be executed more safely considering the traffic dynamics [Zockaie et al., 2014] and risk evolution. In order to maximize the safety of each evacuee, we solve the problem under an offline scheme for planning purposes and in an online setting to readjust our plan towards safer evacuation, taking into account the evolving state of the hazard considered.

The offline phase, representing the planning stage, aims to establish an initial evacuation plan. In the online phase, vehicular communication is considered within the cloud computing paradigm. Recall that from a planning perspective, evacuees face two crucial

decisions in DPE: (i) selecting a shelter as their destination and (ii) choosing a route to reach that destination. To achieve this, two main optimization problems, namely SAP and DTA, must be solved. We formulate the SAP problem to minimize total evacuation time, prioritizing the system operators' interests. This scenario assumes limited knowledge of shelter capacities and conditions, with the system guiding vehicles to their shelters. Conversely, the DTA problem addresses the Stochastic User Equilibrium (SUE), considering evacuees' biased decision-making process. In other words, evacuees selfishly select their paths toward their chosen shelters, aiming to minimize their perceived evacuation time [Idoudi et al., 2022b].

Table 5.1: **Table of notations**

M	Set of all evacuees.
N	Set of all nodes in the network.
A	Set of edges (links) in the network.
T	Set of all time intervals without overlap cover the total duration considered H .
O	Set of origin nodes, a subset of the set of nodes, $O \subset N$.
S	Set of destination nodes, a subset of the set of nodes, $S \subset N$.
F	Set of hazardous nodes, a subset of the set of nodes, $F \subset N$.
i	Index of evacuee, $i \in M$.
n	Index of node, $n \in N$.
o	Index of origin node, $o \in O$.
s, s'	Index of destination node, $s \in S, s' \in S \setminus \{s\}$.
j	Index of hazardous node, $j \in F$
μ	Index of Time interval, $\mu \in T$.
t	Index of the exact clock time, i.e., hh:mm:ss.
ζ_o	Risk level of each origin node $o \in F$
y_s	Binary variable; it is set to 1 if shelter s is selected; 0 otherwise.
x_{os}	Number of evacuees allocated to the origin-destination pair os .
w_o	Amount of demand evacuating from origin o .
D_i	Distance separating vehicle i to the center of the hazard.
D_{max}	Maximal distance separating vehicle i to the center of the hazard.
t_n	Average of the travel time of incoming edges to node $n, n \in N$
D_i	Distance separating vehicle i to the center of the hazard.
D_{max}	Maximal distance separating vehicle i to the center of the hazard.
N_i	Number of vehicles in the following edge that evacuee i approach to.
N_{max}^i	Maximum possible amount of vehicles in the following edge that evacuee i approach to, i.e., the edge maximum capacity.
$t_{n_i s}$	Estimated Travel time from node n_i to node $s, n_i \in N \setminus S$ and $s \in S$.
λ	Safety threshold for rerouting vehicles.
α	Threshold for shelter reallocation for vehicles.

5.3.1 Planning phase

The planning phase corresponds to the optimization problem composed of two subproblems. These subproblems are solved inside a rolling horizon [Peeta and Mahmassani, 1995a] loop to account for new origins or new hazardous zones corresponding to the evolving state of the hazard. The first subproblem is finding the shelter allocation to minimize the total travel time. SAP is formulated in literature as a subclass of the widely known facility location problem [He and Xie, 2022]. The second subproblem objective is to find the optimal routes from origins to destinations that minimize the travel time for each user. You can find more details on planning problem formulation in Section 2.3.

Let us define our DPE problem on a directed graph representing a traffic network $G = (N, A)$, where N is the set of nodes, and A is the set of edges (links). We define O as the set of origin nodes that determines the hazardous zone, including evacuees to be evacuated, S as the set of destination nodes representing safe locations, i.e., shelter sites, and F represents the set of nodes under potential risk. Without loss of generality, we assume that O , S , and F are disjoint subsets of N ($O, S, F \subset N$). We denote by w_o the amount of demand of each origin o , $o \in O$.

This demand represents the number of users that should be evacuated. We note by x_{os} the integer decision variable that determines the number of evacuees allocated to the pair having origin o and destination s . We define the binary variable y_s as the decision variable of the shelter selection s . The t_{os}^* is the minimum travel time between origin o and destination s . In most cases in the literature, the travel time is calculated with a static formulation of the traffic assignment problem using an analytical travel time function (e.g., BPR function) [Bayram, 2016]. In our case, we use a dynamic simulator that provides the travel time of any edge in the network [Lopez et al., 2018b]. Therefore, t_{os}^* is a given parameter at time t from the simulator's time while solving this problem. The full list of the important notations of this chapter is presented in Table 5.1. We solve the shelter allocation problem described by the following steps in Algorithm 1.

Algorithm 1 Solving SAP

Require: State-to-destination mapping dictionary

Require: Capacities-to-locations dictionary

Require: Origins and destinations information

Ensure: Optimized allocation and selection solution

1: **procedure** OPTIMIZEALLOCATIONSELECTION

2: Create a dictionary of capacities mapped to locations.

3: Identify unique origins.

4: Create a dictionary of paths between origins and destinations.

5: **if** not initial state **then**

6: Load shelter new capacities.

7: Create a model.

8: Define decision variables x and y .

9: Define the objective function to minimize the total travel time as

$$\min \sum_{o \in O} \sum_{s \in S} t_{os}^* x_{os} \quad (5.1)$$

10: Add constraints to the model.

11: Solve the model and store the solution.

12: **Output:** The solution to the model represents optimized allocation and selection based on the defined objective and constraints.

The SAP solution assigns the demand from all sources (o) to all shelters (s), i.e., the OD matrix of the DTA model. It should be noted that the UE principle always assumes that all users have complete knowledge of the network information and consistently choose routes to reduce travel expenses [Ameli et al., 2020a]. This presumption is untenable and unrealistic in a rare event like an evacuation situation. The assumption can be further relaxed in accordance with the SUE principle by asserting that no traveler can unilaterally change their course to reduce their perceived travel cost [Lebacque et al., 2022]. In this study, evacuees’ departure time is provided, and we define the shortest path as the one with the least travel (evacuation) time. We deploy a trip-based simulator to produce this first strategy. As a result, rather than the deterministic route selection process used in UE, the dynamic traffic network equilibrium conditions with the given travel demand and departure time distribution include a probabilistic route selection process. The stochastic distribution is assumed to be random in the SUE model to represent the bias term in the route choice model [Balzer et al., 2023].

Algorithm 2 Simulation-based Dynamic Traffic Assignment

Require: Network topology

Require: Origin-destination demand

Require: C-Logit route choice model parameters

Ensure: Optimal traffic assignment and travel times

- 1: **procedure** DYNAMIC TRAFFIC ASSIGNMENT
 - 2: Initialize network topology and demand.
 - 3: Assign initial traffic flow to each link.
 - 4: **while** not converged **do**
 - 5: Simulate traffic flow based on the current assignment.
 - 6: Update link travel times using simulation results.
 - 7: Calculate route choice probabilities using the C-Logit model.
 - 8: Update traffic assignment based on route choice probabilities.
 - 9: **if** convergence criteria met **then**
 - 10: **break**
 - 11: Calculate final travel times, and link flows.
 - 12: **Output:** Optimal traffic assignment and travel times.
-

Algorithm 2 describes the process of computing the simulation-based DTA. In this framework, the objective is to reach the SUE state, where each evacuee cannot reduce its perceived evacuation time by changing its chosen route [Ameli et al., 2023]. To achieve this condition, we deploy an iterative process that involves optimization and simulation phases. The optimization phase determines vehicle route choices, while the simulation phase involves simulating evacuees (vehicles) on the specified routes obtained from the optimization phase. The C-logit mechanism [Cascetta et al., 1996] is used as the model for assigning users to their respective routes.

5.3.2 Online phase

The preceding models were established during the planning phase to generate an initial evacuation plan for evacuees. However, the subsequent model pertains to real-time evacuation management, where we depict the ongoing evacuation process as it unfolds over time. The primary objective is to effectively address unforeseen circumstances and dynamically adapt the initial plan during the evacuation. This is achieved by taking into account the communication capabilities of vehicles, enabling evacuees to receive and transmit new information and accordingly update their routes. The focus shifts from a static plan to a

responsive and adaptable approach ensuring optimal evacuation management throughout the entire process.

