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An Optimization Framework for Dynamic Population Evacuation Problem Using a Vehicular Ad Hoc Network for Emergency Communication

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1 **AN OPTIMIZATION FRAMEWORK FOR DYNAMIC POPULATION EVACUATION**
2 **PROBLEM USING VANET FOR EMERGENCY COMMUNICATION**

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34 **CONFLICT OF INTEREST**

35 The authors declare no potential conflict of interests.

36 **AUTHOR CONTRIBUTION STATEMENT**

37 All the authors have contributed to all aspects of this study, ranging from the conception and
38 design of the methodology, analysis and interpretation of the results and discussion, and the
39 manuscript preparation.

40

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1 ABSTRACT

2 This study proposed a new framework to solve dynamic population evacuation (DPE) problems,
3 considering the planning phase and vehicular communication during the online evacuation man-
4 agement phase. In the planning phase, an initial evacuation plan is obtained by dynamically solv-
5 ing the shelter allocation problem for destination choice and dynamic traffic assignment (DTA) for
6 path choice towards the chosen destinations. The DPE process then starts with the initial plan, and
7 thanks to vehicular ad hoc network (VANET), evacuees communicate during the evacuation. We
8 use VANET under the vehicular cloud computing (VCC) architecture to update vehicle decisions
9 chosen by the initial plan, considering the dynamic evolution of the hazard and traffic congestion
10 levels. To validate the proposed framework, we apply it to a real test case of Luxembourg city. We
11 compare the proposed solution with existing planning methods in the literature. Results show that
12 online solving of DPE can minimize mean evacuation time and network clearance time by more
13 than 10% compared to other models with the only initial plan. In other words, updating evacua-
14 tion guidance messages during the DPE process leads us to a more effective evacuation process.
15 In addition, we analyze the performance of the proposed framework by changing the penetration
16 rate of connected vehicles in VANET, and we observe that by increasing the penetration rate, the
17 clearance time decreases.

18

19 *Keywords:* Network evacuation, disaster online management, Telecommunication network, VANET,
20 shelter allocation, dynamic traffic assignment.

1 INTRODUCTION

2 Natural disasters and catastrophes endanger all the population located in hazardous areas. The fre-
3 quency of these natural disasters is increasing (due to, e.g., climate change), leading to more deaths
4 and significant destruction to the environment (1). To mitigate and decrease losses caused by dis-
5 asters, we need to evacuate people from the affected areas to safe areas, i.e., shelters. Evacuation
6 orders are then vital and should be effective in evacuating people safely. Evacuation orders must
7 dynamically change with the hazard evolution and the evacuees' requirements for real-time guid-
8 ance. This real-time aspect of evacuation orders could only be targeted with telecommunication
9 technology (2). In other words, dynamic population evacuation (DPE) could be studied by new
10 emerging technologies of vehicle-to-everything (V2X) communication (3). Taking into account
11 the characteristics of a disaster is an essential task in determining the best and optimal evacuation
12 plans. In a sense, the type of disaster influences the choice of objectives of the evacuation orders
13 given to evacuees. The most frequent objectives of these orders are minimizing the mean evacua-
14 tion or the total time (4–6), minimizing the network clearance time (7–9), and minimizing the total
15 traveled distance (10, 11).

16 In this context, the success of an evacuation plan depends mainly on two choices of evac-
17 uees: the locations of shelters and the evacuation route toward the selected shelter. (12) developed
18 a model for shelter selection problem (SAP) to tackle the problem of determining shelter locations.
19 Their objective was to have a successful evacuation plan with minimum evacuation time, using a
20 static function to measure travel time in edges, which may affect the accuracy of congestion esti-
21 mation. The route choice models of evacuees used in the literature are based on three principles:
22 user equilibrium (UE), known as Nash Equilibrium (13), system optimum (SO) (14, 15), and the
23 nearest allocation (NA) approach. The difference between these models relies on the evacuees'
24 behaviors. In UE models, each traveler aims to minimize his individual travel time (16).

25 From the system point of view, the ultimate goal is to minimize the total evacuation time
26 or network clearance time. Under the SO principle, travelers may not be assigned to the fastest
27 route for the benefit of the overall system, which could be difficult to accept by evacuees (17). The
28 NA model assigns evacuees the shortest path based on the distance between the origins (hazardous
29 zone) and the destination (shelters). Such a model cannot provide acceptable results from evacuees'
30 and system points of view.

31 Mathematically speaking, finding the solution of UE or SO models considering the dy-
32 namic relationships between paths, time, and network characteristics are known as solving dy-
33 namic traffic assignment (DTA) problems (18, 19). Since the 1970s, DTA models have been used
34 to analyze long-term and short-term planning problems (20).

35 The reactive nature of both SAP and DTA limits their effectiveness during the evacuation
36 process, i.e., they are more contributing to the planning phase compared to online management
37 (21). In this context, adding telecommunication technologies moves one step forward by providing
38 effective methods for proactive rerouting when an emergency is predicted based on real-time traffic
39 information. Since traffic conditions are very time-varying during an evacuation process, updating
40 evacuation guidance messages frequently and quickly is critical.

41 With the emergence of intelligent and connected vehicles, vehicular networks, particularly
42 vehicular ad hoc networks (VANET), were introduced in 2001 as a part of ad hoc mobile networks
43 (22, 23). VANET have received much attention from research communities in the last few years
44 since it opened new doors of research (e.g., on vehicle and road safety, traffic efficiency, etc.) in
45 intelligent transportation systems (ITS) (24, 25).

1 With the growing demands of drivers, vehicles require empowering themselves in process-
2 ing power, computing resources, and storage space. Despite all the efforts made to satisfy all these
3 requirements, VANET show some disadvantages, such as the high costs generated by communica-
4 tion between vehicles due to the high mobility of vehicles (26). To support and serve all drivers'
5 needs and ensure their comfort and safety, we have to increase the resources of VANET. As a
6 result, the concept of vehicular cloud computing (VCC) has emerged (27, 28) to enable vehicles
7 to harness the benefits of cloud computing to satisfy certain requirements. VCC concept refers to
8 the use of cloud computing in VANET (27, 28). VCC allows vehicles to use the cloud resources
9 required for a particular period, representing the time they need to achieve their goals.

