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# Smart dynamic evacuation planning and online management using vehicular communication system

Hassan Idoudi<sup>1,2</sup> | Mostafa Ameli<sup>1</sup> | Cyril Nguyen Van Phu<sup>1</sup> | Mahdi Zargayouna<sup>1</sup> | Abderrezak Rachedi<sup>2</sup>

<sup>1</sup>COSYS, GRETTIA, Univ Gustave Eiffel, Paris, France

<sup>2</sup>LIGM, Univ Gustave Eiffel, Paris, France

## Correspondence

Mostafa Ameli, Univ Gustave Eiffel, 14-20 Bd Newton, 77420 Champs-sur-Marne, Paris, France.

Email: [mostafa.ameli@univ-eiffel.fr](mailto:mostafa.ameli@univ-eiffel.fr)

## Abstract

During disasters, swiftly and efficiently evacuating populations in hazardous situations is crucial to minimize losses. This study proposes a novel framework to address dynamic population evacuation (DPE) problems, which includes planning and online evacuation management phases facilitated by vehicular communication. In the planning phase, a shelter allocation problem (SAP) is solved dynamically for destination choice and a dynamic traffic assignment (DTA) for path choice toward the chosen destinations to obtain an initial evacuation plan. The initial plan is then enhanced by employing a vehicular ad hoc network (VANET) within the vehicular edge computing (VEC) architecture. This enhancement enables communication among evacuees, allowing them to revise their vehicle's route choice and planned destination. These revisions take into account the changing risk and traffic conditions. The proposed online DPE framework is applied to the real evacuation scenario of Mill Valley City, CA. The proposed model is evaluated with different VANET architectures, including vehicular cloud computing (VCC) and VEC. The results show that the VEC framework outperforms other configurations and improves the evacuation process compared to the scenario with an initial plan by more than 30% in network clearance time. Additionally, a performance analysis is carried out for evacuation scenarios with different penetration rates of connected vehicles in VANET.

## 1 | INTRODUCTION

The population residing in hazardous areas faces grave risks from natural disasters and catastrophes, which are becoming increasingly frequent due to climate change. As a result, the toll on human lives and the environment escalates with more deaths and significant destruction (Supian & Mamat, 2022). To mitigate and reduce losses caused

by disasters, evacuating people from the affected areas to safe zones or shelters is imperative. While sheltering in place can be a solution to certain risky situations, our research specifically concentrates on urgent situations like floods and wildfires, which require immediate evacuation. Effective evacuation orders that dynamically adapt to the evolving hazard and the evacuees' need for real-time guidance are critical for a successful evacuation process.

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This real-time aspect of evacuation orders can only be achieved with telecommunication technology (Pan et al., 2016). New emerging technologies, such as vehicle-to-everything (V2X) communication (Wang et al., 2019), offer promising avenues for studying dynamic population evacuation (DPE). To develop the best and optimal evacuation plans, it is essential to consider the disaster's characteristics (Khajwal et al., 2023). The type of disaster influences the objectives of the evacuation process. The most common objectives of evacuation orders include minimizing the mean evacuation or total evacuation time (Bayram & Yaman, 2018; Hajjem et al., 2017), minimizing the network clearance time (Hsu & Peeta, 2014; Zhao et al., 2016), and minimizing the total traveled distance (Alçada-Almeida et al., 2009; Sheu & Pan, 2014).

The effectiveness of an urban population evacuation plan relies heavily on the two factors chosen by evacuees: shelter locations and evacuation routes leading to the chosen shelters. In the literature, the shelter allocation problem (SAP) has been studied using several models (e.g., Chu, 2009), including the p-median and p-center models (Ma et al., 2019). The classical p-median problem aims to determine the optimal location for p shelters, such that the total weighted travel time between evacuee demand points and their assigned shelters is minimized. This provides an aggregated optimization across all demand point assignments. In contrast, the p-center problem aims to determine the optimal location for p shelters such that the maximum travel time between any demand point and its assigned shelter is minimized. This provides a max-min optimization focused on the individual worst-case assignment. Furthermore, from a mathematical standpoint, solving dynamic traffic assignment (DTA) problems involves finding the solution to user equilibrium (UE) or system optimum (SO) models while accounting for the dynamic relationships between paths, time, and network characteristics. DTA models have been utilized since the 1970s for analyzing long-term and short-term planning issues (Ameli, 2019; Zockaie et al., 2014). Sherali et al. (1991) developed a model for SAP to determine shelter locations while minimizing the evacuation time using a static function to measure travel time on edges, which may affect congestion estimation accuracy. The congestion level during evacuation depends on the evacuees' departure time and route choice model. In the literature, evacuees' route choice models are founded on three fundamental principles: UE based on the first principle of Wardrop (1952) (commonly known as Nash equilibrium), SO based on Wardrop's (1952) second principle, and the nearest allocation (NA) approach as outlined by Yamada (1996). These models differ in evacuees' behavior, with UE models involving each traveler seeking to minimize their individual travel time (Ameli et al., 2020b).

TABLE 1 Table of abbreviations.

Abbreviation	Full form
ATD	Average travel delay
DPE	Dynamic population evacuation
DTA	Dynamic traffic assignment
NA	Nearest allocation
OBU	On-board unit
PDCA	Plan-do-check-act cycle
PDR	Packet delivery ratio
PR	Penetration rate
RSU	Roadside unit
SAP	Shelter allocation problem
SDN	Software-defined network
SO	System optimum
SUE	Stochastic user equilibrium
UE	User equilibrium
VANET	Vehicular ad hoc network
VCC	Vehicular cloud computing
VEC	Vehicular edge computing
V2X	Vehicle-to-everything

From a systemic perspective, the primary objective is to minimize the overall evacuation or network clearance time. However, following the SO principle, travelers may not necessarily be directed toward the quickest route to benefit the entire system, which can be challenging to acknowledge, particularly for evacuees. On the other hand, the NA model assigns the shortest path to evacuees based on the distance between their origin (hazardous zone) and destination (shelters). Unfortunately, this approach may not generate satisfactory outcomes for evacuees or the system. All abbreviations used in this study are listed in Table 1.