The proposed online evacuation guidance system consists of three key components, illustrated in Figure 1. The first component is a centralized traffic monitoring and rerouting service, represented by the cloud server (which may be physically distributed across multiple servers). The second component comprises roadside units (RSU), which establish the required network infrastructure to facilitate communication between the cloud server and vehicles. The third layer involves vehicles equipped with onboard units (OBU). These vehicles serve as end communication nodes, periodically exchanging data such as current position, speed, and direction with RSUs nodes through the vehicle-to-roadside unit (V2R) communication [Guo et al., 2022], as Figure 5.1 depicts. Leveraging these three fundamental components of our cloud architecture, we have devised a method to reroute vehicles, ensuring congestion avoidance and prompt evacuation from hazardous areas. This is achieved by estimating the level of congestion on the vehicles' routes and taking into account the updated propagation of risk over the network based on the evolution of hazards.

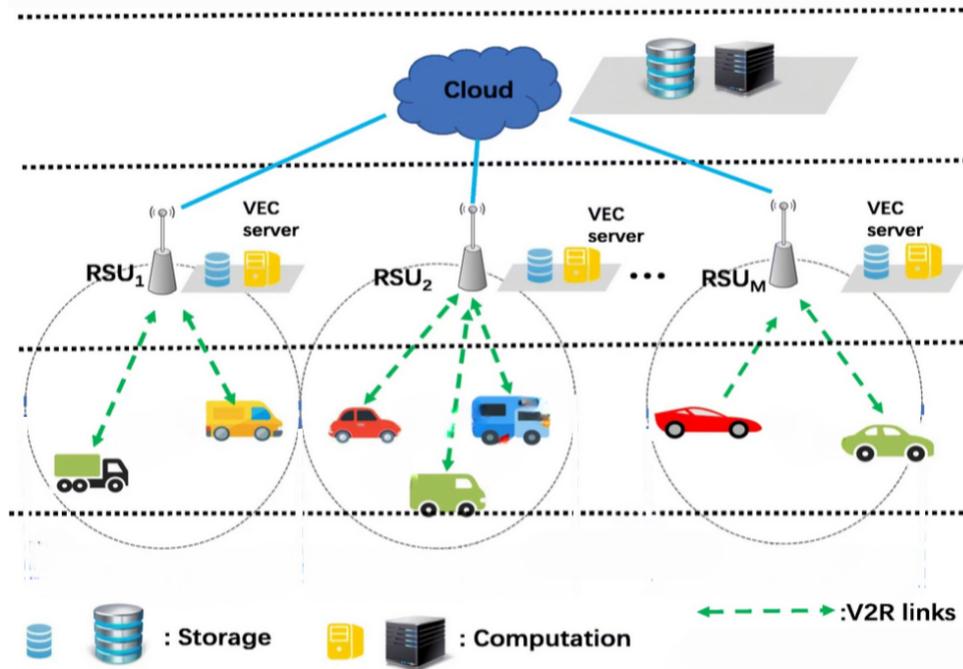


Figure 5.1: Components of the online evacuation guidance system

The proposed cloud-based evacuation guidance system implements a rerouting method to evacuate hazardous zones as quickly and safely as possible. To achieve this goal, the congestion level of each vehicle's route is estimated by measuring vehicular road density. The evolving risk is also considered by measuring the distance between the vehicle and the hazardous zone, as shown in Equation 5.2.

$$(1 - \Delta_t^i) \left(\frac{N_i}{N_{\max}^i} \right) \left(\frac{D_{\max}}{D_i + \epsilon} \right) - \lambda < 0, \quad \forall i \in M \quad (5.2)$$

In order to assess the need for rerouting vehicle i at time t , we introduce the binary variable Δ_t^i . This variable takes on a value of 1 if the vehicle is to be rerouted, and 0 otherwise. Equation 5.2 deploys various normalized fractions to calculate the value of Δ_t^i . More specifically, $\frac{N_i}{N_{\max}^i}$ represents the density of vehicles in the subsequent edge that

vehicle i is approaching. This density measurement helps evaluate the level of congestion to be avoided during the evacuation process.

To give priority to vehicles in close proximity to the hazard, a normalization function is applied to the distance between each vehicle's current location and the hazard. This is achieved by dividing the maximum distance covered by the hazard, denoted as $\frac{D_{\max}}{D_i + \epsilon}$, where ϵ is a small positive value to avoid infeasibility fraction, $0 < \epsilon \ll 1$. By combining these factors, we can determine the necessity of rerouting and identify the safest and most efficient route for each vehicle.

The introduction of the binary variable and the utilization of normalized fractions in Equation 5.2 enable us to make informed decisions regarding rerouting, taking into account both congestion levels and proximity to the hazardous area. This approach ensures that vehicles are directed toward the optimal routes that prioritize their safety and efficiency during the evacuation process.

In certain situations, it may become necessary for vehicles to modify their intended destination due to various factors, such as the distance being too far or the designated shelter being unsuitable for their needs. To tackle this challenge, we introduce the concept of shelter reallocation, which enables the evacuation system to dynamically assign new destinations to evacuees whenever required.

The shelter reallocation mechanism serves as a flexible solution that accommodates unforeseen circumstances and evolving conditions during the evacuation process. It ensures that evacuees are directed towards alternative shelters that are more feasible or appropriate in terms of proximity, capacity, resources, or any other relevant considerations. By updating the destination assignments in real-time, the system can effectively respond to changing requirements and optimize the overall evacuation efforts.

In order to assess the need for reallocation, we introduce the binary variable Ψ_t^i . This variable equals 1 if vehicle i requires reallocation at time t , and 0 otherwise. Equation 5.3 utilizes the fraction $\frac{t_{n_i s}}{t_{n_i s'}}$ to determine whether a new destination s' is closer to the vehicle's current location compared to the initially planned shelter s . Specifically, this fraction measures the time gain achieved by redirecting vehicle i from its current node n_i to the new shelter s' , relative to the time required to reach the initially planned shelter s . In order to be considered for reallocation, the calculated gain must exceed a predetermined threshold α , ensuring that the reallocation results in significant time savings.

$$(1 - \Psi_t^i) \frac{t_{n_i s'}}{t_{n_i s}} - \alpha < 0, \quad \forall i \in M, \forall s \in S, s' \in S \setminus \{s\} \quad (5.3)$$

By evaluating this fraction and comparing it against the threshold α , the system can determine whether reallocation is advantageous in terms of minimizing travel time for the vehicle. This approach allows for efficient decision-making regarding the reallocation of vehicles to alternative shelters, maximizing the effectiveness of the evacuation process at the individual vehicle level.

This section presented the formulation for both the initial planning and the online guidance of the DPE problem. However, finding an optimal solution is challenging and time-consuming. Multiple indicators are needed to measure the proximity of obtained solutions to the optimal one for timely evacuation. Additionally, analyzing the network's evolution during evacuation helps assess the impact of online guidance on the entire network.

