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RESEARCH ARTICLE

An Agent-Based Dynamic Framework for Population Evacuation Management

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ABSTRACT Evacuating the population during crises to safe zones via optimal paths is vital. The evacuation planning process makes two main decisions: which shelter to reach and which path to take towards the chosen shelter. These decisions correspond to shelter allocation and traffic assignment problems, respectively. Many studies tackled these problems with a static formulation in the literature, while only a few considered a dynamic context. We conduct a comprehensive literature review and highlight that most studies independently solve these two problems while both are correlated with traffic conditions. To fill this gap, we propose a new framework to couple the shelter allocation problem (SAP) and the dynamic traffic assignment (DTA) problem and solve them. To capture traffic dynamics, we use a dynamic agent-based simulator. We assume the system determines the evacuees' shelters to minimize the total evacuation time. However, each evacuee's concern is reaching a shelter as fast as possible. Therefore, we formulate the DTA problem under stochastic user equilibrium (SUE) principles, i.e., every evacuee aims to minimize his own perceived travel time. We apply the proposed methodology to the network of Luxembourg City and compare its performance with other advanced methods that solve SAP and DTA separately. The comparison shows that solving the dynamic shelter allocation improves the mean evacuation time and significantly decreases the network clearance time compared to other methods with a fixed plan for SAP. The simulation results prove that considering the network state in the SAP can provide a more effective evacuation plan. Moreover, we perform a sensitivity analysis on optimization parameters and evaluate the computation cost of our methodology.

INDEX TERMS Network evacuation, disaster management, shelter allocation, dynamic traffic assignment.

I. INTRODUCTION

Natural disasters and catastrophes endanger the lives of people in devastated areas. Evacuating people from those areas to safe places or shelters is a feasible solution to decrease or avoid enormous losses [1], [2]. Order and guidance are crucial and decisive to running this process effectively and safely managing the evacuation process [3]. There are two main information pieces that each evacuee should have during the evacuation process: (i) the destination (shelter) and (ii) the route toward that shelter. Both information pieces are obtained by solving shelter allocation and traffic assignment, respectively. Each problem can follow different principles. We can categorize the models based on their principles into three groups [1], [4]: the first addresses the problem of the evacuation process considering the user equilibrium (UE). The second models the evacuation as a system optimal (SO) problem. The third model uses the nearest allocation (NA) approach. These models differ mainly in their objective function. In the UE model, each traveler aims to minimize his benefit by minimizing his own cost. In other words, this principle assumes that the users are perfectly informed, rational and behave selfishly. The SO principle aims to optimize the total benefit of all evacuees. To this end, evacuees may not be assigned to shelters or routes that maximize their own benefits but shelters or routes that optimize the overall system

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benefit. This principle can be difficult to get people to accept, especially in evacuation situations. To minimize the total traveled distance, the NA approach assigns evacuees to the closest shelter in terms of traveling distance between origins (hazardous zones) and destinations (safe nodes). Such a model could not provide supportable results for both evacuees and system operators [5].

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

- Network clearance time: It is defined as the arrival time of the last evacuee to the shelter or safety zone [6], [7], [8].
- Total evacuation time: It denotes the sum of the evacuation time of all evacuees [5], [9], [10].
- Total traveled distance: It is the sum of all trip lengths traveled by all evacuees during the evacuation [11], [12].

The UE or SO route choice approach is represented formally as a traffic assignment problem. The problem could be classified into two main categories: static and dynamic models. Static traffic assignment (STA) models determine the number of vehicles selecting each route between origins and destinations for the demand profile. However, solving the problem of traffic assignment in a static setting cannot capture the changes in the number of vehicles on routes over time. The dynamic traffic assignment (DTA) problem generalizes the static setting to determine at each time instant the flow on each route over the study period [13]. Although static models are used for planning purposes, they cannot accurately describe congestion and do not model spillbacks [14]. DTA aims to determine the relationship between routes, time, and network characteristics. It can produce stable and meaningful solutions, which are crucial for practical applications [15]. Traffic assignment models could also be seen as trip-based or flow-based models. Flow-based models aim at determining the vehicular flow on each route, while trip-based models' objective is to specify the number of travelers (particles) on each route, making the traffic assignment problem more challenging to solve because of the discrete setting [16]. We conduct a comprehensive literature review on all static and dynamic traffic assignment models used in evacuation problems, either flow-based or trip-based.

This study investigates the state of the art of population evacuation management to identify the gaps in providing an effective evacuation plan. Based on the review results, we highlight the research gap in coupling the two main challenges of evacuation problems, i.e., shelter allocation and traffic assignment. Thus, we design a framework that couples both shelter allocation and traffic assignment in a dynamic context to consider the traffic conditions. We solve SAP following a linear formulation of the shelter allocation, considering the number of opened shelters and their capacity. In addition, we deploy the SUMO simulator [17] to address the simulation-based DTA problem. We calculate multiple metrics to measure the quality of the framework and compare the methodology with existing models in the literature. We also establish multiple scenarios to look for the best optimization setting through sensitivity analysis. Finally, we apply the proposed model to the real test case of Luxembourg City.

Regarding the objectives of the evacuation process, the ultimate goal is to evacuate all people from hazardous zones as fast as possible. In other words, we are looking for a minimal network clearance time, considering the evacuees' utilities. We consider the SO objective for the shelter allocation without considering any attraction or individual preferences to shelter as evacuees have no information about these shelters [18]. We have also chosen Stochastic User Equilibrium (SUE) as the assignment principle to consider the heterogeneity in the users' decision-making process. In addition, UE is the special case of SUE in which users have no error in their decision-making process, i.e., users have a perfect knowledge of the network, which is not the case during an emergency period. Thus, we take into account this error with the SUE formulation. We consider two types of decisions that could be conflicting, SO for shelter allocation and SUE for traffic assignment. We compare the results of the proposed method with already used methods by multiple performance measures: mean evacuation time, network clearance time, and average travel delay. We also propose a new measure called *average evacuation travel delay*. It is noteworthy that our method considers a generic concept of risky areas following most of the models proposed in the literature, i.e., the model is independent of the hazard type [19].