The reactive nature of both SAP and DTA models based only on past events of the planning phase limits their effectiveness during the evacuation process, making them more useful in the planning phase than in online management (Pan et al., 2013). To overcome this limitation, adding telecommunication technologies can provide effective methods for proactive rerouting and dynamically adjusting the destinations (i.e., shelters) that people go to during evacuation when a disaster is predicted based on real-time traffic information. Since traffic conditions are highly variable during an evacuation process, frequently and rapidly updating evacuation guidance messages is critical. The emergence of intelligent and connected vehicles has led to the introduction of vehicular networks, particularly vehicular ad hoc networks (VANETs), as part of ad hoc mobile networks (Olariu et al., 2011; Zeadally et al., 2012). VANET has received significant attention from



research communities recently, opening new research doors in intelligent transportation systems, such as traffic modeling (Fan et al., 2020; Ma et al., 2023), investigating vehicle trajectories (Karim & Adeli, 2002), vehicle safety (Han et al., 2023; Karim & Adeli, 2003b), road safety (Kim et al., 2023; Zheng & Li, 2023), traffic efficiency (Jiang & Adeli, 2003; Karim & Adeli, 2003a), and traffic estimation (Hooshdar & Adeli, 2004; Jiang & Adeli, 2004).

However, with growing driver demands, vehicles require greater processing power, computing resources, and storage space. Despite efforts to satisfy these requirements, VANET has some disadvantages, such as high vehicle communication costs due to their high mobility (Qin et al., 2012). To support and serve all drivers' needs, ensure their comfort and safety, and increase VANET resources, the concept of vehicular cloud computing (VCC) has emerged (Gerla, 2012; Mekki et al., 2017). VCC leverages cloud computing capabilities within VANETs to enable advanced applications beyond individual vehicles' limited onboard computation and storage. With VCC, vehicles can utilize scalable cloud resources on demand for specific periods to achieve their goals. Initial research has comprehensively reviewed the literature on population evacuation, with a particular focus on using telecommunication technologies. In recent years, a new networking paradigm called vehicular edge computing (VEC) has been introduced to augment the computing capacity of vehicular networks worldwide. With the rise of modern vehicular applications (Raza et al., 2019), fulfilling the growing demands for both communication and computation has become an increasingly prominent challenge. VEC addresses this by allowing service providers to host services at the edge of the network, in close proximity to smart vehicles. This reduces latency and improves quality of service compared to traditional networks. The emergence of VEC represents a breakthrough in enabling vehicular networks to keep pace with the needs of emerging applications. This analysis revealed that, to the best of our knowledge, no prior studies in the literature had examined the inclusion of vehicle (equivalent to an evacuee) rerouting and rechoosing of destination within the DPE framework. However, the decision to replan is crucial to the evacuation process. It can significantly impact its success, considering congestion levels and changes in the hazard's intensity.

To address this gap in the literature, this study proposes an online evacuation framework to solve the DPE problem. The proposed methodology can dynamically assign evacuees to the best shelter, considering the current traffic and risk evolution. Two phases are designed for the evacuation process:

(1) planning phase, which involves the initial evacuation plan solving both SAP and DTA problems, and

(2) online evacuation management phase, which employs VCC technology to modify the initial evacuation plan by reallocating shelters and rerouting evacuees according to the network's dynamics and the evolution of the risk due to the disaster's status.

In particular, the proposed methodology includes rerouting evacuees based on their distance from the risky zone and the density of vehicles on the way toward the shelters, considering their communication capacity. The designed framework is implemented for a city-scale real test case to validate the model and compare the evacuation results in the presence and absence of telecommunication technology. In addition, a sensitivity analysis is carried out on the penetration rate of equipped vehicles that can use the VANET. The paper is organized as follows. Section 2 provides a literature review on DPE, focusing on traffic assignment and vehicular communication, and highlights the contributions of this study. Section 3 outlines the problem formulation of population evacuation. Section 4 presents the framework to address the online evacuation problem. Section 5 describes the case study and the evacuation scenarios used for numerical experiments. The results of the experiments are discussed in Section 6. Finally, Section 7 presents the concluding remarks of this study.

## 2 | LITERATURE REVIEW

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 the bilevel problem formulation used in many studies to address the complexity of DTA and SAP (Bayram, 2016) is discussed. 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 bilevel 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 & 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.

The study conducted by Gan et al. (2016) presents a sequential approach to integrating shelter allocation and traffic assignment. Notably, their approach addresses traffic assignment using static routing, making it distinct from other methods. This research offers valuable insights into how shelter allocation and traffic assignment can be effectively managed in a step-by-step fashion to enhance emergency response planning and resource allocation.

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. Idoudi et al. (2022b) proposed to use telecommunication networks for the DPE problem with a centralized configuration for a synthetic test case. While the results show the effectiveness of using telecommunication, the evolution of the risk was assumed to be static, and only one VANET architecture was considered. It is important to note that 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 emergencies. They aim to collect data rapidly and

use the data 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, and so forth. 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 nonredundant communication range (NRCR).

Alazawi et al. (2014) applied and evaluated an evacuation strategy called Speed Strategy to quantify driver response to evacuation preplans in emergencies. To implement this strategy, the authors deployed the VCC architecture. However, this paper only considered the responsiveness of evacuees to speed strategy orders and did not propose any replanning orders to evacuees to change their routes or destinations.