5.3.3 METHODOLOGICAL FRAMEWORK

Let us recall that our model for solving the DPE problem taking into account the hazard evolution, consists of two main components: constructing an evacuation plan while consid-

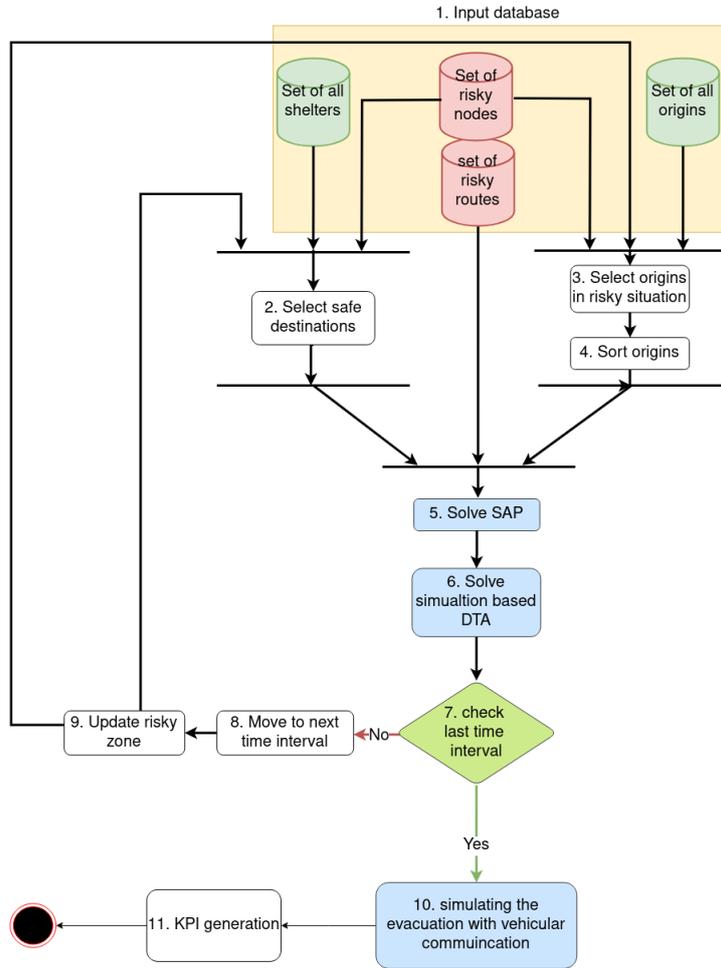


Figure 5.2: Flowchart of the proposed DPE framework with hazard evolution

ering the expected hazard evolution by solving the SAP and DTA problems and providing online guidance to vehicles in congested areas and in risky zones. In this section, we outline the step-by-step execution sequence of each component in our formulation. For the planning phase, we adapt the methodology in Section 2.3 to include the risk dynamics. This phase aims to modify the planning model to go for SUE, considering the potentially hazardous region. In the online phase, we execute the proposed online optimization model for rerouting and reallocation with three dynamical processes running in parallel: (i) Trip-based (simplified agent-based) traffic simulator to capture congestion dynamics; (ii) Telecommunication network synced with the traffic simulator; (iii) Fire simulator which represents the spatiotemporal evolution of risk on the network. In other words, for the online evacuation management phase, we add a network layer for vehicular communication to capture the congestion of the network and the spatiotemporal evolution of the hazard. To this end, we use a cloud computing scheme due to its low implementation cost. This is the main advantage of cloud computing compared to fog or edge architectures as they require a large amount of implementation budget [Gaouar and Lehsaini, 2021]. The proposed methodology of this study is presented in Figure 5.2.

The steps of the framework are detailed as follows:

- Step 1. **Input database:**
- a) Population Distribution: The number of evacuees from each node, $w_o, o \in O$.
 - b) Network Map: The city map is represented as a graph using a network file, $G(N, A)$.
 - c) Risky Zone: The set of origins to be considered as risky zones, F .
 - d) Destination Nodes Set: The set of shelters serving as destinations, S .
- Step 2. **Select safe destination:** This step involves the selection of nodes as destination nodes that satisfy the requirement of the evacuation type. Additionally, a shelter located outside the potentially risky zone is chosen.
- Step 3. **Select origin in risky situation:** From the list of nodes, origins located inside the expected risky zone are selected. These origins are considered potentially hazardous nodes that need to be evacuated.
- Step 4. **Sort origins:** This step involves the prioritization of origins that are closer to the hazard. The risk level value for each node is calculated in this step. We denote ζ_o as the risk level of each origin node o . ζ_o varies based on the evolution of the risk represented by FM_j and the distance to the expected risky zone. $\zeta_o = \max(\frac{FM_j}{distance(o,j)}), \forall j \in F$.
- Step 5. **Solve SAP:** This step involves a processing task where the SAP is solved. The set of origins and the set of destinations are taken into account, and the optimal allocation of demand is found using the SAP formulation in Section 5.3.1: Planning phase.
- Step 6. **Solve DTA:** This step presents a simulation-based method for solving the Dynamic Traffic Assignment (DTA) problem. The solving method balances between simulation and optimization phases using the c-logit route choice model. The DTA solver aims to achieve the SUE (Section 5.3.1: Planning phase).
- Step 7. **Check last time interval:** This step involves verifying if the last time interval has been reached. If so, the process moves to the online phase; otherwise, it proceeds to the next time interval.
- Step 8. **Move to next time interval:** In this step, the travel time is updated to handle the next interval with new risky zones.
- Step 9. **Update risky zone:** This step represents the process of updating the potential risky zone by adding or removing, or resizing (new) zones. The FM_i for each node in the new zones is updated accordingly.
- Step 10. **Simulating the evacuation process of all evacuees with vehicular communication and fire simulator:** This step corresponds to the online phase, which represents the real-life scenario. In addition to the fire simulator representing the hazard evolution, a vehicular communication layer is added under the centralized cloud architecture for rerouting and shelter reallocation services in order to readjust the initial plan for a more effective evacuation operation.
- Step 11. **KPI generation:** After completing the simulation, all results, including various performance metrics (detailed later) are calculated.

5.4 Case study

In the preceding section, our framework for addressing the online DPE problem was introduced. In this section, we aim to apply this methodology to a real network in order to validate the proposed solution. We first describe the test case under consideration and subsequently outline the experimental design.

Figure 5.3 illustrates the fire progression georeferenced from [Coen et al., 2018], transportation network from OpenStreetMap [OpenStreetMap contributors, 2017], and public shelters from Federal Emergency Management Agency (FEMA).