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

II. LITERATURE REVIEW AND CONTRIBUTIONS

This section reviews the related works to the population evacuation problem in static and dynamic contexts. It reviews studies that use STA formulation for evacuation problems and then presents all studies in the dynamic context. Table 1 illustrates the results of the literature review. Here, we present the most advanced methodologies for the evacuation problem.

Many studies using STA models applied bi-level optimization to address SAP and traffic assignment problems with different objective functions [20]. The upper level formulates the shelter location-allocation problem to optimize the system's objectives, and the lower level represents the

traffic assignment in a static setting following the evacuee's interests. [21] used a p-median model to solve the problem of shelter site selection with a traffic assignment model under the SO principle and deployed a heuristic algorithm. [22] proposed a model to study the effect of shelter locations on evacuation management, taking into consideration the interest of system operators and evacuees. At the upper level, they defined the objective to minimize the total network evacuation time based on shelter allocation. The lower level represented the UE model that aims to minimize the individual travel time of each evacuee. The authors have solved the problem with a version of the genetic algorithm. [23] used the same formulation and solved the problem with a simulated annealing algorithm. [24] presented a scenario-based model. The upper level is a two-stage model. In the first stage, they determine the shelter location, and in the second stage, they choose the selected shelters, considering the hurricane conditions. They solve the STA problem at the lower level using the Lagrangian relaxation algorithm. [25] proposed a hybrid model based on scenarios in the central area of Beijing. The upper level makes location-allocation decisions such that the total evacuation distance is minimized subject to capacity and distance constraints. The lower-level model minimized the individual evacuation distance. They have used a modified particle swarm optimization algorithm with simulated annealing heuristics.

As mentioned in Section I, the main drawback of STA models is that they cannot capture the evolving state of traffic conditions [26]. In addition, the solution is calculated by heuristic methods due to the complexity of the bi-level formulation. Before reviewing the dynamic studies, we present recent studies that formulate the evacuation process as a single-level optimization problem. [5] formulated the evacuation problem as a single-level non-linear mixed-integer program. They have proposed a scenario-based approach to minimize the total evacuation time. The decision variables considered in this study are both shelter selection and route assignment variables. The authors propose an exact method based on second-order conic programming to solve the problem. They applied the methodology to a realistic Istanbul traffic network test case. In [10], they revised the formulation and solved it with Bender's decomposition approach. Note that many other studies in the literature addressed only one of the problems, either STA or SAP, for the evacuation problem (see Table 1).

To formulate the evacuation problem dynamically, multiple time-dependent variables should be considered, and consistent assumptions should be made. Due to this difficulty, many studies formulated population evacuation solving only one sub-problem in a dynamic context, either DTA or dynamic shelter allocation. For instance, [7] used DYNASMART simulator [27] to address the traffic conditions in the evacuation process with a given risky zone and shelter allocation plan. [28] coupled simulation and optimization to create an evacuation plan. They considered multiple stages for the iWays simulator with arc capacity penalties to simulate vehicles in departure time intervals. The model aims to minimize the total evacuation time and the sum of the arcs penalties. Besides, [29] came up with a multi-period optimization method including a status variable for the available network capacity, called productivity. They have used the TRANSIMS simulator to represent the evacuation process and solve the network UE problem. However, [30] confirmed that TRANSIMS had not received good exposure, and its capabilities are unknown to many researchers in the transportation field. [31] have used Matsim to solve simulation-based DTA considering UE conditions of the problem. Authors considered the city of north New Jersey and only one type of hazard (Hurricane). Note that all of the abovementioned research studies used given shelter allocation and performed only traffic assignment or solved DTA and SAP separately. This study aims to fill this research gap by combining and solving both simulation-based DTA and SAP.

Table 1 presents the characteristics of the evacuation planning method of 36 studies. We define seven categories to classify the papers. Some papers formulated the problem of shelter allocation as a facility location model by deciding how to allocate evacuees to shelters. Some other studies considered the traffic assignment problem only or with a given shelter allocation plan to decide the path distribution toward the destinations (shelters). When considering the traffic assignment sub-problem, we should also decide on multiple other factors, such as the static or dynamic setting of the problem and the analytical or simulation-based nature of the solving. In addition, we should decide on whether to assume the super sink principal or not. A *super sink* is an artificial node connected to all destination nodes through artificial links with infinite capacity. The objective function definition is also crucial in the mathematical model. Therefore, we present different objectives of the evacuation problem in the literature. Finally, we show the setting of our study compared to state of the art. As shown in Table 1, the evacuation process is tackled as a complex problem that is composed of different sub-problems. In each paper, the authors try to solve a sensitive and decisive part of the evacuation process.

Unlike the existing solutions, we propose a novel model to couple the SAP and the DTA problem in this paper. This model offers for the first time to formulate a fully simulation-based dynamic evacuation problem that integrates the decision of system operators to choose the best allocation of evacuees to shelters and evacuees' interests while choosing their routes to these shelters. Besides, we investigate the impact of the dynamic shelter allocation on network evacuation problems using agent-based simulations. Our framework considers the dynamic location-allocation model distinguished from most literature models that solve the problem in a static setting. The proposed model is multi-period and combines system operators and user needs. We also consider the problem with a realistic network of Luxembourg city without any assumption of super origin nor sink. Afterwards, we propose an iterative procedure to solve the problem for every time interval of the entire evacuation

TABLE 1. The sample of different studies on multi-class traffic assignment in the Literature.