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 model that integrates vehicular edge/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. This proposed methodology enables us to conduct the following tasks, which have not been addressed in the literature on DPE problems: (i) comparing decentralized edge computing architectures against centralized cloud computing models for vehicular networks, (ii) deploying vehicular communication networks to develop real-time models of risk evolution and traffic patterns, and (iii) enabling dynamic reallocation of shelters based on analysis of evolving risk levels and traffic conditions in real time. The proposed methodology considers various factors, such as vehicle travel time, VEC/VCC delays in telecommunication exchanges, and network characteristics, to enable effective replanning. We applied our methodology to an in-depth case study focused on real-world data from the Mill Valley network.

### 3 | PROBLEM STATEMENT

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 edge/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. The evacuation process is considered within a real-world context. The SAP is aligned with system objectives, and the DTA with user objectives. 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.  $a_{os}$  is defined as the integer decision variable that determines the number of evacuees allocated to the origin–destination (OD) pair  $os$  and  $b_s$  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  $c_s^\alpha$  in time interval  $\alpha$  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 paper are presented in Table 2.

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 (1).

$$\min \sum_{o \in O} \sum_{s \in S} t_{os}^{\alpha*} a_{os} \quad (1)$$

To solve the shelter location–allocation problem under a generic type of hazard, which is considered in this study, the p-median model is deployed (Hakimi, 1964), a

TABLE 2 Table of notations.

Symbol	Definition
$M$	Set of all evacuees
$O$	Set of origin nodes, $O \subset N$
$S$	Set of destination nodes, $S \subset N$
$T$	Set of time intervals
$H$	Total duration considered
$i$	Index of evacuee, $i \in M$
$o$	Index of origin node, $o \in O$
$s$	Index of destination node, $s \in S$
$\alpha$	Time interval index, $\alpha \in T$
$b_s$	Binary variable; it is set to 1 if shelter $s$ to be used; 0 otherwise
$a_{os}$	Number of evacuees allocated to the origin–destination pair $os$
$w_o$	Amount of demand evacuating from origin $o$
$c_s^\alpha$	Capacity of shelter $s$ at time interval $\alpha$
$P$	Maximum number of open shelters
$\pi_{os}$	Set of all paths between origin $o$ and destination $s$
$\pi$	Index of path, $\pi \in \pi_{os}$
$Tr_\pi^\alpha$	List of evacuees, which travel on path $\pi$ in departure time interval $\alpha$
$t_{tr,\pi}^\alpha$	Experienced travel time of trip $tr$ on path $\pi$ in departure time $\alpha$
$t_{os}^*$	Global minimum experienced travel time for $os$ ; $t_{os}^* = \min\{t_{os}^{\alpha*}\}, \forall \alpha \in T$
$\hat{t}_{tr,\pi}^\alpha$	Perceived travel time of trip $tr$ on path $\pi$ in departure time $\alpha$
$\xi_{tr,\pi}^\alpha$	Random error term for trip $tr$ on path on $\pi$ departure at time $\alpha$ ; $E(\xi_{tr,\pi}^\alpha) = 0$
$t_{n,s}$	Estimated travel time from node $N_i^t$ to node $s$ , $N_i^t \in N \setminus S$ and $s \in S$
$t_n$	Average of the travel time of incoming edges to node $n$ , $n \in N$
$D_i^t$	Distance separating vehicle $i$ to the center of the hazard
$D_{max}$	Maximal distance separating vehicle $i$ to the center of the hazard
$N_i^t$	Number of vehicles in the following edge that evacuee $i$ approach to
$N_{max}^t$	Maximum amount of vehicles in the following edge that evacuee $i$ approach to
$\lambda$	Safety threshold for rerouting vehicles
$\Delta_i^t$	Value of verifying the condition in Equation (7)
$ A $	Cardinality of set $A$

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 (2) ensures that all the demands are served, meaning that all evacuees exit the hazardous



zone and enter a shelter.

$$\sum_{s \in S} a_{os} = w_o; \quad \forall o \in O. \quad (2)$$

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, with respect to the assignment in the previous time interval, as shown in Equation (3).

$$\sum_{o \in O} a_{os} \leq c_s^\alpha b_s; \quad \forall s \in S \quad (3)$$

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

$$\sum_{s \in S} b_s \leq P \quad (4)$$

It is worth noting that the model presented in this paper is classified as an NP-hard problem (Sherali & 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 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 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 & 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 3.1), and online management (cf. Section 3.2).

### 3.1 | 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.

$$\hat{t}_{tr,\pi}^\alpha = t_{tr,\pi}^\alpha + \xi_{tr,\pi}^\alpha, \quad \forall \pi \in \pi_{os}, \alpha \in T, tr \in Tr_\pi^\alpha \quad (5)$$

where  $\hat{t}_{tr,\pi}^\alpha$  is the perceived travel time on route  $\pi$ .  $\xi_{tr,\pi}^\alpha$  is a random term with  $E(\xi_{tr,\pi}^\alpha) = 0$  that represents the traveler's perception error (Daganzo & Sheffi, 1977). Using the perceived travel time concept, the SUE conditions can be characterized by the following equation (Daskin, 1985):

$$Tr_\pi^\alpha = a_{os} pr_\pi^\alpha, \quad \forall \pi \in \pi_{os} \quad (6)$$

where  $pr_\pi^\alpha$  is the probability that travelers choose route  $\pi$  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 | Online management