10 In this study, we first perform a literature review on population evacuation, focusing on the
11 application of telecommunication technologies. Based on this, we realize that there is no study
12 in the literature about considering vehicle rerouting in the DPE context. However, the rerouting
13 decision is a critical part of the evacuation process and can impact the success of the evacuation.
14 This study proposes an online evacuation framework to solve the DPE problem. The proposed
15 methodology can dynamically assign evacuees to the best shelter considering the current traffic
16 conditions. Our model uses an initial plan for evacuation that represents the output of solving SAP
17 and DTA based on (29). In our model, we consider two phases of the evacuation process:

- 18 • Planning phase, considering the initial evacuation plan solving both SAP and DTA prob-
19 lems, and
- 20 • Online evacuation management phase, which employs vehicular cloud computing tech-
21 nology to modify the initial evacuation plan by rerouting evacuees according to the dy-
22 namics of the network and evolution of the risk due to the disaster status.

23 Our methodology includes rerouting evacuees based on their distance from the risky zone
24 and the density of vehicles on the way toward the shelters, considering their communication ca-
25 pacity. We implement the designed framework for a city-scale real test case to validate the model
26 and compare the evacuation results in the presence and absence of telecommunication technology.
27 In addition, we perform a sensitivity analysis on the penetration rate of equipped vehicles that can
28 use the VANET.

29 Prior research has delved into evacuation simulations using diverse methodological frame-
30 works. An approach includes simulating traffic dynamics through multi-agent systems, as evi-
31 denced by (30–32). Recent developments have emphasized the integration of traffic simulation
32 with evacuation processes, as highlighted by (33–35), which is further elaborated in the sections
33 that follow.

34 The rest of the paper is organized as follows. In the next section, we review the literature
35 on DPE, focusing on traffic assignment and vehicular communication. Then, we highlight our
36 contributions to the literature. In Section 4, we illustrate the population evacuation problem. Then,
37 in Section 5, we present the framework to solve the evacuation problem. Section 6 is dedicated to
38 present the case study and optimization scenarios. We discuss the results in Section 7 and present
39 the concluding remarks in Section 8.

40 LITERATURE REVIEW AND CONTRIBUTION STATEMENT

41 In the literature, two main categories of studies focus on evacuation models. The first group solves
42 both shelter allocation or/and traffic assignment to minimize users' or/and system costs. The sec-
43 ond group focused on vehicular communication techniques and protocols to handle the DPE. In
44 this section, we carry out a literature review of these two groups and highlight the existing research

1 gaps.

2 In many studies, the problem of evacuation planning is formulated as a bi-level problem.
3 The upper level is the shelter location-allocation level dedicated to the system operator's point of
4 view, and the lower level is the routing level that represents the evacuee's route choice behavior.
5 We list the studies that used the bi-level programming approach:

6 (36) proposed a planning model to study the effects of shelter locations on the evacuation
7 process. They considered the interest of system operators and evacuees at the same time. However,
8 they address the problem with a static formulation.

9 (37) used a hybrid model to tackle the problem of evacuation planning. The upper level was
10 dedicated to shelter site selection in a system optimal fashion, and the lower level was for static
11 traffic assignment in a UE manner. The presented model was solved by employing a simulated
12 annealing heuristic, and for calculating the arcs congestion level, they used the BPR function.

13 (38) presented a scenario-based model. The upper level is a two-stage model. In the first
14 stage, the shelter location is determined, and in the second stage, the selected shelters are chosen,
15 considering the hurricane conditions. Then the lower level is for traffic assignment between origins
16 and destination selected by the upper one. They solved the problem using the Lagrangian relaxation
17 algorithm. For calculating each edge's travel time, they used the BPR function.

18 (39) proposed a hybrid model based on scenarios in the central area of Beijing. They
19 modeled the problem based on distance measures to choose the nearest shelters and shortest path.
20 In their solving method, they have used modified particle swarm optimization (PSO) algorithm
21 with a simulated annealing heuristic.

22 Few studies considered both SAP and traffic assignment in the dynamic context. (7) con-
23 sidered the evacuation planning process, including the DTA problem with a fixed shelter allocation
24 schema. In our previous study, (29), we tackled both dynamic problems sequentially, minimizing
25 the total travel time in SAP, and calculating UE for DTA. However, we did not consider telecom-
26 munication networks. To the best of our knowledge, no study in the literature address DPE prob-
27 lem considering both the planning phase (optimization methodology for SAP and DTA) and the
28 online management phase (take into account vehicle communication). However, DPE problem
29 is addressed with telecommunication technologies in the literature independently of the planning
30 phase.

31 Many studies focus on evacuation models with vehicular communication capacity. These
32 papers consider evacuation in different aspects using different communication architectures, pro-
33 tocols and types of emergency messages. Here, we review the related works to DPE problem.

34 Some studies focused on network architectures used for emergencies situation. They aim
35 to rapidly collect data and use it to ensure a successful evacuation process. For instance, (40)
36 used Software Defined Network (SDN) to manage emergencies. The control part of the SDN
37 collects the data from the different Internet of Things (IoT) networks formed by traffic lights,
38 traffic surveillance cameras, etc (41–43). It combines them to obtain the best and fastest evacuation
39 routes and access roads to the emergency services units. In addition, the authors used the delay
40 measure to quantify the quality of their solution. However, this study did not propose any rerouting
41 process and did not consider a realistic test case. Other studies target evacuation by proposing
42 different and less redundant emergency message exchange schema. To this end, (44) focused on
43 only highway scenarios and proposed a novel safety-related message exchange protocol based on
44 the Non-Redundant Communication Range (NRCR).

45 (45) applied and evaluated an evacuation strategy called Speed Strategy (SS) to quantify

1 driver response to evacuation pre-plans in emergencies. To implement this strategy, the authors
 2 deployed the VCC architecture. However, this paper only considered the responsiveness of evac-
 3 uees to SS orders and did not propose any replanning orders for evacuees to change their routes
 4 or destinations. Our study considers the VCC architecture for rerouting and includes the bi-level
 5 programming in the initial planning phase.

6 The main contributions of this study are two folds: (i) investigating the impact of VANET
 7 on the success of solving the DPE problem by having an initial plan determined by solving the
 8 SAP and DTA; (ii) developing a novel model to integrate the vehicular cloud computing, SAP,
 9 and the DTA problem. The application of our methodology offers a simulation-based optimiza-
 10 tion framework for the DPE problem, integrating online orders, system operators' decisions and
 11 evacuees' interests. Our model considers the travel time in rerouting vehicles and VCC delays in
 12 the telecommunication exchanges. Besides, we apply our methodology to the realistic network of
 13 Luxembourg city to validate and evaluate its performance.