Research	Problem		Objectives				Traffic Assignment		Traffic network		Research approach		Level of optimization		Super Sink
	Traffic assignment	Shelter allocation	Traffic assignment		Shelter allocation		Dynamic	Static	Trip based	Flow based	Analytical based	Simulation based	Single	Multilevel	
			UE or SUE	System optimum	Evacuees optimum	System optimum									
Lu et al., 2005 [32]	x		x				x			x	x		x		
Sbayti et al., 2006 [33]	x			x			x		x			x	x		
Balakrishna et al.,2008 [34]	x		x				x		x			x	x		
Yao et al.,2009 [35]	x			x			x			x	x		x		x
Xie et al., 2009 [36]	x			x				x		x	x			x	x
Kalafatas et al., 2009 [37]	x			x			x			x	x		x		
Xie et al.,2010 [38]	x			x				x		x	x			x	
Ng et al.,2010, [23]	x	x	x			x		x		x	x			x	
Ben-Tal et al.,2011 [39]	x			x				x	x		x		x		x
Bretschneider et al., 2011 [40]	x			x				x	x		x		x		x
Li et al.,2011 [41]	x	x	x			x		x		x	x			x	
Karoonsoontawong et al., 2011 [42]	x			x			x			x		x		x	
Lim et al.,2012 [43]	x			x			x			x	x		x		x
Liu et al., 2012 [44]	x			x				x		x	x			x	x
Duanmu et al.,2012 [45]	x			x			x			x		x	x		
Coutinho-Rodrigues et al.,2012 [46]		x				x		x			x		x		
Wang et al.,2012 [47]	x			x			x			x		x	x		
Li et al.,2012 [24]	x	x	x			x		x		x	x			x	
Goerigk et al.,2014 [48]	x	x		x		x		x	x		x		x		
Kılcı et al.,2015 [49]		x				x		x			x		x		
Lim et al.,2015 [8]	x			x				x		x	x		x		
Bayram et al.,2015 [5]	x	x		x				x		x	x		x		
Zhang et al.,2015 [29]	x		x				x			x		x	x		
Wang et al.,2016 [50]	x			x				x	x		x		x		
Heßler et al., 2016 [51]		x				x		x			x		x		
Liu et al., 2016 [52]	x		x					x		x		x	x		
Shahparvari et al.,2016 [53]		x				x		x			x		x		
Gama et al.,2016 [54]		x				x		x			x		x		
Gan et al.,2016 [28]	x			x			x		x			x	x		
Zhao et al.,2017 [18]		x				x		x	x		x			x	x
Bayram et al., 2018 [10]	x	x		x				x		x	x		x		
Shimamoto et al.,2018 [55]	x		x				x			x	x		x		
Zhu et al.,2018 [31]	x		x				x		x			x	x		
Yuan et al. 2019 [1]	x			x				x		x	x		x		
Escribano-Macias et al.,2020 [56]	x			x			x			x	x			x	
Tanaka et al.,2021 [57]		x				x		x				x	x		
This study	**x**	**x**	**x**			**x**	**x**		**x**			**x**		**x**	

horizon. In the next section, we formulate both problems and present our methodology.

III. METHODOLOGY

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

A. ASSUMPTIONS

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

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

B. OPTIMIZATION FRAMEWORK

The process of solving population evacuation planning comprises three main parts: the SAP problem, the DTA problem, and the traffic simulation. Here, we propose a new scheme for the sequence of execution of each step. We solve these steps in a time-dependent manner. In each period, we optimize all of these parts iteratively based on the data provided by the dynamic simulation until all the demand is satisfied. Recall that, according to state of the art, these steps are solved together using static traffic assignment models as a single-level optimization [5], [10], or bi-level programming problem originally proposed by [58] (see, e.g., [22], [23], [25], [59]).

In the dynamic setting, [7] proposed a dynamic evacuation framework with multiple time intervals wherein they considered the evolution of the network. They do consider the problem of risk assessment based on risk estimation; however, they do not address the SAP, i.e., the shelters are predetermined in their methodology. Their methodology is equivalent to solving the DTA under SO in multiple time intervals. Here, we also address the SAP in addition to the DTA using a simulation-based approach. Figure 1 presents the proposed methodology in this study.

The proposed framework consists of two loops that combine all three mentioned parts. The first loop, called the outer loop, represents the SAP under SO. The loop updates the network information needed by the SAP at each time interval. The second loop inside the outer loop addresses the simulation-based DTA. The solution method starts with initialization and solves the SAP for the first departure time interval. The results of the SAP are used as the input of the inner loop. The DTA calculation under SUE is started by the all-or-nothing assignment. Then the dynamic simulation is executed, and all users' travel times are updated. Afterwards, we check the convergence test for the SUE conditions (presented in the following subsection). If we do not converge, we reassign the users to the new paths based on a DTA optimization method and rerun the simulation.