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 1: The first component

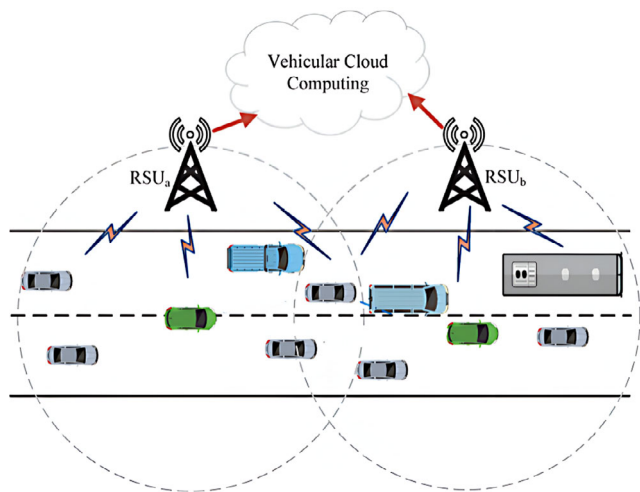


FIGURE 1 Vehicular cloud computing.

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 roadside units (RSUs) set, representing the edge layer and 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 on-board units (OBUs), which allow vehicles to communicate with each other and with infrastructure (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 1. The VANET technology is simulated using an existing VANET simulator that emulates real-world vehicle-to-vehicle communication networks. This enabled us to model the capabilities of currently deployed VANET systems for real-time traffic management through intervehicular communication (Chetlur & Dhillon, 2019).

### 3.2.1 | 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. These data are transmitted to a central server, which uses it to analyze the current traffic conditions and identify areas of congestion.

The proposed cloud/edge-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 (7).

$$\left( \frac{N_i^t}{N_{max}^i} \right) \left( \frac{D_{max}}{D_i^t + \epsilon} \right) - \lambda > 0, \quad \forall i \in M \quad (7)$$

$$\Delta_t^i = \begin{cases} 1 & \text{if Equation 7 is satisfied;} \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

The rerouting decision has two components: First, the server detects congestion and vehicles in risky situations by monitoring traffic conditions on all roads. Second, the vehicle reroutes only those whose next turn would put them onto one of the congested, high-risk roads. This selective rerouting happens before vehicles reach the problematic areas, avoiding unnecessary jams. To determine whether vehicle  $i$  should be rerouted at time  $t$ , the binary variable  $\Delta_t^i$  is the value of verifying the condition in Equation (7), which equals to 1 if the vehicle is rerouted and to 0 otherwise. Equation (7) uses various normalized fractions to calculate  $\Delta_t^i$ . Specifically,  $\frac{N_i^t}{N_{max}^i}$  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  $\frac{D_{max}}{D_i^t + \epsilon}$ . 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  $\lambda$  is defined, which limits the acceptable level of risk. In addition, several conditions must be met for Equation (7) to be valid. Specifically, the distance  $D_i^t$  must be positive and fall within the hazard zone, that is,  $0 \leq D_i^t \leq D_{max}$ . Additionally, for  $\epsilon$ , a small positive value is set to avoid dividing by zero, such that  $0 < \epsilon \leq 1$ .

### 3.2.2 | 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. In this study, we consider the shelter capacity to be time dependent and equal to the inflow rate of the road determined by the road density.



These data are 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.

$$\frac{t_{n_i j}}{t_{n_i s}} - \alpha < 0, \quad \forall i \in M, \forall s \in S, j \in S \setminus \{s\} \quad (9)$$

$$\Psi_t^i = \begin{cases} 1 & \text{if Equation 9 is satisfied} \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

To determine whether a vehicle needs to be reallocated, the binary variable  $\Psi_t^i$  is defined, which equals 1 if vehicle  $i$  needs to be reallocated at time  $t$  and 0 otherwise. Equation (9) 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  $N_i^t$  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  $\mathfrak{N}$ , which ensures that the reallocation is beneficial in terms of time saved. When a shelter allocation is changed for an evacuee during the evacuation process, an automatic recalculation of the optimal route is conducted to get them to their newly allocated shelter. This includes the immediate computation of the shortest viable path from the evacuee's current location to their newly designated shelter destination. 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.

### 3.3 | Solution quality indicators

This section will define the performance metrics utilized to evaluate the optimality of the solution and track the net-

work'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.

On the other side, to evaluate the quality of the traffic assignment solution, the average travel delay (ATD) is used in the literature as the average gap (Ameli et al., 2020a). This measure represents the effectiveness of the SUE assignment. The ATD is computed for each OD pair, defined as the average amount of delay experienced by an evacuee compared to the evacuee with the minimum evacuation time for that OD pair. The formula for ATD is presented in Equation (11):

$$ATD = \frac{\sum_{\alpha \in T} \sum_{o \in O} \sum_{s \in S} \sum_{\pi \in \pi_{os}} t_{tr, \pi}^\alpha - t_{os}^*}{\sum_{o \in O} w_o} \quad (11)$$

An indicator is utilized, namely the average evacuation delay (AED), to evaluate the performance of the solution. AED represents the mean delay experienced by each evacuee compared to the evacuee with the minimum evacuation time from the same origin. In this context, this indicator is highly relevant as the primary objective of each evacuee is to reach the safe zone as quickly as possible (refer to Equation 12).

$$AED = \frac{\sum_{\alpha \in T} \sum_{o \in O} \sum_{s \in S} \sum_{\pi \in \pi_{os}} t_{tr, \pi}^\alpha - t_o^*}{\sum_{o \in O} w_o} \quad (12)$$

In Equation (12),  $t_o^*$  represents the minimum travel time required for the evacuation trip from origin  $o$ . Recall that  $\hat{t}_{tr, \pi}^\alpha$  represents the perceived travel time of trip  $tr$  on path  $\pi$  in departure time  $\alpha$ , and  $w_o$  is the amount of demand evacuating from origin  $o$ . It is worth noting that  $t_{os}^*$  represents the optimal travel time from origin  $o$  to destination  $s$ , while  $t_o^*$  represents the optimal travel time of origin  $o$  to all destinations. To successfully evaluate the DPE problem, multiple indicators are required to measure the performance of the online management phase. The metric used in this study 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 & 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, that is, 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.