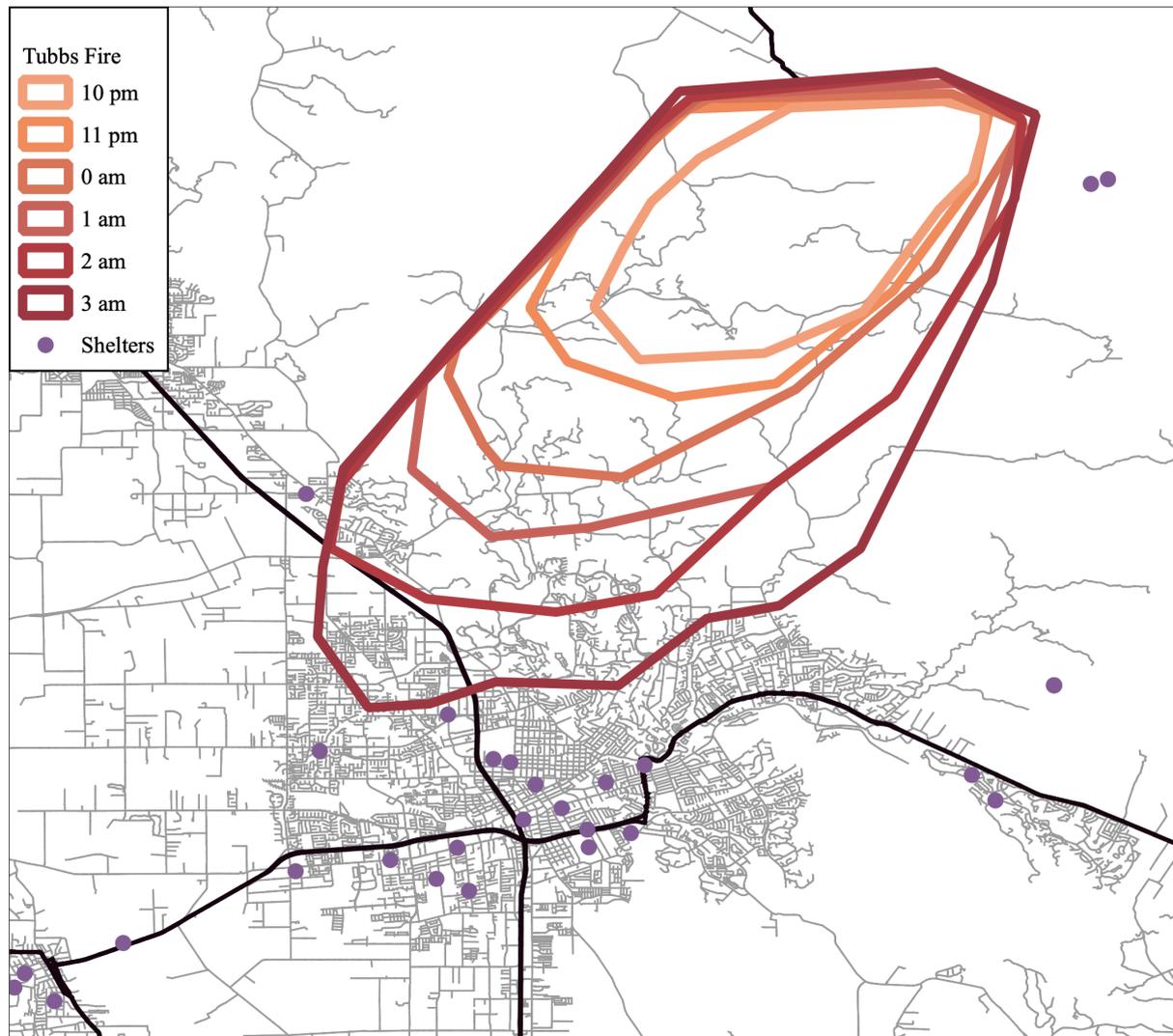


Figure 5.3: Map of study area

5.4.1 Study case: 2017 Tubbs Fire in Calistoga, California

In October 2017, Northern California experienced several deadly large wildfires: the Tubbs, the Nuns, and the Atlas fires. Altogether, these fires burned over 140,000 acres with evacuations of 100,000 people [Wong et al., 2020]. Ignited near Calistoga, California, the Tubbs fire was the first one of this series of fires and led to 22 fatalities. The fire started around 9:45 pm on October 8th, and later in the event, the fire parameter was detected at 3:09 am on October 9th past Highway 101 in Fulton, California. [Coen et al., 2018] applied the CAWFE® fire modeling system to reconstruct the fire perimeter progression

of the event. We georeferenced the perimeters derived from the model outputs and satellite imagery from MODIS and VIIRS [Xiong and Butler, 2020] and added a buffer of 500 m to include the network at risk (see Fig. 5.3). The region that was impacted by the fire was mostly residential areas with residential roads of up to two lanes.

5.4.2 Mobility data

Including urban mobility measures in planning for evacuation allows planners to understand the traffic dynamics of a large region. However, high-resolution urban-scale mobility data are not usually available [Jiang et al., 2016]. Previous work developed the TimeGeo framework using Call Details Records (CDR) data to generate individual trajectories in high spatial-temporal resolutions, which enables large-scale traffic modeling at the city-scale level when combined with mobility simulation tools.

We computed a synthetic population of the study area of millions of CDR provided by an anonymized cell phone data provider. Each time a mobile phone makes a call/SMS/data transaction, a CDR is generated, including metadata of the antenna tower and the date-time of the activity. We applied the TimeGeo framework (designed by [Jiang et al., 2016]) on the CDR data to simulate reliable mobility traces of users in the study area. The data covers 6.4 million mobile phone users in the San Francisco Bay Area. The framework simulated 27,000 residents with home locations within the Tubbs Fire perimeters. Combining with vehicle usage rate on the census tract level provided by National Household Travel Survey [NHTS, 2017], we applied SUMO traffic simulation [Lopez et al., 2018b] on the simulated origin-destination (OD) data of a typical weekday of the study area. Using the simulated results, we extracted the dynamic regional population on an hourly basis in the studied area to account for the changing dynamics of the transportation network at different times of the day. Based on our simulation, when the fire comes, there are 30,000 people within the fire perimeters.

5.4.3 Scenarios

To account for the real-life evacuation situation, we assumed that 2 or 3 persons share one vehicle, which makes sense based on the household size from the census data [Bureau, 2019]. The departure time of the population follows a gamma distribution [Chen et al., 2020]. We implemented four scenarios: a basic scenario and three other simulation scenarios with the combination of fire progression, shelter allocation (SAP), and dynamic traffic assignment (DTA), illustrated in Table 5.3.

- **Scenario S1:** A naive scenario that represents the basic scenario assumes that people living in fire-prone regions choose to leave their current locations towards the nearest shelter after receiving an evacuation order. We assume that policy planners have an estimation of the current population based on daily mobility data in fire-prone regions.
- **Scenario S2:** We coupled the Tubbs Fire progression with SAP and DTA. We assumed that when a fire ignition is reported, evacuation planners would hold a vision of the fire progression with the use of operational fire simulation models. Using the predicted fire progressions, phased evacuation orders are sent out with an estimate of the arrival time of the fire to inform fire risk and the latest departure time. Coupling with both SAP and DTA, an evacuation order, a recommended shelter resulting from SAP, and an evacuation route based on the current state of the network are given out to the people in the fire-prone regions.

- **Scenario S3:** We combined a static fire-prone region, SAP, DTA, and VANET in our simulation. The VANET system is used to communicate with vehicles on the network to inform changing routes and destinations. When a link becomes congested, if an alternative route is available, the cloud system would communicate with the vehicles to suggest rerouting without considering the fire’s progression.
- **Scenario S4:** This scenario activates all four components as changing dynamics in the simulation system. The progressive Tubbs fire, SAP, DTA, and VANET are integrated to optimize and simulate the evacuation process.

Table 5.3: Simulation scenarios

Scenario	Fire Progression	SAP	DTA	VANET
S1	Static	Static	Static	no
S2	Dynamic	Dynamic	Dynamic	no
S3	Static	Dynamic	Dynamic	yes
S4	Dynamic	Dynamic	Dynamic	yes

5.5 Results

In this section, we present and discuss the results of the four mentioned scenarios using the same evacuation demand profile. Our methodology’s effectiveness was assessed based on metrics such as the exposure rate, the number of vehicles in gridlock, and the clearance time. In the context of VANET scenarios, with a penetration rate set at 30%, each vehicle transmits a message packet to the server approximately every 1.66 minutes. We note that we use an RSU communication range of 1km [Siddiqua and Jahan, 2022, Idoudi et al., 2023d]. For rerouting and shelter reallocation thresholds, we have set λ to 0.2 and α to 0.8 due to the small penetration rate values. The results for the four scenarios are presented in Table 5.2. For the definition and formulation of metrics in this Table, please refer to 3.2.3.

Table 5.2: Performance metrics

Metrics / Scenario	S4	S3	S2	S1
Network clearance time [s]	98745.0	99846.0	99684.0	107723.0
Mean in gridlock time [s]	1.02	1.01	1.03	32.16
Mean evacuation time [s]	500.70	505.14	662.49	2966.62
Average evacuation delay (AED) [s]	104.04	103.78	101.93	1615.86
End-to-end delay [ms]	400.22	400.10	-	-
Packet Delivery Ratio	80.20%	80.50%	-	-

The findings reveal a noteworthy enhancement in the quality of the ultimate solution achieved through Scenario S4, which incorporated both planning and online guidance models, taking into account the evolving state of the fire. For example, compared to the basic Scenario S1, there is a reduction of over 2 hours (8%) in the time taken to clear the network. Moreover, Scenario S4 exhibited an improvement of more than 15 minutes (1%) compared to Scenario S2.