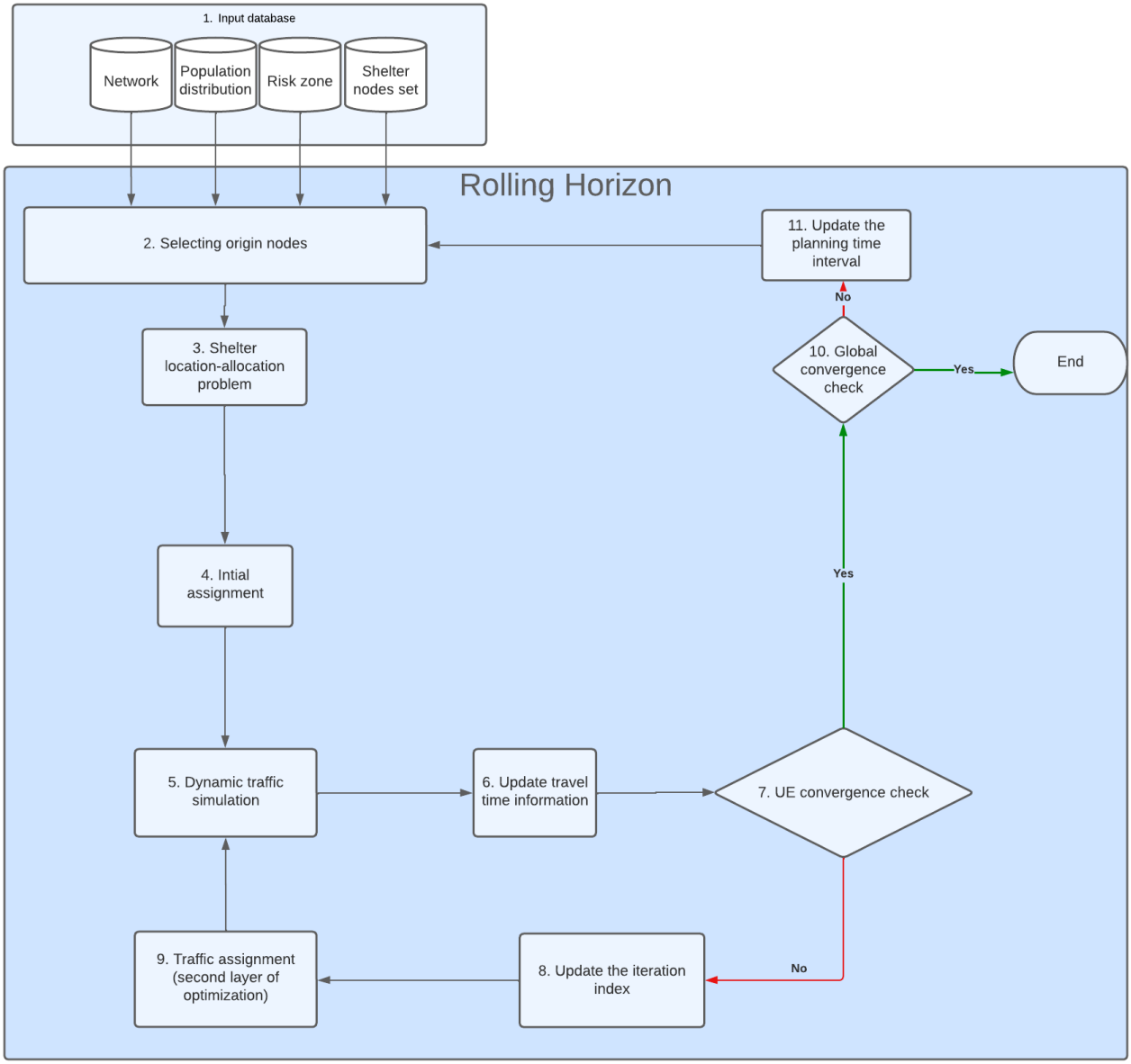


FIGURE 1. Flowchart of the process solving the evacuation problem.

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

C. PROBLEM FORMULATION

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

Let us define the evacuation problem on a directed graph representing a traffic network $G = (N, A)$, where N is the set

TABLE 2. Table of notations.

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

of nodes, A is the set of edges (links). We define O as the set of origin nodes that determines the risky zone to evacuate and S as the destination nodes representing safe locations, i.e., shelter sites. Without loss of generality, we assume that O and S are disjoint subsets of N ($O, S \subset N$; $O \cap S = \emptyset$). We denote by w_o the amount of demand of each origin o ($o \in O$). This demand represents the number of vehicles that should evacuate. We note x_{os} the integer decision variable that determines the number of evacuees allocated from origin o to destination s in the current time interval. y_s is a binary variable for the shelter selection. $y_s = 1$ if a shelter is selected ($x_{os} > 0$), otherwise $y_s = 0$. $t_{os}^{\alpha\,*}$ denotes the minimum travel time between origin o and destination s in time interval α. Table 2 presents this paper's full list of important notations.

A large number of studies in evacuation planning calculate travel time based on the STA using a convex travel time function, e. g., BPR function [60]. Here, we use a dynamic simulator to provide real-time information for the travel time. We used that information to solve SAP and DTA sub-problems sequentially (cf. Figure 1).

The finite period of interest is the planning horizon H defined as the total duration considered. This total duration is discretized into a set of small intervals of time, indexed by α ($\alpha \in T = \{\alpha_0, \alpha_0 + \eta, \alpha_0 + 2\eta, \ldots, \alpha_0 + M\eta\}$ and $\alpha_0 + M\eta = H$). η is the duration of the time intervals. At each evacuation time step α, we need to solve SAP for a given evacuation demand profile. In other words, we separate each two SAP problems by the index of the time interval (α). Then we solve the simulation-based DTA based on the results of SAP. Therefore, $t_{os}^{\alpha\,*}$ is defined as a time-dependent variable in this problem. At each time interval α, $t_{os}^{\alpha\,*}$ calculated by the simulator and replaced as a fixed value in Equation 1. This assumption transforms the model into a linear form. Thus, we can formulate it with linear integer programming. We define c_s^α as the capacity of shelter s in time interval α and P as the maximum allowable number of opened shelters. For simplicity, we do not use the time interval index for parameters and variables that are not updated by the dynamic simulator, e. g., x_{os} and w_o. First, we propose to solve SAP for each time interval α. The goal is to allocate evacuees to shelters for the minimum total evacuation time (TET) based on the currently observed travel times (from risky nodes to shelters). The p-median model is the most common approach to represent the shelter location-allocation problem under different types of hazards [61]. The model prioritizes efficiency and fairness over users' preferences by minimizing the overall evacuation time, equivalent to the SO optimization. We formulate the SAP based on the p-median model proposed by [62]. In the following formulation, the α is fixed to the current time interval when we are at Step 3 of the framework (cf. Figure 1).

$$\min \sum_{o\in O}\sum_{s\in S} t_{os}^{\alpha\,*} x_{os} \tag{1}$$

$$s.t. \sum_{s\in S} x_{os} = w_o; \quad \forall o \in O, \tag{2}$$

$$\sum_{o\in O} x_{os} \le c_s^\alpha y_s; \quad \forall s \in S, \tag{3}$$

$$\sum_{s\in S} y_s \le P, \tag{4}$$

$$x_{os} \le w_o y_s; \quad \forall o \in O,\ \forall s \in S, \tag{5}$$

$$x_{os} \ge 0; \quad \forall o \in O,\ \forall s \in S, \tag{6}$$

$$-\ y_s \in \{0, 1\}; \quad \forall s \in S. \tag{7}$$

The number P is a predetermined parameter that restricts the number of shelter sites that can open due to budgetary and management issues [4]. In Objective function (1), we minimize the total travel time of evacuees from all origins to all chosen shelters. Constraint (2) ensures that all the demand from origin o is evacuated. Constraint (3) forbids assigning evacuees to shelters exceeding the capacity of the shelter (c_s^α), taking into account the used capacity in the previous time interval $\alpha - 1$ [55]. Constraint (4) specifies a fixed number of open shelters. Constraint (5) forbids assigning evacuees to non-opened shelters. Constraints (6) and (7) represent logical variable restrictions. For each time interval, we are solving the above linear formulation where we use a fixed capacity