## 4 | METHODOLOGY

The proposed methodology of this study 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 Idoudi et al. (2022a) 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 replan the evacuation route and shelter during the evacuation process and provide them with instructions in real time. An edge/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 & Lehsaini, 2021). The proposed methodology is presented in the plan-do-check-act (PDCA) diagram format in Figure 2 (Realyvásquez-Vargas et al., 2018).

The online management of the evacuation process provides several advantages over just planning. Real-time access to data allows for quick identification and response to emerging issues, which is particularly important in fast-paced environments such as 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 these 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.

The methodological process, as illustrated in Figure 2, is structured into several well-defined steps, each falling under distinct phases, ultimately aimed at effective evacuation management. The initiating phase sets the groundwork for the entire process. Step 1 (adaptation of initial trips) involves preparing the simulation of urban mobility (SUMO) scenario for the city of Mill Valley, simplifying it for user-friendliness. In Step 2 (initial evacuation plan), the initial evacuation plan is established, leveraging multilevel DTA and static assignment problem, taking into account SO and SUE conditions. The methodology used in this step is detailed in Idoudi et al. (2022a). The "Plan" Phase commences with Step 3 (simulation of the current time step and set  $t = t+1$ ). It simulates the evacuation process for the current time step, considering previous plans and accommodating potential new events resulting from evacuees' decisions. This phase also involves increasing the simulation time index. Simultaneously, Step 4 (data collection in each RSU) focuses on data collection, forming the foundation for the edge/cloud computing architecture by having vehicles transmit data to RSUs. The "Do" Phase involves real-time actions. Step 5 (congestion update) continually updates congestion levels based on vehicle location data to enable real-time routing adjustments. In Step 6 (prediction of new travel time), a prediction model forecasts changes in edge travel times based on risk and congestion, utilizing a model embedded in the simulator. The "Check" Phase, the system's analytical stage, begins with Step 7 (risk-level update), which updates risk based on data from Step 4, considering distance from hazardous areas and updated congestion levels. Step 8 (check for replanning) assesses the need for replanning based on Greenshield model criteria, identifying users in congestion. Subsequently, Step 9 (evacuees selection for replanning) selects vehicles for rerouting and shelter reallocation. The "Act" Phase is where the system takes responsive measures. Step 10 (creating messages of rerouting or reallocation) formulates messages for rerouting and reallocation, directing users to the path with

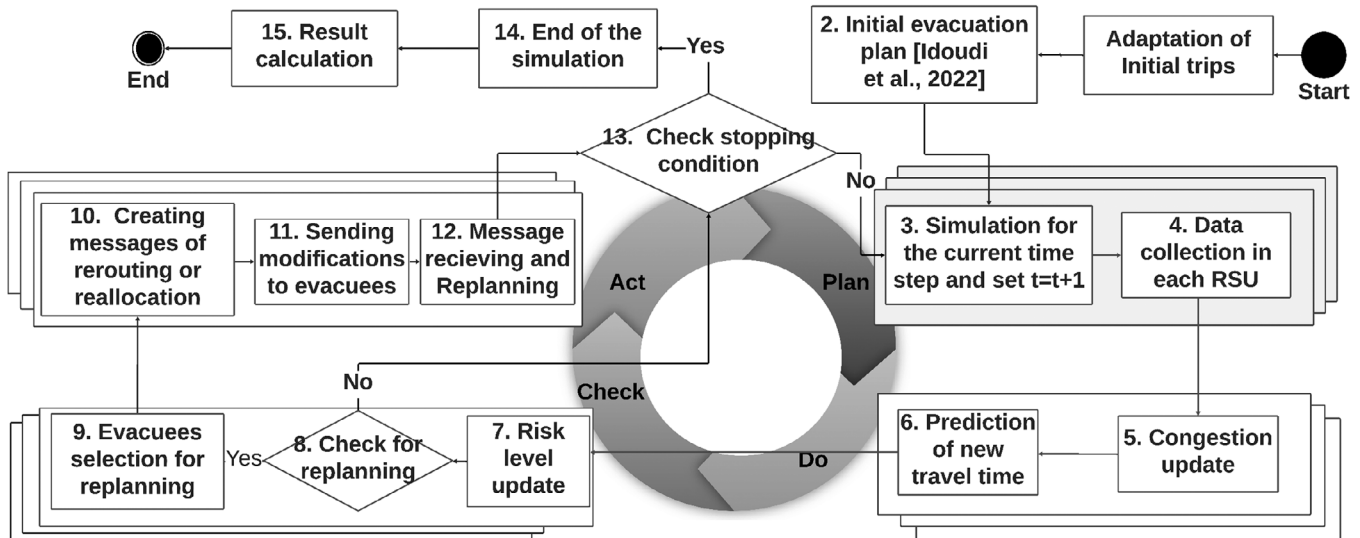


FIGURE 2 The flowchart of solving the dynamic population evacuation (DPE) problem.

the shortest travel time and their new shelter destination. Step 11 (sending modification to evacuees) involves sending notifications to evacuees through the cloud server in cloud architecture and RSUs in edge architecture. Step 12 (message receiving and replanning) facilitates the dissemination of notifications to relevant vehicles, allowing them to adapt their behavior as per notification content. The Finishing Simulation Phase encompasses the final stages. Step 13 (check stopping criterion) assesses whether all demand has been evacuated. If not, the process returns to Step 2 for further simulations. Lastly, Step 14 (finishing simulation) concludes the simulation process, with subsequent calculations of various performance metrics, as detailed in Section 3.3, to evaluate the overall effectiveness of the online management solution in Step 15 (result calculation). This well-structured and organized process ensures a systematic approach to emergency evacuation management, from initial setup to real-time actions and postsimulation evaluation.