The decrease in mean evacuation time in Table 5.2 shows that the online DPE improves the evacuation solution by providing routes with less average travel time. Also, the

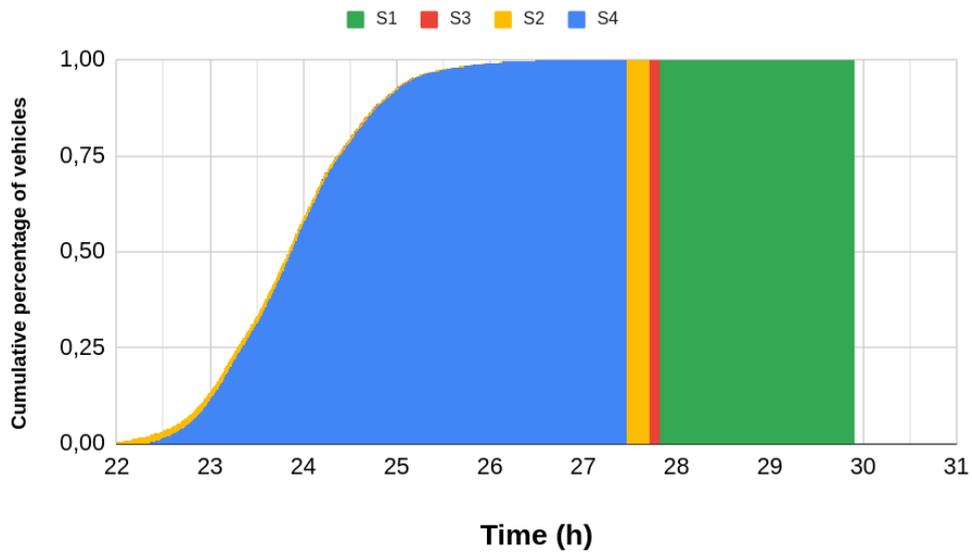
improvement is remarkable for the AED of S2 compared to Scenario S1 which proves the positive impact and the effectiveness of the planning process. We mention that including telecommunication networks provides us with some errors and delays in sending and receiving messages. In both cases, S4 and S3, we have around 400 ms for end-to-end delay and PDR around 80%.

Figure 5.4(a) presents the distribution accumulation over time for four scenarios. The accumulation at each time is the number of users traveling in the network. The figure shows that the scenarios having evacuation plans (S4, S3, S2) outperform the other scenario (S1). The clearance time and network capacity usage in Scenario S2 and S4 are better than in Scenario S1 and S3, which highlights the importance of including hazard evolution estimation in the planning phase. There is a significant difference between Scenario S2-S4 and Scenario S1. Note that the gain of more than 2 hours in clearance time between Scenario S4 and S1 is remarkable in our test case. We expect a better result by increasing the number of evacuees and deploying larger networks.

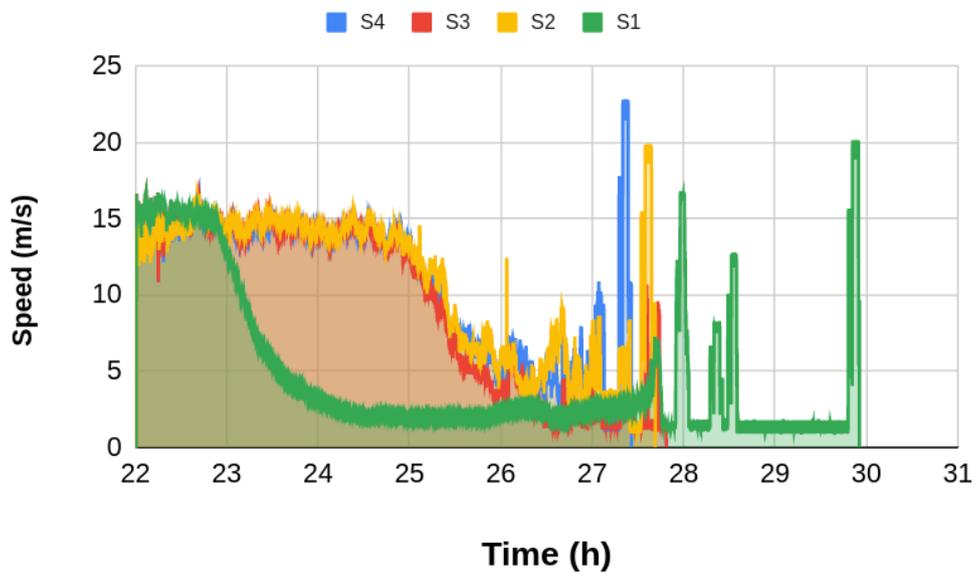
Figure 5.4(b) shows the evaluation of network mean speed during the evacuation process. This figure followed the results of the accumulation distribution. Scenario S4 outperforms other scenarios meaning that the blue curve representing Scenario S4 stands upper than the other curves in most cases. We can observe a dramatic decrease in the speed before the end of evacuation because of queues formed in front of shelter sites.

To comprehensively assess the influence of considering fire evolution in our study, we employ the exposure rate to fire as a fundamental metric. This measurement, widely recognized and utilized in the literature, plays a pivotal role in determining the number of individuals exposed to hazardous situations [Soga et al., 2021]. As successful evacuation operations aim to minimize the risk posed to people, fewer users exposed to potential hazards signify more effective and safer evacuation strategies. In Figure 5.5, we present a detailed visualization of the evolution of vehicles exposed to fire throughout the various evacuation scenarios. A substantial disparity emerges between the results of the basic Scenario S1 and Scenario S3, which have not considered the fire evolution over time, and Scenarios S2 and S4, which incorporate advanced planning techniques in their evacuation procedures. Figure 5.5 also shows the distinction in the maximal values observed in Scenario S4 and S3. Remarkably, Scenario S4 demonstrates a reduction in the maximal value, indicating that a notably smaller number of users are exposed to fire risks when compared to the results of Scenario S3. This compelling evidence derived from the comparison unequivocally supports the conclusion that Scenario S4 represents the most optimal evacuation strategy. By significantly reducing the number of users in the risky zone, Scenario S4 showcases its superiority over other alternatives. Its integration of both planning and online guidance models, accounting for the evolving state of the fire, leads to more efficient and secure evacuation operations. Consequently, our findings emphasize the importance of considering fire evolution in devising evacuation plans, ultimately enhancing overall safety and minimizing the potential harm to evacuees during emergencies.

In Figure 5.6, we present the evolution of traffic network congestion, focusing on Scenario S4, S3, and S2. Scenario S1, known for having significantly high congestion, is excluded from the figure. Notably, Scenario S3 exhibits greater congestion levels compared to Scenario S4. These results align with the exposure rate data shown in Figure 5.5, revealing a correlation between safety outcomes and congestion patterns. Additionally, the figure highlights that Scenario S2 experiences a comparable number of vehicles in gridlock with Scenario S3 when comparing the maximum values of the graphs. However, it takes a longer time to resolve all the congestion in this scenario. The second peak observed in the congestion level curves can be attributed to the formation of queues in front of shelters. As evacuees seek safety during emergencies, they tend to converge toward



(a) Accumulative number of active users in the network variation



(b) Network mean speed variation

Figure 5.4: Performance measures variation over scenarios

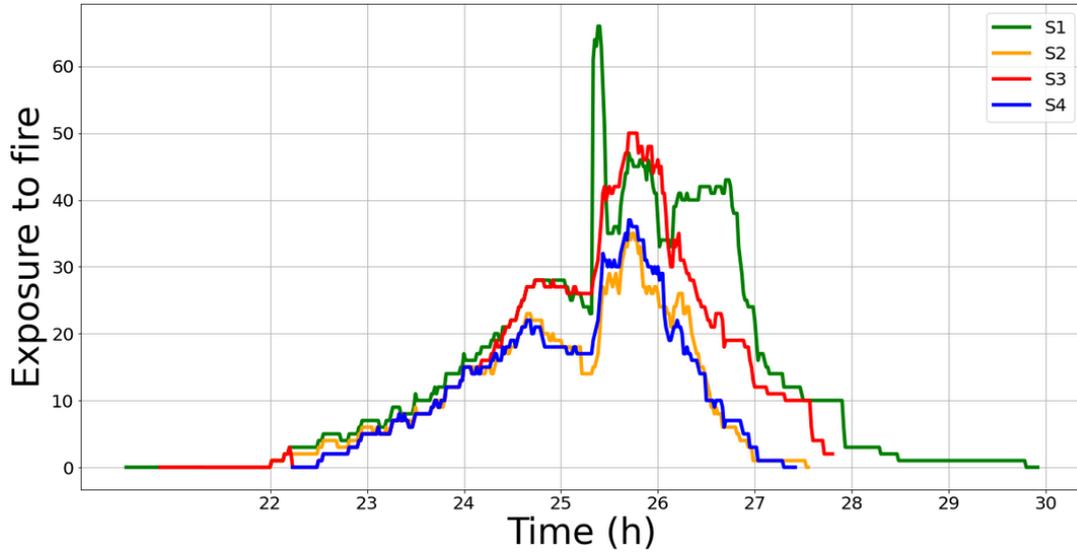


Figure 5.5: Exposure rate variation over time

designated shelter areas, leading to temporary accumulations of vehicles. These queues may arise due to limited shelter capacity, causing delays in the entry process.