term that changes over time intervals. The residual shelter capacity denotes the effect of the arrival of users on shelters. This capacity is updated after the arrival of evacuees, and it is used afterwards in the next time interval based on the following formula $\forall s \in S$:

$$\begin{cases} c_s^{\alpha} = c_s^{\alpha-1} - \sum_{o \in O} x_{os} & \alpha \geq 1 \\ c_s^{1} = c_s^{0} - \sum_{o \in O} x_{os} \end{cases} \tag{8}$$

where c^0 is the initial capacity that shelters have at the beginning of the process. The presented model is an NP-hard problem [63]. The result of the SAP is the demand from each origin o to each shelter s, i.e., the OD matrix needed for the DTA model.

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

The SUE model is deployed to represent the network equilibrium. Because the UE principle, [64], always supposes that all users have perfect knowledge of the network information and consistently choose paths to minimize their travel costs. The assumption is so rigorous for users that it cannot hold on to a realistic scenario. The principle of SUE can further relax the assumption and be stated that all travelers cannot improve their perceived travel cost by unilaterally changing paths [65]. Based on the SUE principle, the perceived travel cost can be expressed by the actual travel cost and a random error for each traveler as follows:

$$\hat{t}_{tr,\pi}^{\alpha} = t_{tr,\pi}^{\alpha} + \xi_{tr,\pi}^{\alpha}, \quad \forall \pi \in \pi_{os},\ \alpha \in T,\ tr \in Tr_{\pi}^{\alpha} \tag{9}$$

The C-logit SUE condition on the road network is expressed as follows for each departure time interval (α) [65]:

$$Tr_{\pi} = x_{os} pr_{\pi}, \quad \forall \pi \in \pi_{os} \tag{10}$$

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

In the simulation-based DTA, we tend to attain the SUE state at each departure time interval so that each vehicle could not reduce their trip travel time by changing the chosen route. To achieve this condition, we iteratively run both phases, optimization and simulation. The optimization determines the route choice of vehicles, while in the simulation part, we simulate the trajectories on paths by executing a dynamic simulation of vehicles taking specified routes. The model used to assign users to the route is the C-logit mechanism [66].

The C-logit model is based on the logit model [66] with the assumption that all route alternatives travel times are identically and independently distributed Gumbel variates [13]. C-logit presents a probability pr_{π} for selecting path π. The formula is shown below:

$$pr_{\pi} = \frac{\exp\left[\theta \cdot (t_{\pi} - CF_{\pi})\right]}{\sum_{h \in \pi_{os}} \exp\left[\theta \cdot (t_h - CF_h)\right]} \quad \forall \pi \in \pi_{os} \tag{11}$$

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

$$CF_{\pi} = \beta_0 \ln \sum_{h \in \pi_{os}} \left[\frac{ID_{h\pi}}{t_h^{0.5} \cdot t_{\pi}^{0.5}} \right]^{\gamma} \tag{12}$$

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

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

In this section, we presented our methodology to solve the evacuation problem. As mentioned before, simultaneously finding the optimal solution for both problems (SAP and DTA) is hard to achieve, so indicators are required to measure the distance between the found solutions and the optimum.

D. SOLUTION QUALITY INDICATORS

In this section, we define the metrics that we use to evaluate the optimality of our solution and monitor the network performance. The first metric we use to compare the quality of solutions is the network clearance time. We define the clearance time as the arrival time of the last evacuee to his shelter. This metric gives us information about the total duration of the evacuation process. Note that the best solution method provides the minimum clearance time. The second metric we use is the mean evacuation time, defined as the average travel time of all evacuees. The third metric we consider is the mean waiting time calculated for each vehicle, defined as the amount of time the vehicle speed was less or equal to 0.1 m/s. The fourth metric we consider is the network speed, which is the mean speed of the network on all simulation time steps, to quantify the network usage [67].

To evaluate the quality of the DTA solution, we define the average travel delay (ATD), which is the mean amount of

delay compared to the best evacuee of each *OD* pair [16].

$$ATD = \frac{\sum_{\alpha\in T}\sum_{o\in O}\sum_{s\in S}\sum_{\pi\in\pi^{\alpha}_{os}}\sum_{tr\in Tr^{\alpha}_{\pi}} t^{\alpha}_{tr,\pi} - t^{*}_{os}}{\sum_{o\in O} w_o} \tag{13}$$

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

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

$$AETD = \frac{\sum_{\alpha\in T}\sum_{o\in O}\sum_{s\in S}\sum_{\pi\in\pi^{\alpha}_{os}}\sum_{tr\in Tr^{\alpha}_{\pi}} t^{\alpha}_{tr,\pi} - t^{*}_{o}}{\sum_{o\in O} w_o} \tag{14}$$

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

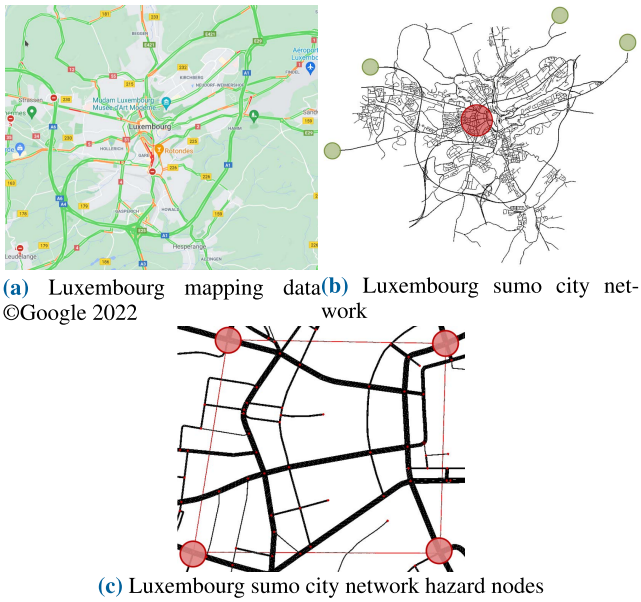
IV. NUMERICAL EXPERIMENTS AND RESULTS

The previous section presented our framework to solve the agent-based population evacuation problem with dynamic shelter allocation. In this section, we apply the methodology to a real network to validate our solution method.