## 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.

### 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 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 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 an edge/cloud computing architecture based on previous works (Wang et al., 2020).

Specifically, a coupled simulation approach is employed by leveraging two well-established tools:

- (1) SUMO: An open-source microscopic traffic simulator that enables real-time manipulation of vehicles and infrastructure through its TraCI library. This TraCI connectivity allows SUMO to interface with other tools like the OMNet++ communication network simulator, permitting integrated simulations.
- (2) OMNet++: A discrete event network simulator used for modeling the communications layer.

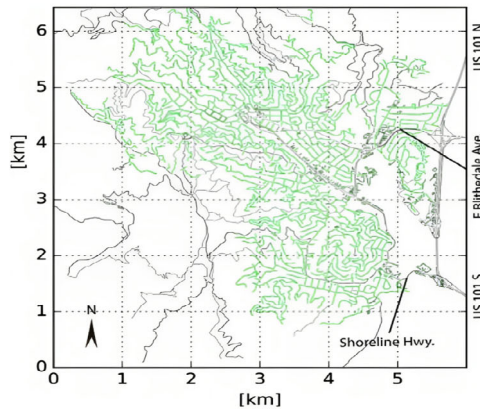
To integrate SUMO and OMNet++, the Veins framework is used and linked the mobility and network components. This coupled simulation technique allows us to leverage the unique capabilities of both traffic and networking tools for an integrated evaluation of our proposed approach. Note that all operational constraints of the communication system, including network capacity and delay, are simulated in this framework.

#### 5.1.1 | Mill Valley City

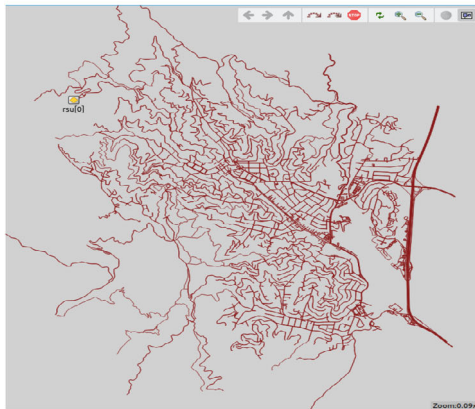
The proposed framework is applied to plan and manage the DPE problem in Mill Valley in California (cf. Figure 3a).



(a) Mill Valley Google map



(b) Mill Valley map



(c) OMNet Mill Valley city network

FIGURE 3 Vehicular communication maps.

The state has determined that a large part of the city is in an area of wildfire hazard (Chen et al., 2020).

The Mill Valley network’s total length of residential roads is 337 km as depicted in Figure 3b. 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 nodes with artificial locations or unlimited capacity,

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. In this case, the shelter capacity is time dependent and equal to the inflow rate of the road determined by the road density. The departure time distribution is defined by the scenario (Chen et al., 2020), with an average demand of two vehicles for each household. Figure 3c illustrates the vehicular communication network in the OMNET++ simulator.

## 5.2 | Experiment design

This study designs six scenarios to investigate the impact of planning and online orders on the DPE problem. The scenarios are detailed below:

- **Scenario Edge P+C: Scenario with both planning and edge vehicular communication:** This scenario follows a decentralized communication architecture framework. The approach in this scenario follows the methodology depicted by Figure 2. The approach involves creating an initial plan for optimal shelter allocation and traffic assignment across some time periods. Also, it uses VEC to give new directions to vehicles, letting them shorten their routes and reach safety fast.
- **Scenario Cloud P+C: Scenario with both planning and cloud vehicular communication:** This scenario follows a centralized communication architecture framework. The approach involves creating an initial plan for optimal shelter allocation and traffic assignment across several time intervals. Additionally, it utilizes VEC to provide updated instructions to vehicles, enabling them to shorten their routes and reach safety quickly.
- **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 evacuees are not rerouted during the evacuation process; they just follow the initial plan.
- **Scenario Edge C: Scenario with vehicular edge communication only:** In this setting, identical to the one depicted in Figure 2, the divergence occurs in Step 2. Here, evacuees prioritize the closest shelter and select their routes following the SUE method. This particular scenario illustrates a circumstance in which system operators lack a pre-established optimal evacuation plan. Rather, they allocate evacuees to the nearest shelter solely based on proximity, disregarding traffic optimization. Nonetheless, this scenario presents



TABLE 3 Performance metrics.

Metrics/scenario	Edge P+C	Cloud P+C	P	Edge C	Cloud C	N
Network clearance time (s)	17,179	19,625	28,006	20,270	20,968	41,423
Mean evacuation time (s)	1535.06	1915.47	2250.40	2053.32	2155.26	2737.31
Mean speed (m/s)	3.82	3.49	2.32	3.00	2.93	1.54
Average travel delay (ATD)	532.20	708.42	451.0	857.81	920.05	1137.07
Average evacuation delay (AED)	1192.76	1491.78	700.41	1281.18	1358.76	1665.51

a prospect for system operators to obtain fresh directives for their evacuation strategies via vehicular edge technology.

- **Scenario Cloud C: Scenario with vehicular cloud communication only:** In this scenario, 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 before 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.