14 **PROBLEM FORMULATION**

15 Evacuation operation needs to be fulfilled as fast as possible. We use two phases to represent
 16 the achieving steps to this goal. The first phase is carried out offline, creating an initial plan for
 17 evacuation and solving two main problems, SAP and DTA. While the second phase is online,
 18 in which we consider vehicular communication under the cloud computing paradigm. From the
 19 planning point of view, an evacuee has two main decisions to be made in DPE: (i) Which shelter
 20 to choose as the destination and (ii) Which route to choose to reach the destination. By taking
 21 into account all evacuees, the first decision problem is the SAP and the second one is the DTA
 22 problem. We formulate the SAP to satisfy the system operators' interests (SO) to minimize the total
 23 evacuation time. In a sense, this scenario could be seen as a real-world scenario where the system
 24 guides vehicles to their shelter (destination) as they do not have any information about shelter
 25 capacities and conditions. However, the DTA problem is formulated to address the Stochastic User
 26 Equilibrium (SUE), which also considers the bias in the decision-making process of evacuees in
 27 an emergency situation. In other words, evacuees selfishly choose their path toward their chosen
 28 shelters to reach the destination with a perceived minimum travel time.

29 Let us define our DPE problem on a directed graph representing a traffic network $G =$
 30 (N, A) , where N is the set of nodes, and A is the set of edges (links). We define O as the set of
 31 origin nodes that determines the hazardous zone to be evacuated and S as the set of destination
 32 nodes representing safe locations, i.e., shelter sites. Without loss of generality, we assume that
 33 O and S are disjoint subsets of N ($O, S \subset N$). We denote by w the amount of demand of each
 34 origin o , $o \in O$. This demand represents the number of users that should be evacuated. We note
 35 by x_{os} the integer decision variable that determines the number of evacuees allocated to the pair
 36 having origin o and destination s . We define the binary variable y as the decision variable of the
 37 shelter selection s . The t_{os}^* is the minimum travel time between origin o and destination s . In
 38 most cases in the literature, the travel time is calculated with a static formulation of the traffic
 39 assignment problem using an analytical travel time function (BPR function) (46). In our case, we
 40 use a dynamic simulator that provides the travel time of any edge in the network. Therefore, t_{os}^* is a
 41 given parameter from the simulator's time while solving this problem. We define c_s^α as the shelter
 42 s capacity in time interval α , and P as the maximum allowable number of opened shelters. The
 43 full list of the important notations of this paper is presented in table 1.

The SAP represents the system operator's objective. The solution to this problem is the

TABLE 1: Table of notations

M	Set of all evacuees.
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 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, $s \in S$.
α	Time interval index, $\alpha \in T$.
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 .
c_s^α	Capacity of shelter s at 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_π^α	List of evacuees which travel for os on path π in departure time interval α .
$t_{tr,\pi}^\alpha$	Experienced travel time of trip tr on path π in departure time α .
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 π in departure time α .
$\xi_{tr,\pi}^\alpha$	Random error term for trip tr on path on π in departure time α ; $E(\xi_{tr,\pi}^\alpha) = 0$.
pr_π	Path choice probability for path π in the C-logit model.
R_i	Distance separating vehicle i to the center of the hazard.
R_{max}	Maximal distance separating vehicle i to the center of the hazard.
U_i	Number of vehicles in the edge that evacuee i approach to.
U_{max}	Maximum amount of vehicles in an edge i that evacuee i can approach to
w_i	Evacuee i indicator to be selected for replanning.
λ	Threshold for rerouting vehicles.
$n(A)$	Cardinality of set A .

allocation of evacuees to shelters for the minimum total evacuation time based on the current travel time from risky nodes to shelters. Equation 1 presents the objective function of the SAP problem.

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

We have employed the p-median model (47), which is a common approach to solve the shelter location-allocation problem under a generic type of hazard (48). In the employed model, all the demands have to be served (equation 2), meaning that all evacuees should quit the hazardous zone and enter a shelter.

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

Also, our model does not suppose an infinite capacity of shelters. Thus, we have to assign users to shelters respecting the limited capacity of shelters that change over time intervals with

respect to the previous assignment (equation 3).

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

Finally, we have a fixed limited number of opened shelters to P in the studied network:

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

1 Note that the presented model is categorized as an NP-hard problem (49). The SAP solution
2 provides the demand from each origin o to each shelter s , i.e., OD matrix for the DTA model.

3 In the DTA model, we calculate SUE to represent the network equilibrium. Note that the
4 UE principle always supposes that all users have perfect knowledge of the network information
5 and consistently choose paths to minimize travel costs (50). This assumption is so rigorous for
6 users that it cannot be held in a realistic scenario. The principle of SUE can further relax the
7 assumption and be stated that all travelers cannot improve their perceived travel cost by unilaterally
8 changing paths (51). Note that the departure time of evacuees is given in this study, and we define
9 the shortest path as the path with the minimum travel time. To have this initial plan, we use a
10 trip-based simulator. Thus, The dynamic traffic network equilibrium conditions with given travel
11 demand and departure time distribution include a probabilistic route choice process rather than the
12 deterministic one used in UE (52). In SUE model, The route choice model is derived by assuming
13 a random component associated with the travel cost (53):

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

14 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 rep-
15 resents the traveler's perception error. Using the perceived travel cost concept, the SUE conditions
16 can be characterized by the following equation (e.g. (18)):

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

17 where pr_π is the probability that travelers choose route π of os . In this case, the equilibrium
18 model is dependent on the congestion effect and the stochastic effect, which is associated with the
19 distribution of the random terms. An equivalent unconstrained optimization formulation for the
20 SUE problem was provided by (54) under a general distribution assumption of random terms.

21 In the simulation-based DTA, we tend to attain the SUE state so that each vehicle cannot
22 reduce its perceived travel time by changing the chosen route. To achieve this condition, we it-
23 eratively run both phases of optimization and simulation. The optimization determines the route
24 choice of vehicles. In the simulation part, we simulate vehicles on paths by running a dynamic
25 simulation of vehicles taking specified routes (output of optimization). The model used to assign
26 users to the route is the C-logit mechanism (55).

27 All the models mentioned above are defined in the planning phase and used to create the
28 initial plan for evacuees. The next model corresponds to online evacuation management, wherein
29 we represent the evacuation process over time. The goal is to respond to unexpected events and
30 dynamically modify the initial plan during the evacuation by considering vehicles' communication
31 capacity that permits evacuees to receive and send new information and update their routes.