A. CASE STUDY

We implement our framework for the scenario [68], representing the city of Luxembourg (cf. Figure 2). We base the demand profile on synthetic data of the evacuation scenario. To include the simulator in the optimization process, we implement the rolling horizon approach [69]. To solve the simulation-based DTA problem, we use the SUMO simulator with its C-logit optimization function [17]. We set the simulation time-step to 1 second. In addition, to tackle the shelter location-allocation problem, we employ ILOG CPLEX version 12.9. We performed all simulations on a personal computer with 1.7 GHz and 16 GB of RAM.

Figure 2 presents the network of Luxembourg with the size of 155.95 km^2 and the traffic network graph considered by SUMO for dynamic simulation. We examine a hypothetical threat in the center zone affecting people of the region colored in red (cf. Figure 2b). While the origin nodes are in the same area, we do not assume a super origin (source) node. We consider multiple origin nodes as evacuation sources in the risky zone, as described in Figure 2c. Vehicles carrying



(a) Luxembourg mapping data ©Google 2022 **(b)** Luxembourg sumo city network

(c) Luxembourg sumo city network hazard nodes

FIGURE 2. Evacuation network map.

people should be evacuated to the shelters, colored in green in Figure 2b, located at the network's periphery. In this evacuation context and without a loss of generality, the S-shape response curve model is employed based on [70] with its parameter $\alpha = -0.005$ and $\beta = 15$ for the departure time of each evacuee. We have set each departure time interval (λ) to 5 minutes for the simulation. The demand at each node is 200 vehicles at each period. We consider four origin nodes selected and four shelters, each with the capacity of holding 1500 evacuees. Therefore, the total demand is 600 vehicles per origin for the planning horizon H.

B. SIMULATION-BASED OPTIMIZATION SCENARIOS

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

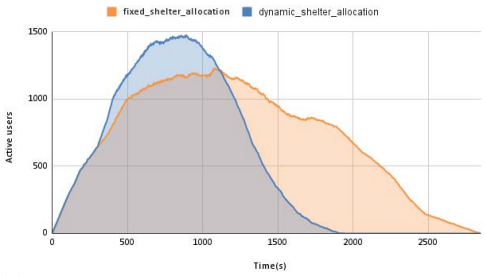
- **Dynamic shelter allocation:** This scenario includes our proposed framework (illustrated in Figure 1). It sequentially solves the shelter allocation and the traffic assignment coupled in a loop at multiple time intervals.
- **Fixed shelter allocation:** This scenario represents one of the advanced existing approaches to address the evacuation problem in the literature via DTA (proposed by [7]). In each departure time interval, the DTA problem is solved without modifying the choice of shelters. Note that several studies choose the shelters based on euclidean distance or network distance, which is not realistic compared to this setting as they do not consider the network's characteristics, e.g., road capacities.

C. NUMERICAL RESULTS

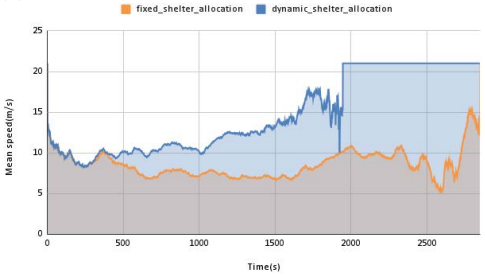
This section presents the results for the two scenarios mentioned above—both scenarios run with the same evacuation

TABLE 3. Performance metrics.

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



(a) Number of active users in the network variation



(b) Network mean speed variation

FIGURE 3. Performance measures variation.

demand profile, source nodes, and shelter set. We measure multiple performance indicators to evaluate the efficiency of the solution method in each scenario. We use the metrics defined in the subsection III-D. Table 3 presents the indicators values for the two scenarios. The results show a significant improvement in the quality of the final solution obtained by our model compared to the fixed shelter allocation scenario. For instance, we reduced the network clearance time by 15 minutes (31%). It means that the dynamic allocation of evacuees to shelters, considering the network congestion, improves the evacuation process. The high congestion level around shelters during the evacuation could explain this difference. With the fixed shelter plan in all time intervals, we observe a higher congestion level in paths leading to these shelters. However, solving the dynamic allocation problem ensures that we assign evacuees to the shelters based on the time-dependent shortest path and not the closest shelters by distance or free-flow travel time.

Moreover, the reduction of mean evacuation time in Table 3 confirms that the dynamic allocation improves the evacuation planning solution. In addition, it also provides better AETD for evacuees. The improvement amount is even higher for ATD, 39%, which shows that the DTA solution of our method is closer to the SUE solution.

Figure 3 illustrates the results graphically, comparing the two scenarios in terms of active users in the network (Figure 3a) and network mean speed variation (Figure 3b).

Figure 3a presents the evolution of the number of vehicles evacuating in the network. The network is initially empty; thus, we have the same solution for the SAP for both scenarios for the first time interval. Then the two curves are separated because we have different shelter allocation approaches. In addition, the curve representing our method arrives at the final state of zero running vehicle before the second curve, proving that the network clearance time is decreased compared to the other method.