## 6 | RESULTS

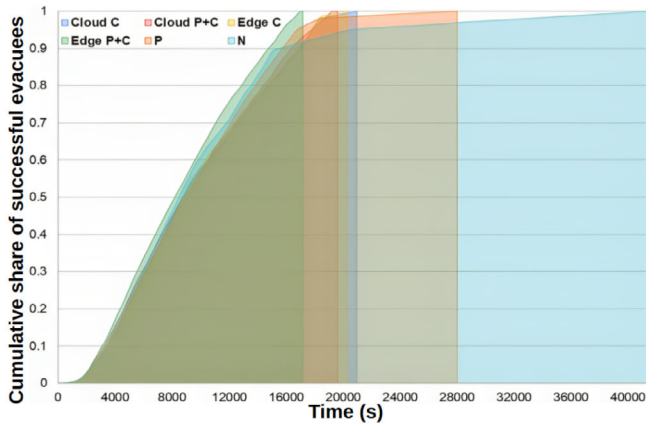
The six mentioned scenarios were executed on the same evacuation demand profile. The evaluation metrics presented in Section 3.3 measure the solution quality to converge to the UE state over the entire evacuation duration  $H$ . Section 6.1 highlights the results of our model applied to the Mill Valley City test case. Section 6.1.1 analyzes the effect of different penetration rate values of connected vehicles to VANET.

### 6.1 | Results for the Mill Valley case

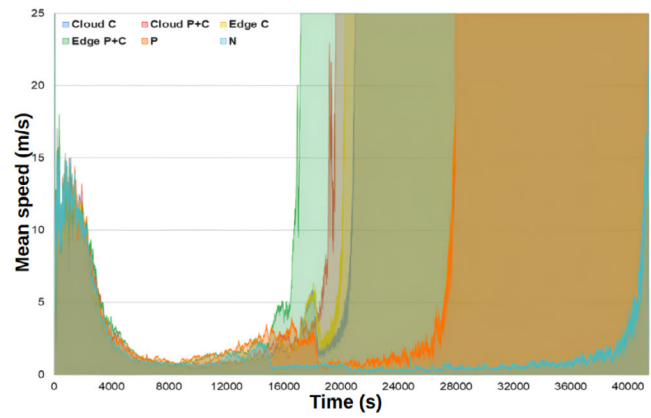
The outcomes of the six scenarios are summarized in Table 3. The initial comparison in Table 3 evaluates various vehicular communication architectures. It shows a notable gain of over 40 min (9%) in clearance time just between the two best scenarios, including the real-time aspect scenario “Edge P+C” and scenario “Cloud P+C.” The findings indicate that Edge Computing offers superior performance in emergency evacuation operations, particularly in delay-

sensitive applications, compared to scenarios employing centralized cloud architecture. The findings indicate that the “Edge P+C” scenario attains the highest mean speed value compared to all other scenarios, which is considered the most favorable outcome since a higher mean speed is preferable. In other words, this suggests that, on average, vehicles in this scenario are faster, thus enhancing the efficiency of the evacuation process. Additionally, the results indicate a considerable advancement in the final solution quality obtained by the “Edge P+C” scenario that employed both planning and online guidance models using distributed vehicular communication. For instance, the network clearance time was reduced by over 6.73 h (51%) compared to the naive scenario. Moreover, there was an improvement of more than 3 h (31%) compared to the P scenario. Besides, the scenarios with only vehicular communication, scenario “Edge C” and scenario “Cloud C,” provide a better solution than scenario P, meaning that using the telecommunication network only 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 scenarios “Cloud C” and “Edge C” illustrates that telecommunication contributes more than planning during the evacuation operation. Table 3 also provides results for the two scenarios of “Edge C” and “Cloud C.” The comparison between the two scenarios reveals how distinct vehicular communication architectures impact the effectiveness of the evacuation operation. The results affirm the initial findings from scenarios incorporating planning and real-time guidance.

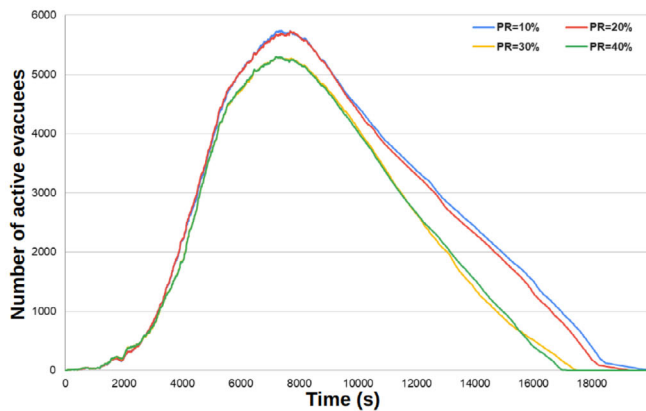
The decrease in mean evacuation time in Table 3 shows that the online DPE improves the average evacuation solution. Recall that including telecommunication networks gives us some errors and delays in sending and receiving messages. Both scenarios, “Edge P+C” and “Edge C,” have around 0.24 ms for the end-to-end delay and PDR around 49%, which is acceptable in this kind of latency-sensitive application with many network users (Noor-A-Rahim et al., 2020). Figure 4a shows the cumulative percentage variation over the considered scenarios. In Figure 4a, it can be observed that there is a substantial improvement in



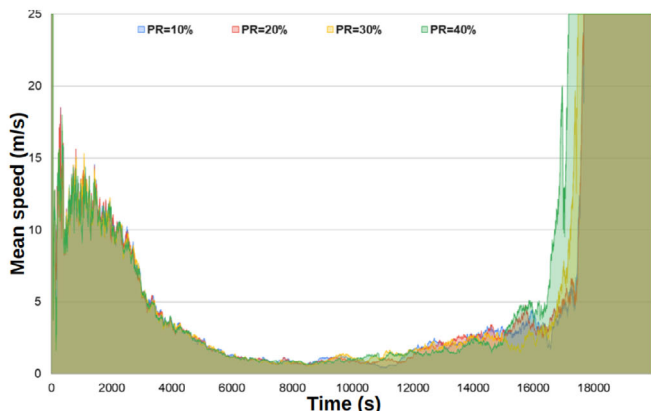
(a) Cumulative percentage of evacuees variation in the network of Mill Valley city