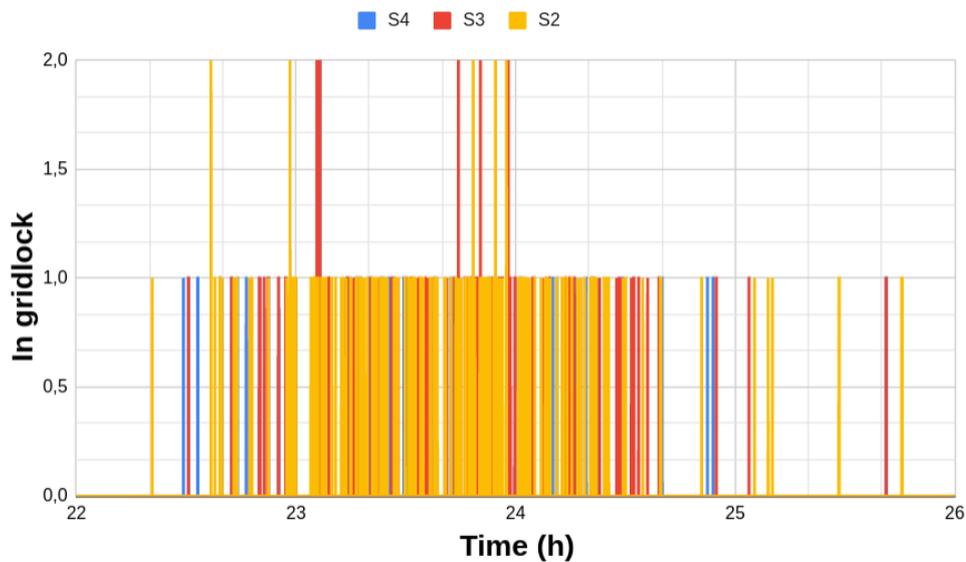


Figure 5.6: Gridlock rate variation over time

5.6 Discussion

The evacuation of people during a disaster is essential. The goal is to move people from dangerous areas to safe areas as quickly as possible to reduce the loss of life and property. We address the dynamic population evacuation (DPE) problem. We can save more lives by successfully modeling and optimizing this problem more efficiently. In this chapter, we examine the existing literature on models utilized for evacuation planning and Vehicular Ad hoc Network (VANET) establishment and implementation during evacuations. In addition to the existing research on evacuation planning and VANET implementation, the field of wildfire evacuation brings valuable insights from both quantitative and qualitative perspectives. Qualitative studies delve into comprehending the underlying factors

that influence the evacuation decisions of residents residing in fire-prone areas. Simultaneously, quantitative research is crucial in wildfire evacuation analysis by combining wildfire modeling and transportation simulation. This integration allows for a comprehensive examination of transportation network resilience and the overall travel time required for a community to evacuate its inhabitants to designated safe locations safely. By quantifying the potential impacts of wildfires on evacuation routes and travel times, decision-makers can make informed choices regarding optimal evacuation strategies and resource allocation during emergencies. By incorporating insights from both qualitative and quantitative approaches, the proposed framework in this study aims to address the complexity of DPE. By considering the challenges posed by unpredicted events and accounting for the human behavior aspect, the comprehensive approach strives to enhance evacuation using planning and VANET systems.

To address the challenges posed by the DPE in evacuation scenarios, we present a comprehensive framework that leverages a traffic simulator to capture the dynamic nature of the evacuation process. The framework involves two key stages: first, a planning process is devised to determine shelter allocation using the System Optimum (SO) approach and route planning using the Stochastic User Equilibrium (SUE) setting. Second, an online management procedure is implemented during the evacuation phase to enable real-time adjustments to vehicle routes. This is facilitated by a networking layer, where vehicles can exchange data to receive updates on the best routes and shelter. To establish this networking infrastructure, we have designed a cloud computing architecture. Within this architecture, vehicles act as the final nodes, Roadside Units (RSUs) serve as the network infrastructure, and a powerful remote computer functions as our cloud server.

To implement our methodology, we used a trip-based dynamic simulator that provides travel information at each time step. We coupled this simulator with a network simulator to add vehicular cloud computing communication. This framework includes an additional dynamic layer to capture the spatiotemporal evolution of hazards during the evacuation process. We applied our proposed methodology to the real-world evacuation scenario from the Tubbs fire in California.

The results show that the proposed model exceeds the model with only evacuation planning by more than a 15-minute decrease in network clearance time. This means that using vehicular communication for giving new orders improves the evacuation operation because it considers new events and emerging congestion not initially determined by the plan. More importantly, we analyzed the exposure rate of vehicles to fire. The results show that solving the online DPE considering the fire-evolving state saves more lives and shortens the evacuation operation. This is also confirmed by the results on the number of vehicles in gridlock over time. Besides, we have calculated end-to-end delay and packet delivery ratios to evaluate the performance of the cloud computing architecture for vehicular communication. Results show acceptable values in the case of delay-sensitive applications.

Chapter 6

General Conclusion

Summary and global overview

This Ph.D. thesis proposed a framework to tackle the dynamic evacuation problem and in particular real-time evacuation management. Our research has focused entirely on simulation-based models. This research has concentrated exclusively on simulation-based models, for which extensive and productive literature has emerged over the past decade, as reviewed in the introductory chapter and the opening sections of subsequent chapters. Simulation-based models are well-suited for extensive urban transportation networks. As highlighted in the literature review, analytical models are still prevalent in some evacuation studies due to their simplicity and their ability to elucidate equilibrium conditions. Nevertheless, depending solely on simulation-based traffic assignment methods is not sufficient. It is equally vital to incorporate destination choice modelling to comprehensively formulate and solve for globally optimal plans. In order to develop truly coordinated evacuation strategies, the decisions of selecting a destination and determining the route to reach it must be integrated and addressed simultaneously. Treating destination and routing as independent elements overlooks their intrinsic correlation. An integrated destination-routing optimization framework is crucial to capture their inherent interdependence and to jointly optimize for the ideal evacuation plans, taking into account both components at the same time.

Furthermore, evacuations in response to natural or human-induced disasters are inherently dynamic events. Relying solely on planned strategies is insufficient due to this unpredictability. To address such fluid situations, real-time management systems that can recalibrate evacuation plans are critical. Accordingly, the objectives of this work are: (i) constructing an evacuation planning framework; (ii) integrating a real-time service for rerouting or reallocation orders atop initial plans; (iii) assessing alternative vehicular communication architectures to support evacuation operations; and (iv) accounting for time-evolving risk in both planning and online adjustment phases. Parallel to these objectives, the storyline of this manuscript encompasses constructing an optimization framework to solve the dynamic planning and evacuation problem with efficiency. Regarding the first objective, the core contributions were benchmarking existing methods and formulating an effective simulation-based framework to rapidly attain traffic network equilibrium inclusive of destination allocation.

In Chapter 2, the initial focus was on conducting an in-depth investigation and analysis of the current state-of-the-art solution algorithms that have been utilized for this problem area. Several potential improvements and modifications were proposed to the existing algorithms with the goal of enhancing their performance and efficiency compared to the most recent methodologies in the literature. This comprehensive examination and assessment of current algorithms provided critical groundwork and served as a foundation

for moving forward with the design and development of an innovative new computational framework intended for application to large-scale evacuation networks. The knowledge gained through the review of existing techniques and identification of limitations guided the creation of the new framework to effectively address challenges at a large scale while leveraging the advantages of the current approaches. Moreover, another significant contribution of the present work was developing a new approach based on the online management of the evacuation process. Chapter 3 includes two major components designed and adapted to address the disaster preparedness and evacuation problem. The first part focuses on planning for evacuation operations, while the second part examines vehicular communication aspects. The vehicular communication architecture developed in this chapter helped reduce network clearance times and mean evacuation times.