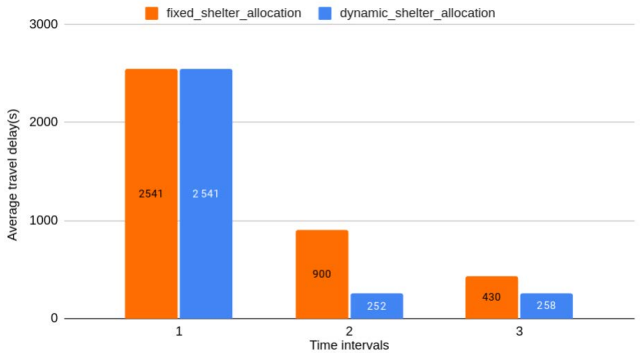
Figure 3b presents the evolution of the mean speed in the evacuation process. The network's maximum speed is equivalent to the mean free-flow speed (75.6 km/h). At the beginning of the evacuation, the speed curve is the same because the two scenarios had the same solution in the first time interval. After that, the speed increases considering dynamic shelter allocation and stays higher than fixed shelter allocation until the end. It means that the dynamic shelter allocation scenario uses the network's capacity better than fixed shelter allocation and finishes the evacuation process faster. The network speed for the dynamic allocation scenario (blue curve in Figure 3b) varies a lot at the end of the evacuation process. The multiple queues formed at the entrance of the shelters but rapidly cleared explain this variation.

We illustrate in Figure 4 the variation of ATD and AETD measures and the number of arrived vehicles over time intervals to capture the differences between the two scenarios. Most studies use *ATD* to characterize the found solution of DTA under SUE principles. *ATD* could be seen as the mean distance between the travel time of users and the minimum travel time of that OD pair. Figure 4a illustrates the evolution of this measure over time intervals. The difference in *ATD* between the scenarios becomes more significant in the second time period, indicating that having flexible shelter allocation offers evacuees the possibility to reduce their travel time by changing their choice of destination.

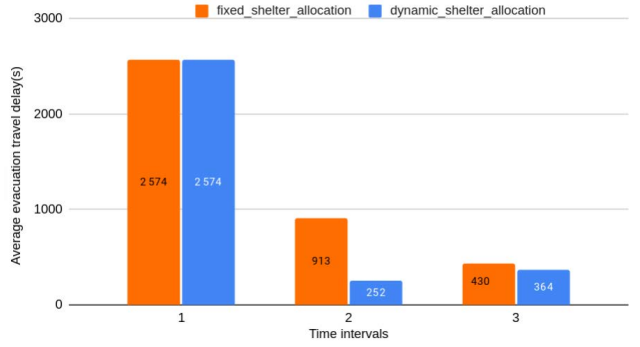
Figure 4a presents *AETD* variation over time intervals. Recall that the main difference compared to *ATD* is that the user evacuation delay is calculated w.r.t minimum evacuation time of all users from the same origin. In other words, we compute the average difference between the travel time of each user and the shortest travel time having the same origin node. Similar to Figure 4a, *AETD* has the same shape as *ATD*. This proves that our method is better than the second method, even for the destination-free measure.

Figure 4c compares the number of evacuees that arrived at shelters at each time interval. Our method evacuates vehicles faster than the second scenario by using the remaining capacity of the network. That is why, in dynamic shelter allocation, more evacuees finish their travel in the second interval.

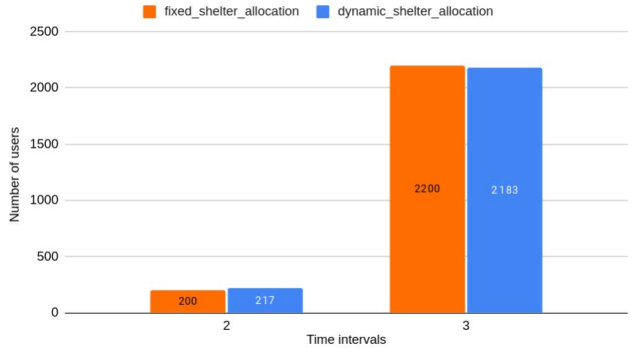
Moreover, we measure the computation time for each optimization scenario (see Table 4). The results show no significant difference between the two scenarios, so the dynamic



(a) Average travel delay variation



(b) Average evacuation travel delay variation



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

FIGURE 4. Delay and number of arrival measures variation.

shelter allocation optimizer does not require a long calculation time. Note that the shelter location-allocation is a simple linear formulation solved with the branch and bound technique. In Table 4, the computation time of the shelter allocation is defined only for the first scenario because the second scenario does not consider it. Note that a small difference in the DTA calculation is due to the probabilistic nature of the C-logit model. The computation time needed for DTA calculation in the second stage is lower because the SAP generates a less computationally expensive allocation for the DTA simulation.

As shown in Table 4, the major part of the computation time is the DTA calculation. Therefore, it is worth performing a sensitivity analysis on DTA iterations because the number of iterations directly impacts the computation time.

TABLE 4. Computation time of the solution methods.

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

TABLE 5. The impact of the number of DTA iterations on the final solution.

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

D. CONVERGENCE ANALYSIS

This section analyzes the effect of the convergence test threshold, i.e., the impact of changing the maximum number of iterations in the DTA calculation on the final solution. We conduct our comparison based on performance measures used in subsection IV-C. Table 5 presents the results. As expected, the ATD is minimized in addition to the AETD and the mean evacuation time. However, the network clearance time oscillates in the value of measures for many iterations (20 or 30). We expected this oscillation because the optimizer aims to achieve the SUE, not the SO. Therefore, our algorithm minimizes the individual travel time, which may affect the whole system's performance. Table 5 shows that by increasing the number of iterations to search for the optimal solution for the SUE, we decrease the network production factors. From these results, we can conclude that if we fix the number of iterations to 20, we could have a good evacuation plan for this test case from both points of view: users and the system.

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

E. SENSITIVITY ANALYSIS ON THE ROLLING HORIZON APPROACH

In our methodology, we use a rolling horizon approach for DTA solving. The idea behind this approach is to use currently available information and near-term forecasts with some degree of reliability to solve the assignment problem [69]. We consider simulation time intervals responsible for acquiring the near-term forecast of traffic evolution and optimization time intervals for optimizing the current assignment problem. This section evaluates the influence of the simulation duration and the optimization time intervals on our optimization framework. First, we capture the impact of simulation time intervals on the effectiveness of the

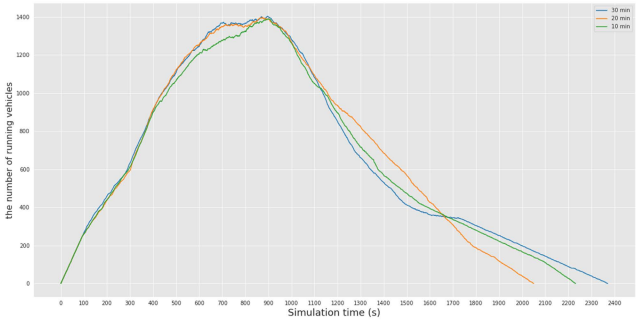


FIGURE 5. Active users for multiple simulation time intervals.