32 Our online evacuation guidance system is composed of three components, as depicted by
33 Figure 1: The first component is a centralized traffic monitoring and rerouting service representing
34 the cloud server (which can physically be distributed across several servers). The second one is
35 the set of roadside units (RSU) that represent the network infrastructure that should be existent
36 to ensure communication between the cloud server and vehicles. The third layer is represented
37 by vehicles equipped with onboard units (OBU). OBU permits vehicles to communicate with each

1 other and with infrastructure (V2X). The vehicles are considered end communication nodes. These
 2 nodes send and receive data (e.g., current position, speed, and direction) periodically, as shown by
 3 yellow arrows in Figure 1. Based on these three principal components of our cloud architecture, we
 4 developed a method to reroute vehicles to avoid congestion and quit the hazardous zone as soon as
 5 possible. To do so, we estimate the congestion level of the vehicles' routes by measuring vehicular
 6 road density. We also take into account the risk evolution by measuring the distance between the
 7 vehicle and the hazardous zone (equation 7).



FIGURE 1: Vehicular cloud computing.

$$(U_i/U_{max}) * R_{max}/(1 + R_i) \geq \lambda \quad 0 \leq R_i \leq R_{max}, \quad \forall i \in M \quad (7)$$

Constraint 7 ensures that the density of vehicles on edge multiplied by the distance to hazardous nodes ratio of vehicle i is more than a specified threshold λ . Also, we denote by Δ if a vehicle is rerouted or not as expressed by equation 8

$$\Delta_t^i = \begin{cases} 1 & \text{if vehicle } i \text{ is rerouted at time } t \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

8 In this section, we presented the formulation for both the initial planning and the online
 9 instructions to revise the solution to the DPE problem. However, as mentioned before, finding an
 10 optimal solution for the DPE problem is not trivial. Therefore, we need indicators to measure the
 11 distance between our solutions and the optimal solution. Besides, we need to analyze the evolution
 12 of the network during the evacuation to investigate the impact of online guidance on the entire
 13 network.

14 **Solution quality indicators**

15 In this section, we define the performance metrics used to evaluate our solution's optimality and
 16 monitor the network performance. We have calculated the network clearance time to compare the
 17 quality of solutions obtained with different methods. The clearance time is defined as the arrival
 18 time of the last evacuee to its shelter. This time provides us with information about the speed of
 19 the evacuation operation. Note that the best solution method provides the least value of clearance

1 time.

2 We have also used the mean evacuation time, defined as all evacuees' average travel time.
3 In addition, we measure the average network speed to evaluate the network usage rate (56).

4 Besides, to evaluate the quality of the traffic assignment solution, we used the average
5 travel delay used in the literature as the average gap (57, 58). This measure represents the mean
6 amount of delay compared to the evacuee with the minimum evacuation time of each *OD* pair. We
7 have calculated this measure to compare the effectiveness of the SUE assignment. The formula for
8 ATD is as follows.

$$ATD = \frac{\sum_{\alpha \in H} \sum_{o \in O} \sum_{s \in S} \sum_{\pi \in \pi_{os}} t_{tr,\pi}^{\alpha} - t_{os}^*}{\sum_{o \in O} w_o} \quad (9)$$

9 We have also used an indicator called the average evacuation delay, representing the mean
10 amount of delay over the evacuee with the minimum evacuation time of each origin. This indicator
11 is meaningful in our context because the final goal of each user is to reach the safe area as soon as
12 possible.

$$AED = \frac{\sum_{\alpha \in H} \sum_{o \in O} \sum_{s \in S} \sum_{\pi \in \pi_{os}} t_{tr,\pi}^{\alpha} - t_o^*}{\sum_{o \in O} w_o} \quad (10)$$

13 where t_o^* denotes the minimum travel time of the evacuation trip from origin o . To successfully
14 evaluate the DPE problem, we need to have indicators to measure the performance of the online
15 management phase. In this study, we measure the packet delivery ratio (PDR) that represents the
16 percentage of generated data packets that reach their destination. Some factors like disconnections
17 of nodes or bad radio transmission conditions cause the decrease of the PDR by the increased
18 amount of retransmissions. Note that a message being retransmitted multiple times can cause a
19 high PDR; thus, other metrics, such as the delay, need to be investigated.

20 Many papers rely first and foremost on the transmission delay as a key metric (59). This
21 metric is relevant to safety-critical and latency-sensitive applications. The delay is usually mea-
22 sured in seconds (s) or milliseconds (ms). Here we are interested in the end-to-end delay, i.e., the
23 time from creating a message until the destination node finally receives it. This measure depends
24 on how good radio conditions are (many retransmissions will increase the PDR and delay). The
25 best value for PDR is the larger one and the smallest for the delay.

26 METHODOLOGICAL FRAMEWORK

27 Recall that solving the DPE problem with our model comprises two principal parts: building an
28 evacuation plan by solving both problems SAP and DTA, and giving online guidance to reroute
29 vehicles in congestion areas. Herein, we present the sequence of execution of each step of our
30 formulation.

31 For planning purposes and in the dynamic setting, we adopt the methodology used (60)
32 to provide the initial plan. Here, we aim to modify the planning model to go for SUE instead of
33 a pure UE solution. For the online evacuation management phase, we add a network layer for
34 vehicular communication to capture the congestion of the network. Through this communication
35 network, we can re-plan the evacuation route and shelter during the evacuation process and provide
36 them with the instructions in real-time. To this end, we use a cloud computing scheme due to its
37 low implementation cost. This is the main advantage of cloud computing compared to fog or
38 edge architectures as they require a large amount of implementation budget (61). The proposed

1 methodology of this study is presented in Figure 2.