The work in Chapters 2 and 3 laid the foundation for developing an effective tool to address the disaster preparedness and evacuation problem. To address the third research objective, Chapter 4 provided the main contribution of developing and comparing centralized and decentralized vehicle communication systems for evacuation scenarios. Two different communication architectures were proposed and examined - one utilizing a fog computing-based decentralized approach and one utilizing a cloud computing-based centralized approach. The overarching goal was to analyze how these two vehicle communication systems could potentially improve the performance and efficiency of large-scale evacuation processes, considering impacts on both mobility factors like traffic congestion and communication factors like network latency. By creating and simulating these two systems, the research aimed to determine if a decentralized fog-based model or a centralized cloud-based model would be better suited to enabling seamless vehicle coordination and information sharing during evacuation events. With regards to our fourth objective of developing a framework that incorporates how risk evolves over time into the process of optimizing evacuation plans and online orders, as we outlined in Chapter 5, there are multiple metrics we can use to quantify the success of an evacuation process. These metrics allow us to evaluate how efficiently and effectively people are evacuated from an area, how orderly the evacuation takes place, and how well-prepared and informed evacuees are throughout the process. By taking into account how various risks and uncertainties change throughout an evacuation event, our framework aims to continuously update and adapt evacuation plans and logistics to maximize the likelihood of a successful evacuation according to these key measures of performance. The dynamic risk evolution component is intended to make the framework responsive to changing conditions on the ground, allowing for evacuation plans and online order systems to be optimized in real time as an event unfolds. Tracking the progression of different risk factors enables data-driven adaptation of plans and systems to best serve evacuees as the situation develops.

Finally, the practical output of our research was the development of an optimization framework, presented in Section 3.4, that serves as a platform bringing together all of the implementations and technical contributions made throughout this thesis work. A major highlight of this framework is the inclusion of an automation tool we developed to advance the field of evacuation simulation. This tool automates key aspects of the simulation process, including model creation, experiment configuration, and result analysis. The framework also encompasses our implementations of cloud-based and fog-based computing projects that enable parallel execution of traffic and network simulators. By leveraging cloud and fog resources, we are able to run large-scale, high-fidelity evacuation simulations with integrated models of transportation networks, traffic flows, and communication networks.

Contributions to our initial research questions

According to the list of research questions that was presented in section 1.6.2, our main contributions are listed below in the same order:

- we conducted a comprehensive benchmarking of all existing models and methodologies for the two key problems of evacuation planning: the Shelter Assignment Problem (SAP) and the Dynamic Traffic Assignment (DTA) problem. This benchmarking reviewed analytical and simulation-based approaches across the literature. Based on the findings from this review, we proposed a novel framework that couples SAP and DTA models to more realistically capture the entire evacuation process. The core innovation of our framework is the integration of SAP and DTA through a rolling horizon approach, where SAP solutions continually update DTA simulations. Our experiments validated that this framework drastically reduces network clearance times compared to purely static planning approaches. These results conclusively demonstrate the benefits of dynamic, adaptive allocation during evacuations, as opposed to reliance on pre-determined static plans. By repeatedly solving SAP at each time interval, our framework provides an optimal evacuation routing that accounts for transportation networks' inherent dynamics and congestion during crisis events. Moreover, our analysis showed that repeatedly solving SAP requires minimal computational overhead while significantly shortening the evacuation duration. In summary, the unique integration of SAP and DTA models within a rolling horizon optimization framework marks a novel contribution, enhancing state-of-the-art evacuation modelling research.
- Chapter 3 explored real-time adaptation and improvement of evacuation plans through the lens of VANET architectures. Specifically, we proposed modifications to emergency message routing techniques in VANETs to account for different message types and enable enhanced data transfer between vehicles during evacuations. Building upon this, we developed a framework for dynamically solving the DPE problem in real time. The framework creates an initial optimal evacuation plan but then provides online routing orders to evacuees that adapt based on unpredictable events not captured in the original plan. Our experiments demonstrated that solving the DPE problem online, even with low VANET penetration rates, can significantly improve the quality of solutions and utilize more of the transportation network capacity. The capabilities for real-time adaptation and communication between vehicles unlock the potential for more dynamic, responsive evacuation guidance to be provided to citizens during crisis events. Rather than relying solely on static plans, the connectivity offered by VANETs allows evacuation routes and shelter assignments to be continuously optimized based on current road conditions and congestion. This work represents an important advancement in leveraging vehicle-to-vehicle networks to enable more effective real-time management of large-scale urban evacuations.
- Chapter 4 introduces a comprehensive framework to address the dynamic population evacuation (DPE) problem. This framework incorporates strategic evacuation planning as well as real-time management using VANET (vehicular ad hoc network) technology. First, the chapter analyzes various models used for evacuation planning and creating and executing VANETs in an evacuation context. A key finding from this analysis is that even a low penetration rate of connected vehicles can provide major benefits for managing real-time DPE, leading to better use of network capacity. Next, in analyzing vehicular communication architectures, the chapter compares Vehicular Fog Computing (VFC) and Vehicular Cloud Computing (VCC) implementations. It finds that VFC results in lower message transmission

delay, with evacuation clearance times comparable to the more centralized VCC architecture.

- Chapter 5 develops a framework to account for the dynamic state and rapid evolution of hazards during an evacuation. The framework adds a dynamic layer to capture how hazards like wildfires change over time and location during an evacuation. We applied this proposed methodology to a real-world case - the Tubbs fire evacuation in California. The results demonstrate that incorporating the fire’s evolution into the model, beyond just evacuation planning, decreases network clearance time. More significantly, we analyzed vehicle exposure rates to the spreading fire. The results show the model solving the online dynamic population evacuation (DPE) problem, considering the fire’s state saves more lives and shortens the evacuation operation, compared to a model without the hazard’s evolution.

Limitations

In the following part, we propose limitations for current work:

- One challenge encountered in the research was locating genuine, applicable data regarding evacuation situations that could be used for modelling and analysis. Evacuation scenarios encompass complex dynamics with many variables at play, from traffic patterns to human behaviours. To accurately simulate and assess different evacuation strategies and systems, access to real-world data that realistically reflects the conditions of an evacuation is crucial. However, finding detailed data that captures the nuances and uncertainties of real evacuations proves difficult. Much data remains proprietary or restricted. Other data offers only high-level approximations rather than granular insights. This presents obstacles in acquiring comprehensive, credible datasets that contain specific information on factors like traffic flows, routing decisions, vehicle densities, and congestion levels during evacuations. Without such data richness and realism, modelling and analyzing evacuation scenarios become more speculative and less grounded in real-world behaviours and constraints.
- When it came time to select a vehicular network simulator for smoothly and seamlessly simulating the VANET environment, the options were incredibly limited due to compatibility requirements with the SUMO traffic mobility simulator. VANET simulation necessitated identifying a network simulator sufficiently robust to handle modelling the intricate dynamics and communications between large numbers of vehicles in the network. Yet exhaustive investigations uncovered very few network simulators capable of fulfilling this key criterion while integrating properly with SUMO to enable joint traffic mobility and network modelling.
- The computational resources and time required to execute large-scale simulation models using a simulation-based methodology proved extremely demanding. Simulation-focused approaches aim to recreate complex real-world systems and scenarios in a virtual setting. However, simulating intricate systems and interactions on a sizable scale necessitates massive computing power. Detailed traffic simulations modelling thousands of individual vehicles with advanced mobility and communication patterns call for substantial processing capabilities. Sophisticated evacuation scenarios covering wide geographic areas with whole cities of modelled entities push hardware infrastructure to its limits. Exhaustive parametric studies and comparative analyses can involve running simulations repeatedly across different configurations and conditions, multiplying the computation times. The computational load became

a major impediment with the project utilizing an agent-based modelling paradigm across massive multi-agent simulations. Running simulations of such scale required leveraging high-performance computing infrastructure and distributing simulations across supercomputer processors and parallel cores. Yet even with such advanced computing systems, simulation runtimes regularly spanned hours or days for individual models.