(b) Variation in the mean speed of the Mill Valley city network



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



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

FIGURE 4 Numerical results variation over the networks.

the scenario “Edge P+C” scenario compared to the naive scenario. The results clearly indicate that the difference between the scenarios is significant, especially when subjected to greater and more realistic demand. In other words, the figure provides evidence that the “Edge 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 than the scenario “P” evacuation approach. Specifically, the graph displays a clearance time reduction of over 31% 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 dangerous situations. Also, Figure 4b demonstrates a significant contrast in the effectiveness of reducing congestion between scenarios. This is shown in the graph’s decline in the “Edge 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. Figure 4b shows the evaluation of network mean speed during the evacuation process. This figure followed the results of accumulation Figure 4a. The scenario denoted as “Edge P+C” consistently exhibits superior performance compared to all other scenarios. This is evident by the green curve representing scenario “Edge P+C” consistently surpassing the other curves in most instances. However, it is important to note that there is a significant reduction in vehicle speed toward the end of the evacuation due to the formation of queues in front of shelter sites.

### 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


**TABLE 4** Different penetration rate performance measures.

Metrics	PR 00%	PR 10%	PR 20%	PR 30%	PR 40%
Network clearance time (s)	28006	19951	19280	17488	17179
Mean evacuation time (s)	2250.40	2008.42	1937.67	1584.05	1535.06
Average travel delay (ATD)	451.00	895.66	889.23	531.70	532.20
Average evacuation delay (AED)	700.41	1333.27	1316.96	1108.12	1192.76
End-to-end delay (ms)	–	0.251	0.247	0.245	0.243
Packet delivery ratio	–	49.88%	49.38%	49.18%	48.78%

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 Mill Valley City. Assuming more than 40% of evacuees are using connected vehicles is futuristic but can be reachable in 2030 (Griffith et al., 2023). That is why multiple penetration rates under 40% 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 RSU nodes monitor and guide only this  $x\%$  of the vehicles. The proposed evacuation framework is executed for four values of penetration rate, and the results are illustrated in Table 4. There is no communication in the case of a 0% penetration rate, so the end-to-end packet delay or the PDR 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 4 presents the different values of the performance measures used for multiple penetration values. The table clearly shows that the case of a 40% penetration rate is the best scenario in this study. Table 4 also illustrates acceptable values of PDR measure for 40% scenario. This PDR level means that around 49% generated packets are received correctly in the range of network infrastructure and without the need for retransmission. Also, the decrease in PDR values when the penetration rate is increasing can be explained by the fact of higher packets sent toward each RSU node, and naturally, the RSU cannot handle all of the packets having a limited processing capacity. Also, the delay measure is crucial, especially in this case dealing with population evacuation. The average end-to-end delay of packets considering the VEC architecture employed is around 0.24 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 4 highlights the substantial distinctions between scenarios involving both ATD and AED with vehicular communication when compared to scenar-

ios solely involving planning. This disparity underscores the role of vehicular communication in influencing users toward an SO state. This alignment can be attributed to the fact that when RSU nodes make routing decisions, they account for all vehicles, shaping their decisions to align more closely with the SO state. Figure 4c depicts the variation in the number of vehicles participating in the evacuation process across five distinct scenarios. The curves within the figure correspond to varying penetration rates.

In addition, Figure 4d depicts the evolution of the mean speed in the evacuation operation. The maximum network speed limit is the free-flow speed (25 m/s) attained when the network has no vehicles. This value is proposed by Dixit and Wolshon (2014). The network speed illustrated in Figure 4d shows that having a 40% 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 30% and 20% penetration rate on network clearance time (the arrival to the free-flow speed). Figure 4d 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 40% of the penetration rate is the best over other values.

## 7 | CONCLUSION

During emergency, efficient and quick evacuation of the affected population is crucial to minimize the loss of life and reduce overall costs. This paper addresses the DPE problem, which involves modeling and optimizing the evacuation process to save as many lives as possible faster and more efficiently.

A comprehensive literature review is provided, as well as an 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 bilevel 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 VANET architectures, modifying the emergency message routing techniques, considering different types of messages, and transferring data between nodes. This study 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, an edge-computing architecture is deployed, composed of vehicles representing final nodes and RSU representing the network infrastructure. The system can effectively reroute vehicles to avoid congestion and prioritize safety during evacuation. In the implementation of the methodology, a trip-based dynamic simulator is utilized to provide travel information at each time step. Besides, a network simulator is incorporated to enable VEC communication. The proposed methodology is applied to the real large-scale evacuation scenario of Mill Valley. The proposed model exceeds the model with only evacuation planning by more than a 30% decrease in network clearance time and more than 50% compared to the naive scenario. This means that using VANET to give new orders improves evacuation 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 even with a low penetration rate, the online DPE could improve the quality of the proposed solution and use more of the network capacity.

Nevertheless, some limitations of the current study lie in the compliance rate and the acceptance behavior of

evacuees to these new rerouting decisions or reallocation to other shelter messages. In addition, this study considers only rerouting and shelter reallocation to manage the online evacuation process. The departure time can also be optimized before and during the evacuation. For future work, the authors plan to use this framework with vehicles, buses, and other modes of transport. The authors also aim to improve this framework by including the system's adaptability to respond to real-time changes in network topology, as this may impact the new decisions. Another interesting extension is to consider the behavioral model to include the different reactions of users to evacuation orders.

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