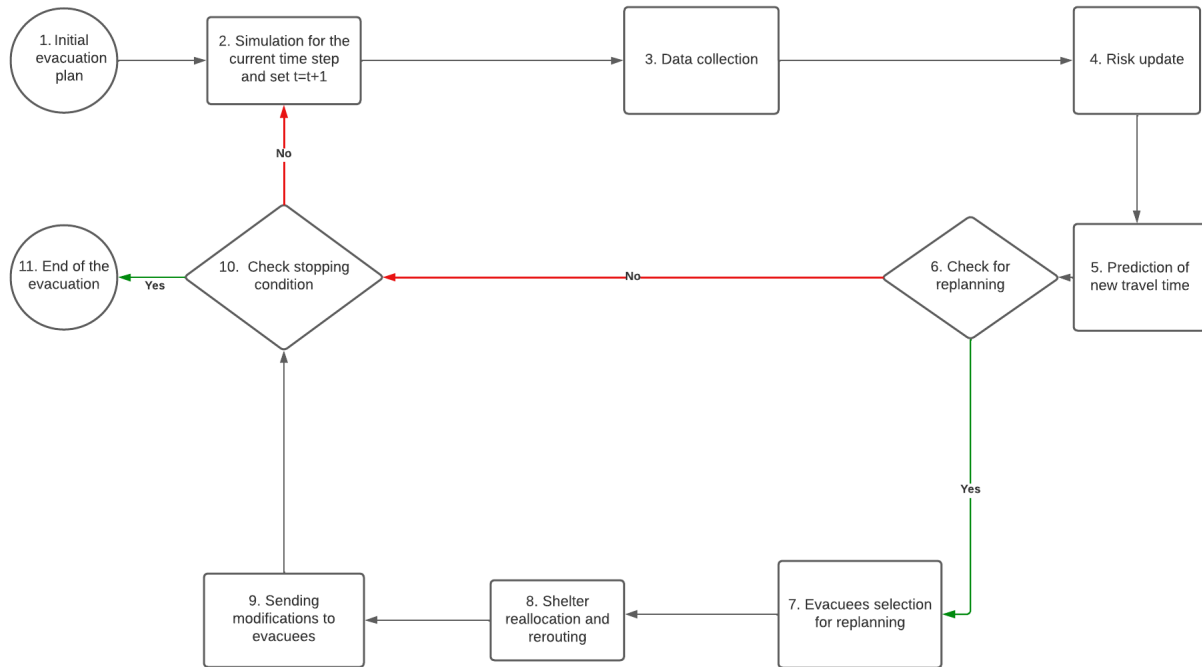


FIGURE 2: flowchart of the solving the DPE problem

2 The steps of the framework are detailed as follows:

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.

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. We have also to increment the simulation time index. Note that any trip-based dynamic simulator can be used in this step.

Step 3. Data collection: This is the first part of our cloud computing architecture wherein each vehicle (node) broadcasts data messages, using their OBU, to RSUs that send it to the cloud server.

Step 4. Risk update: In this step, we update 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 congestion levels of the vehicle location.

- Step 5. **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. In this step, we use a prediction model to predict new travel time. Here we use the prediction model embedded in the used simulator.
- Step 6. **Check for replanning:** This step is for deciding whether a user i is concerned by the rerouting process or not. For user i we estimate edge density, including the road speed and traffic density based on the Greenshield model (2). The user i is considered to be in congestion if his current edge density is above a certain threshold.
- Step 7. **Evacuees selection for replanning:** This step corresponds to selecting vehicles that have to be rerouted before getting inside a congested edge (road). In this step, we select all users with the congested edge as the next planned edge of their initial journey. In addition, we prioritize vehicles that are closer to the hazard zone. To this end, we have calculated an indicator w_i for each user having two main components: the congestion level of his next edge and his distance from hazardous nodes.
- $$W_i = (U_i/U_{\max}) * R_{\max}/(1 + R_i) \quad 0 \leq R_i \leq R_{\max} \quad (11)$$
- Step 8. **Shelter reallocation and rerouting:** In this step, we prepare a message to the targeted users to ask them to reroute to the path with the current shortest travel time having their planned shelter as a safe destination.
- Step 9. **Sending notification to evacuees:** The step represents the second essential part of our cloud computing scheme where the cloud server sends its decisions to RSUs that forward the results to vehicles to react accordingly.
- Step 10. **Check stopping condition:** This step checks if all the demand is evacuated or not. If that is true, we had to end the process. Otherwise, we go to simulating the next step.
- Step 11. **End of the simulation/** In this step, we end the evacuation process, and we calculate different performance measures to evaluate the performance of our online management solution.

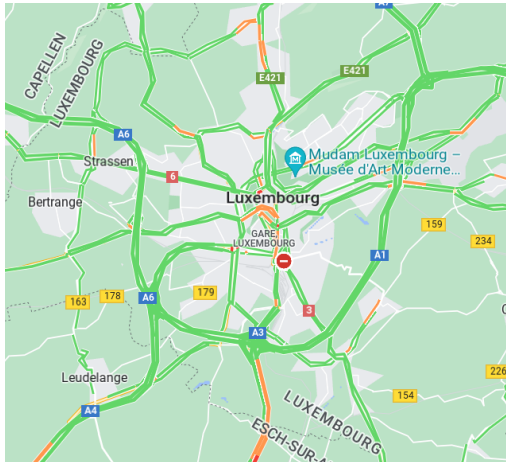
1 NUMERICAL EXPERIMENTS

2 In the previous section, we presented our framework to solve the online DPE problem. Here, we
 3 tend to apply the methodology to a real network to validate the proposed solution. We present the
 4 considered test case and then the experiment design.

5 Case study

6 We implement our proposed solution in order to model the DPE problem on the realistic network of
 7 the LuST scenario (Figure 3a), which represents Luxembourg city (62). For the network and evac-
 8 uation scenario characteristics, please refer to (60). We have used a laptop with 1.7 GHz. and 16

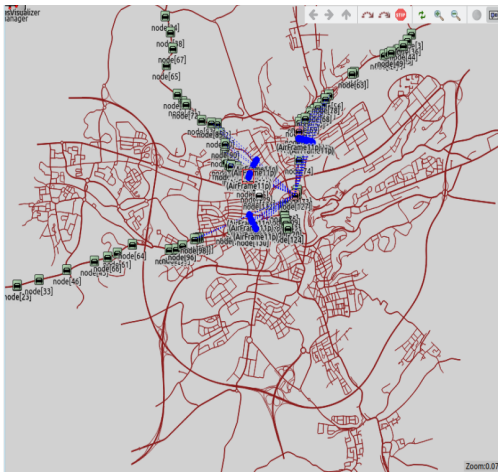
1 GB of RAM to generate all the results. We employed a solution method using the simulation-based
 2 DTA. For this, we performed all simulations by SUMO simulator, and we calculated the C-logit
 3 model and the prediction of travel time by SUMO (63). In addition, we used ILOG CPLEX version
 4 12.9 to implement the SAP model and solve it. To simulate the scenario taking into account ve-
 5 hicular communication, we used the Veins/Omnet++ simulator and a cloud computing architecture
 6 based on works done in (64).