Research perspectives

In the following part, we propose recommendations for future research:

- This study considers only rerouting and shelter reallocation to manage the online evacuation process. However, departure time is another critical component that could be optimized before and during an evacuation to further improve the overall efficiency and effectiveness of evacuation planning and operations.
- For future work, we plan to build upon this framework by incorporating modelling of additional modes of transportation such as privately owned vehicles, public transit buses, passenger rail, etc. Adding these additional options to the simulation and optimization models would provide more flexibility and realism in analyzing and designing evacuation plans. It would capture the transportation diversity and complexity of real-world evacuations.
- We also aim to improve the predictive accuracy of the framework by implementing a more sophisticated, data-driven travel time prediction model rather than solely relying on the agent-based simulator's simple model. By leveraging real-time and historical traffic data, a more precise model could be developed to reflect better actual road speeds and congestion levels during evacuations under various conditions. This would enhance the fidelity and reliability of the overall optimization.
- Another valuable extension is considering the human element and modelling behavioural reactions to evacuation orders. Public compliance and orderly evacuations depend heavily on human psychology and behaviour under stress. Incorporating models of how the population makes decisions, complies with orders, and moves under varying conditions could allow for refinements that maximize safe and efficient evacuations. This could draw on insights from social sciences and emergency management research on human behaviours in disasters.
- Our future work aims to significantly expand the capabilities of the current framework by incorporating customized safety protocols, instructions, and objectives that account for varied hazardous scenarios. Specifically, we intend to program hazard-specific response plans tailored to threats such as hurricanes, wildfires, chemical spills, nuclear events, and other emergencies. The system would provide targeted guidance to maximize public safety based on the unique risks, evacuation routes, shelter needs, and countermeasures required for the hazard. To accomplish this, we will integrate a wider array of data sources on hazard conditions and effects, disaster management best practices, population vulnerabilities, and at-risk infrastructure. The end result will be an evacuation optimization framework equipped with enhanced situation awareness, threat intelligence, and specialized safety response features to protect lives and property against numerous dangers.
- In disaster situations, not only is physical road infrastructure impacted, but communication infrastructure like antennas and servers can also be disrupted, complicating

evacuation coordination. As such, developing specialized system architectures resilient to these infrastructure disruptions should be a priority area for future work. Specifically, we aim to build redundancy across servers in distributed geographic locations to minimize single points of failure. The system could automatically failover to backup servers if primary evacuation coordination servers are disabled. The system architecture will be designed for reliability, adaptability, and continued operation even when infrastructure is degraded. Machine learning capabilities can help the system dynamically and autonomously respond to these infrastructure disruptions and routing failures. With robust and fault-tolerant architectural design, the evacuation optimization framework will be capable of maintaining coordination and reducing risks even amidst infrastructure damages and loss of communications capabilities. Planning for these disaster contingencies will improve system resilience and public safety outcomes.

- A major area for future work is developing customized evacuation recommendations for populations with special needs and vulnerabilities. The system could incorporate modelling of different categories of evacuees, such as the elderly, disabled, hospital patients, those without vehicles, people with medical dependencies, etc. Unique preparations and response plans tailored to each group could be programmed into the system. For example, evacuations for mobility-impaired individuals may need paratransit vehicles dispatched with additional time buffers built into routes. Evacuations of hospital patients may require coordination with receiving facilities to arrange ambulance transports and transfer of medical records. Elderly residents may need door-to-door assistance registering for evacuation transit. By accounting for diverse populations and needs, the optimization framework could provide targeted guidance to authorities to help safely evacuate all groups, especially the most vulnerable. Integrating awareness of demographics, resources, and response procedures for specialized populations would enhance the system's equity, inclusiveness, and effectiveness. This ability to customize evacuation plans is a valuable domain for researchers to explore further.

6.1 Publication list

Journal papers

- [Idoudi et al., 2022a] H. Idoudi, M. Ameli, C. N. Van Phu, M. Zargayouna and A. Rachedi, "An Agent-Based Dynamic Framework for Population Evacuation Management," in IEEE Access, vol. 10, pp. 88606-88620, 2022, doi: 10.1109/ACCESS.2022.3199445.
- [Idoudi et al., 2023a] H. Idoudi, M. Ameli, C. N. Van Phu, M. Zargayouna and A. Rachedi. Smart Dynamic Evacuation Planning and Online Management Using Cloud Computing for Population Evacuation. Computer-Aided Civil and Infrastructure Engineering, 2023.

Book chapter

- [Idoudi et al., 2023d] Idoudi, H., Ameli, M., van Phu, C. N., Zargayouna, M., & Rachedi, A. (2023) Streamlining Disaster Response: A Benchmark Study on Population Evacuation Planning with Telecommunication Network. International Conference on Intelligent Transportation Systems (ITSC). IEEE.
- [Idoudi et al., 2022d] Idoudi, H., Ameli, M., Van Phu, C. N., Zargayouna, M., & Rachedi, A. (2022, December). Vehicular Cloud Computing for Population Evacuation Optimization. In 2022 IEEE/ACS 19th International Conference on Computer Systems and Applications (AICCSA) (pp. 1-8). IEEE.

Peer-reviewed conference proceedings

- Idoudi, H., Ameli, M., van Phu, C. N., Zargayouna, M., & Rachedi, A. (2023) Dynamic Evacuation Management: Shelter Allocation and Traffic Assignment with Telecommunication Networks. In the 9th International Symposium on Dynamic Traffic Assignment.
- [Idoudi et al., 2023c] Idoudi, H., Ameli, M., van Phu, C. N., Zargayouna, M., & Rachedi, A. (2023). An Optimization Framework For Dynamic Population Evacuation Problem Using Vanet For Emergency Communication. In TRB 2023, Transportation Research Board 101st Annual Meeting.
- [Idoudi et al., 2022b] Idoudi, H., Ameli, M., van Phu, C. N., Zargayouna, M., & Rachedi, A. (2022). Impact of dynamic shelter allocation in online population evacuation management. In TRB 2022, Transportation Research Board 101st Annual Meeting.

International conference presentations

- [Idoudi et al., 2023b] Idoudi, H., Ameli, M., van Phu, C. N., Zargayouna, M., & Rachedi, A. (2023, June). Enhancing Evacuation Planning and Management through Vehicular Communication. In The 11th symposium of the European Association for Research in Transportation (hEART).
- [Idoudi et al., 2022c] Idoudi, H., Ameli, M., van Phu, C. N., Zargayouna, M., & Rachedi, A. (2022, June). Simulation-based Optimization Framework for Stage-based Evacuation Planning. In The 10th symposium of the European Association for Research in Transportation (hEART).

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A. APPENDIX FOR CHAPTER 2

SUMO uses a measure that integrates the mean travel time of all previous simulations. It also uses the coefficient of deviation of average travel times for termination and tests if the value of this measure is below a chosen threshold. Here, we present the formulas for calculating this measure:

$$a = \frac{\sum_{o \in O} \sum_{s \in S} \sum_{p \in \pi_{os}} t_{tr,\pi}}{\sum_{o \in O} \sum_{s \in S} n(\pi_{os})} \quad (6.1)$$

$$CV = \frac{\sigma(a)}{E(a)} = \frac{\sqrt{\frac{1}{Nr} \sum_{i \leq Nr} (a_i - \sum_{i \leq Nr} \frac{a_i}{Nr})^2}}{\sum_{i \leq Nr} \frac{a_i}{Nr}} \quad (6.2)$$

Note that Nr is the number of iterations considered. We test this measure on three values: 0.1, 0.04, and 0.004 to understand the computation time needed to achieve each of these measures and compare the found results.

Table 6.1: Convergence iterations

Maximum deviation	0.1	0.01	0.004
Computation time (s)	248.39	534.00	1730.35
Number of iteration	3	11	50

Table 6.1 shows the time difference between the tree solution calculated. Having better results in terms of deviation requires surely more iteration calculation and more consumed resources. We have set 50 iterations as the maximum number of iterations to find the result, and we attain this limit while having a maximum deviation of 0.004. In addition, Table 6.1 demonstrates no linear relation between the amount of computation time needed for solution finding and the deviation measure. Results shown by Table 6.1 are only for the last time interval of the evacuation process.