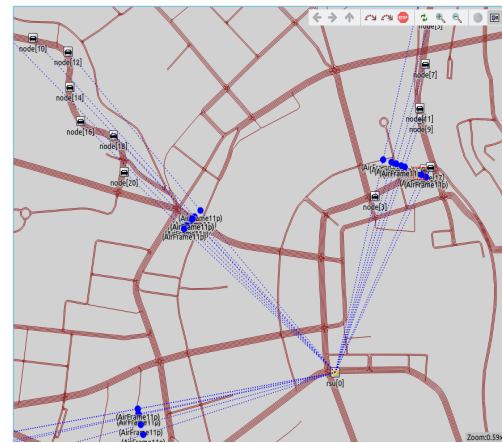
(a) Luxembourg mapping data ©Google 2022



(b) SUMO city network



(c) OMNET++ communication network



(d) Communication between nodes in VANET

FIGURE 3: Evacuation network map of Luxembourg city

7 Figure 3 presents the evacuation network map of the city of Luxembourg. Figure 3a
 8 presents the real network of Luxembourg with the size of 155.95 km² and the traffic network
 9 graph considered by Veins for dynamic simulation. We examine a hypothetical threat in the center
 10 zone affecting people of that region colored in red in Figure 3b. We do not assume any super source
 11 nodes (risky nodes) in this study. Four origin nodes are considered as evacuation sources in the
 12 risk zone (see Figure 2c in (29)). Vehicles carrying people should be evacuated to safe destinations
 13 (shelters), colored in green in Figure 3b, placed at the border of the network. We set the duration
 14 of each planning departure time interval (η) to 20 minutes for the simulation, considering the net-
 15 work's size. The demand at each node is 200 vehicles at each period. We have selected four origin

1 nodes and four shelters, each with a capacity to hold 1500 evacuees. Therefore, the total demand
 2 is 600 vehicles per origin for the planning horizon (H). Figure 3c shows the vehicular communi-
 3 cation network in OMNET++ simulator. The process of message exchange between vehicles and
 4 the network infrastructure is illustrated by Figure 3d We have used 4 km for RSU coverage in our
 5 model. Also, we have fixed a small value for λ to be 0.2 because of the small penetration rate
 6 values, and we assume that our maximal radius of the risk scenario R_{max} is 4km.

7 **Study optimization scenarios**

8 This study aims to examine the effects of planning and online orders on the DPE problem by
 9 creating four different scenarios. The following section provides a detailed description of each
 10 scenario.

- 11 • **Scenario P+C: Scenario with both planning and vehicular communication:** This
 12 scenario follows the proposed framework (demonstrated in Figure 2).
- 13 • **Scenario P: Scenario with the initial plan only:** This scenario illustrates the case of
 14 just planning for evacuation without any communication between vehicles or vehicles to
 15 RSUs. It means that we do not reroute evacuees during the evacuation process; they just
 16 follow the initial plan.
- 17 • **Scenario C: Scenario with vehicular communication only:** This scenario is the same
 18 as Figure 2) except in step 1 where evacuees consider the nearest shelter and choose their
 19 routes following the SUE.
- 20 • **Scenario N: Naive scenario without any optimal plan and vehicular communication:**
 21 This scenario represents the case where the system operators do not provide guidelines
 22 for evacuees. It means that the evacuees choose the nearest shelter and choose their routes
 23 following the SUE.

24 **RESULTS**

25 In this section, the results for the four mentioned scenarios were executed on the same evacuation
 26 demand profile. We use the evaluation metrics presented in Subsection 4.1 to measure the quality
 27 of the solution provided by our methodology. Table 2 presents the results for the four scenarios.

28 In the scenarios considering VANET, the penetration rate is set at 100%, and each vehicle
 29 sends a message packet to the server every 1.66 minutes. The results show a significant improve-
 30 ment in the quality of the final solution obtained by scenario P+C wherein we used both planning
 31 and online guidance models. For instance, the reduction of more than 18 minutes (39%) in the net-
 32 work clearance time compared to the naive scenario. Also, there is an improvement of more than
 33 2 minutes (10%) between scenario P+C, and scenario P. Results show that scenario P represents
 34 the second best solution. The comparison between scenarios P+C and P proves that new orders
 35 handling new events not expected in planning create a more successful evacuation operation.

36 Besides, scenario C provides a better solution compared to scenario N, meaning that using
 37 the telecommunication network can improve the evacuation solution, even without any planning
 38 phase. This observation could prove the effectiveness of online communication and highlights the
 39 importance of giving new orders to evacuees to revise their route choice during the evacuation pro-
 40 cess. Inspecting the result for scenario P and scenario C, we can observe that planning contributes
 41 more than telecommunication during the evacuation operation. One of the reasons behind this ob-
 42 servation is that in scenario C the shelter allocation was done without considering the congestion
 43 level. We have monitored scenario C to have a better view and understand more of the effect of

1 online evacuation guidance. We observe that allocating all users to the same nearest shelters in all
 2 evacuation operation generate congestion that could not be escaped even by using online vehicle
 3 rerouting. That is why different shelters like in scenario P in each state will ensure that we as-
 4 sign evacuees to the closest destinations in terms of time-dependent shortest path and not distance
 5 measure.

TABLE 2: Performance metrics

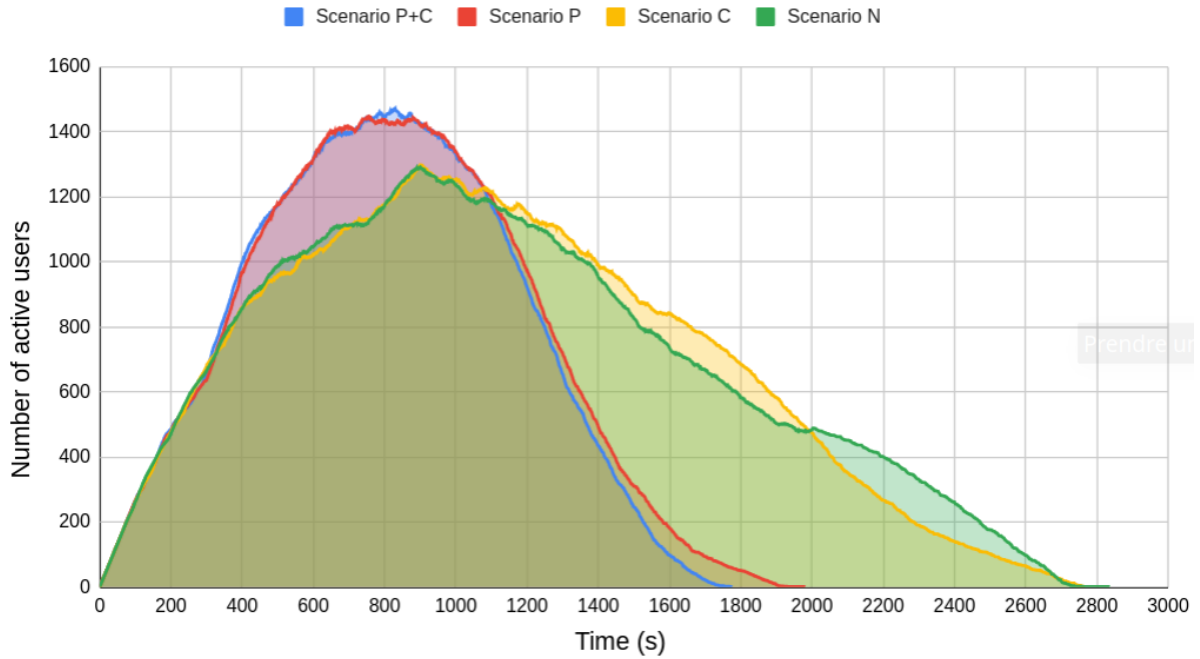
Metrics / Scenario	P+C	P	C	N
Network clearance time(s)	1775.00	1980.00	2765.00	2835.0
Mean evacuation time(s)	1071.54	1093.70	1407.92	1447.61
Average travel delay (ATD)	205.47	220.62	341.63	349.78
Average evacuation delay (AED)	241.32	366.65	366.65	392.12

6 The decrease of mean evacuation time in table 2 shows that the online DPE improves the
 7 evacuation solution. The proposed model used in scenario P+C generates better ATD for evacuees
 8 with more than 6% of reduction compared to the second best. The improvement is remarkable for
 9 AED (34%). We mention that including telecommunication network provides us with some errors
 10 and delays in the sending and receiving messages. In both cases, P+C and C, we have around
 11 205.30 ms for end-to-end delay and PDR around 74%.

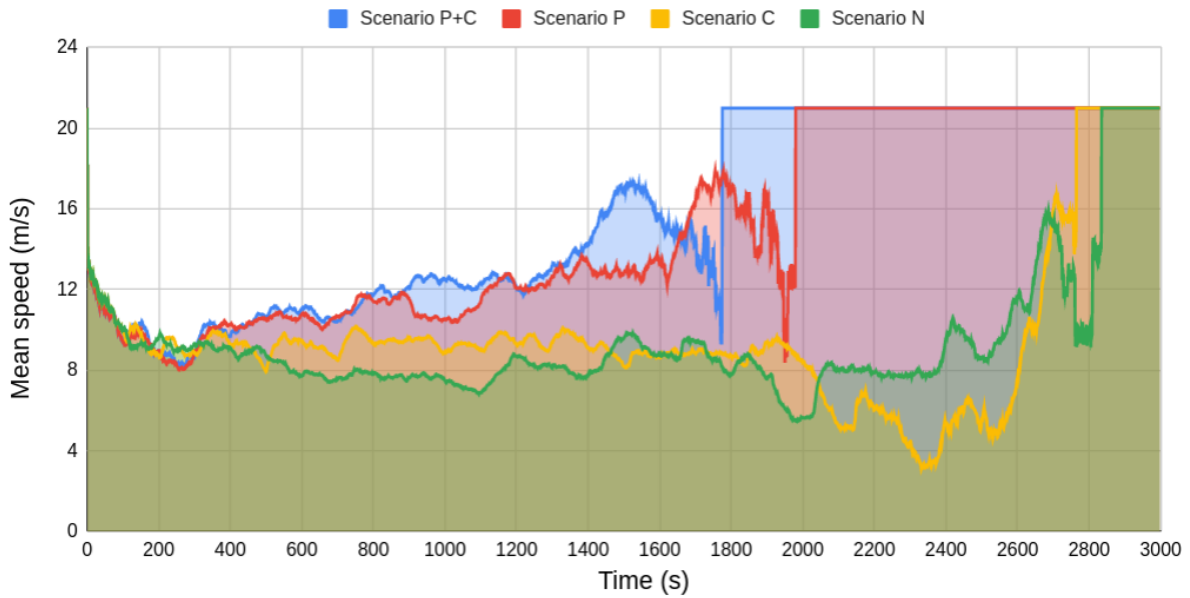
12 Figure 4a presents the distribution accumulation over time for four scenarios. The accu-
 13 mulation at each time is the number of users traveling in the network. The figure shows that the
 14 scenarios having an initial evacuation plan outperforms the other two scenarios. The clearance
 15 time and network capacity usage in scenario P+C are better than in scenario P. There is a signif-
 16 icant difference between scenario P+C and scenarios C and N. Note that the gain of around 60
 17 seconds in clearance time between scenarios C and N is remarkable in our test case that includes
 18 only 2400 users. We expect a better result by increasing the number of evacuees and deploying
 19 larger networks. Figure 4b shows the evaluation of network mean speed during the evacuation
 20 process. This figure followed the results of the distribution of accumulation Scenario P+C outper-
 21 forms other scenarios meaning that the blue curve representing the scenario P+C stands upper than
 22 the other curves in most cases. We can observe a dramatic decrease in the speed before the end of
 23 evacuation because of queues formed in front of shelter sites.

24 Assuming that 100% of the evacuees are using connected vehicles is not currently realistic,
 25 and it can be reachable in future. That is why we should consider multiple penetration rate values.
 26 In the case of $x\%$ of penetration rate, we select connected vehicles with a random distribution.
 27 Only this $x\%$ are sending positioning information and receiving online orders. Thus, the cloud
 28 server sees and guides only this $x\%$ of the vehicles. We execute our evacuation framework for five
 29 values of penetration rate, and the results are illustrated in table 3.

30 There is no communication in the case of a 0% penetration rate, so we cannot calculate or
 31 measure the end-to-end packet delay or the packet delivery ratio, and "-" means that there is no
 32 possible value. The DPE problem is solved in our proposed framework for all penetration rates.
 33 The table 3 presents the different values of the performance measures used in the case of multiple
 34 penetration values. The table clearly shows that the case of a 100% of penetration rate is the best
 35 scenario in our study. The table 3 also illustrates acceptable values of PDR measure for 70%,
 36 50% and 30% scenarios. This PDR level means that around 75% generated packets are received



(a) Number of active users in the network variation



(b) Network mean speed variation

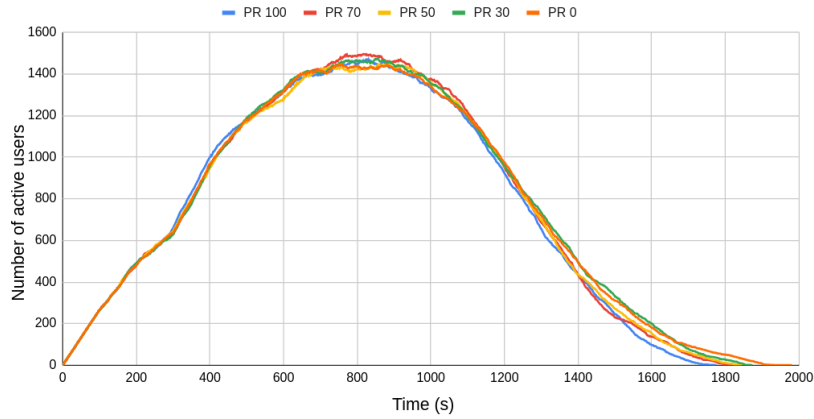
FIGURE 4: Performance measures variation over scenarios

1 correctly in the range of network infrastructure and without the need for retransmission. Also, the
 2 delay measure is crucial, especially in our case dealing with population evacuation. The average
 3 end-to-end delay of packets considering the vehicular cloud computing architecture employed is
 4 around 203 ms which is the same in the literature with this number of nodes (65). In addition, each
 5 scenario's values of network clearance time show that communication positively impacts the evac-
 6 uation process by decreasing the clearance time. table 3 show fewer values for *ATD* when having a

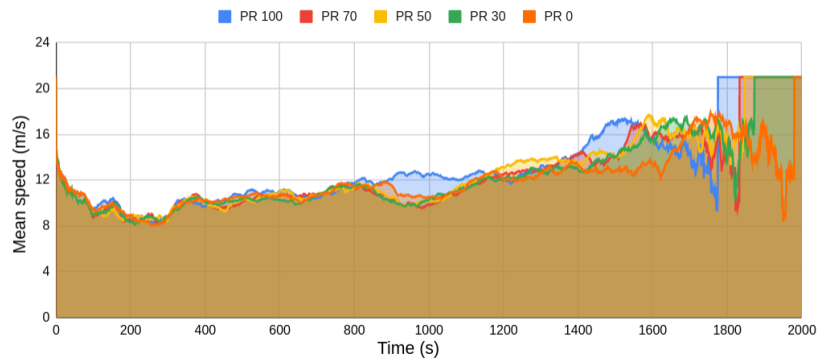
1 bigger penetration rate. This demonstrates that increasing the number of connected vehicles could
 2 enhance the traffic assignment by ordering evacuees to choose the route that minimizes their travel
 3 time going more to the pure UE state. Figure 5a illustrates the change in the number of vehicles
 4 evacuating in the network for five different scenarios. The curves shown in this figure represent
 5 different penetration rate values.

TABLE 3: 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	245.49	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	-



(a) Number of active users in the network variation



(b) Network mean speed variation

FIGURE 5: Performance measures variation over different penetration rate

6 Figure 5b follows the results of the distribution of accumulation of users in the network.
 7 In addition, Figure 5b depicts the evolution of the mean speed in the evacuation operation. The
 8 maximum network speed limit is the free-flow speed (21 m/s) attained when the network does

1 not have any vehicle. The network speed illustrated by Figure 5b shows that having a 100%
2 penetration rate is the fastest curve by arriving at the free-flow speed in the shortest time. Also, the
3 figure presents the result of mean speed variation of other penetration rates showing that there is
4 not a huge difference between 70% and 30% penetration rate on network clearance time (the arrival
5 to the free-flow speed). Figure 5b shows that adding the communication layer even with different
6 penetration rates positively affects the evacuation process. It means that the online solving of DPE
7 uses the network's capacity better than just planning.

1 CONCLUSION

2 The population evacuation process during a disaster is vital, so the idea is to evacuate the population
3 as soon as possible from hazardous zone towards safe areas to reduce the losses and the cost of
4 the disaster. This paper is dedicated to solving the dynamic population evacuation (DPE) problem.
5 Successfully modeling this problem and optimizing it faster and more efficiently saves more lives.

6 In this paper, we perform a literature review and analyze multiple models used both in
7 evacuation planning and VANET creation and execution in an evacuation context. Based on the
8 literature, we decomposed the evacuation problem into two essential parts: firstly, creating an
9 optimal evacuation plan considering dynamic shelter allocation and traffic assignment; secondly,
10 considering new orders for the online guiding system. For the first part, known as evacuation
11 planning, many models are employed in the literature: bi-level models. These different studies
12 employ mainly static traffic assignment coupled with shelter allocation formulation for the network
13 evacuation problem. Despite resolving both planning problems of SAP and traffic assignment in
14 a static setting, few consider the DPE in a dynamic case for both shelter allocation and routing.
15 For the second part, researchers made different proposals to improve evacuation operations by
16 considering it from different sides of using architectures of a vehicular ad-hoc network (VANET),
17 modifying the emergency message routing techniques, considering different types of messages,
18 and transferring data between nodes. This study proposed a framework to solve the DPE problem,
19 including creating an initial optimal plan and giving online orders considering unpredicted events
20 not considered by the plan. In order to solve the DPE problem, we provide a framework to capture
21 the dynamics of the evacuation process by using a traffic simulator. Building a planning process is
22 achieved to determine shelters in the SO manner and routes in the SUE setting. Afterward, we try
23 to perform an online management procedure during the evacuation. To this end, vehicles can send
24 and receive data needed to update their route accordingly. To add this networking layer, we have
25 considered a cloud computing architecture composed of vehicles representing final nodes, RSU
26 representing the network infrastructure, and a distant, powerful computer representing our cloud
27 server.

28 For implementing our methodology, we have considered a trip-based dynamic simulator
29 that provides us with travel information every time step coupled with a network simulator to add
30 vehicular cloud computing communication. We apply our proposed methodology to the real-world
31 network of the city of Luxembourg. The results show that the proposed model exceeds the model
32 with only evacuation planning by more than a 10% decrease in network clearance time. This
33 means that using vehicular communication for giving new orders improves the evacuation opera-
34 tion because it considers new events and emerging congestion not initially determined by the plan.
35 Moreover, we performed an analysis of the penetration rate of connected vehicles. The results
36 show that solving the online DPE even with a low penetration rate could improve the quality of the
37 proposed solution and use more of the network capacity in terms of network speed, for example.
38 Besides, we have calculated end-to-end delay and packet delivery ratios to evaluate the perfor-
39 mance of the cloud computing architecture for vehicular communication. Results show acceptable
40 values in the case of delay-sensitive applications.

41 This study considers only rerouting as a single strategy to manage the online evacuation
42 process. We can also consider the departure time and shelter choice before and during the evacu-
43 ation, respectively. For future works, we aim to use this framework with vehicles and buses, and
44 other modes of transport. Second, we want to improve our framework by implementing a more ac-
45 curate travel time predictor as we currently use the prediction model of the agent-based simulator.

1 Another interesting extension is to consider the behavioral reaction of users to evacuation orders.

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