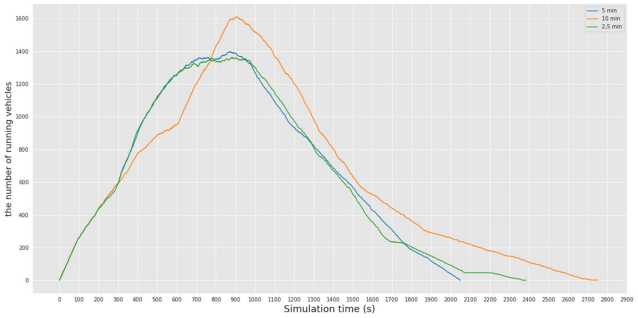


FIGURE 6. Active users for multiple optimization time intervals.

population evacuation process while we fix the optimization time interval. Second, we illustrate the influence of optimization time interval variation on the efficiency of the process. Third, we highlight the most reasonable values for the duration of time intervals for the rolling horizon configuration.

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

Having a long simulation period (e.g., 30 minutes time intervals) is inefficient in terms of needed computational resources when considering people under evacuation conditions. On the other hand, short simulation time is not beneficial either since it does not give the vehicles of the current stage enough information about future events to optimize their trips. Therefore, finding the appropriate duration for the simulation time interval is crucial. Figure 5 illustrates the impact of simulation time interval on the evacuation duration and network usage. It presents three curves for three different values of the simulation time interval 30 (blue), 20 (orange), and 10 (green). Figure 5 specifies that there is a remarkable effect, especially on clearance time measure. There is an increase in network clearance of more than 5 minutes between the blue and the orange curve. This figure also demonstrates that it is not beneficial for evacuation to take long simulation time intervals. The network clearance time, our global objective, is higher when simulating 30 minutes than 20 minutes. In Figure 5, in the range between 1200 sec and 1700 sec, the scenario with 20 min (orange curve) benefits from the network's capacity compared to other scenarios, and it leads to better results in terms of clearance time.

For the second part of the analysis, we conduct multiple simulations, varying the optimization time interval and fixing 20 minutes for simulation and 5 minutes for departure time. Figure 6 depicts the effect of the optimization time interval variation on the number of active users in the network and the impact on the clearance time measure. The figure points out that fixing the optimization interval to 5 minutes provides the minimum clearance time compared to the other curves. Indeed, having a short optimization time, such as 2.5 minutes, needs more computation resources. It also prioritizes users from the first and second departure time interval to optimize their utilities. On the other hand, the users in the third time interval cannot achieve a comparable value for their objectives compared to the other users. Because after the two first intervals, the evacuees experience a long ending queue (after 1500 sec).

In addition, the long optimization interval (10 minutes) leads to having a longer clearance time than 5 minutes interval. We expected this effect because if users are not assigned well due to the network dynamics in the previous time interval, we must wait for another 10 minutes to revise the optimization solution. Figure 6 highlights this point between 300 sec and 800 sec, where the two other curves are above the orange curve. We conclude that the best simulation time interval for this test case is 20 minutes and the best optimization interval is 5 minutes.

F. REAL CASE STUDY

The proposed framework is applied to a more extensive demand profile to address a realistic population of Luxembourg city. We conducted the simulation with the best parameters of the optimization framework specified in the previous subsections. We consider 60,000 vehicles, which represent 70% of the actual population of Luxembourg City (125, 000 inhabitants [71]). Note that a vehicle carries a maximum of three individuals to evacuate [72].

Increasing the evacuation demand level significantly affects the simulation duration. We consider the fixed shelter allocation methodology to benchmark our solution method in the real test case. Table 6 shows that solving shelter allocation dynamically improves the efficiency of evacuation planning. Table 6 illustrates a reduction of more than 9 hours in network clearance time, and the mean evacuation time decreases by 49% between the two methods of solving the problem. In addition, mean waiting time and mean speed are two measures that allow us to monitor the speed of the evacuation process. Lower values of these measures mean that solving SAP in each time interval provides a better solution. The comparison between the final solutions shows that around 15% of

TABLE 6. Real case performance metrics.

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

the evacuees (more than 10, 000) have different destinations. It means our framework switches the evacuees' destination to the other rapidly reachable shelter (less congestion in paths leading to new shelters). Thus, the shelter allocation allows us to revise the current shelter allocation plan for a new one that considers the evolving state of the network.

V. CONCLUSION

Catastrophes threaten the entire population of the devastated areas and put them in high-risk situations. Evacuating people from risky zones to safe areas is one of the urgent tasks that should be done to avoid life losses caused by these disasters. Each evacuee must determine the destination (shelter) and evacuation path from hazardous areas as quickly as possible. This paper focuses on solving the population evacuation problem to determine these two pieces of information.

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

To solve the evacuation problem dynamically, we have considered multiple departure time intervals by allocating shelters under the SO principle and assigning routes in the SUE manner. To couple the two problems, we consider the network dynamics in solving the SAP. We determine actual vehicle evacuation time using a trip-based dynamic simulator that provides the travel information every timestep. We apply our methodology to the network of Luxembourg City and compare it with a model using a fixed shelter allocation plan. The results show that the proposed model outperforms the model with the fixed shelter plan by more than 31% reduction in network clearance time. We conclude that using dynamic allocation improves the evacuation process because it provides the optimal evacuation plan considering the dynamics of the network. Besides, the analysis of the computation time shows that solving the SAP in each time interval needs tiny computational resources, while it significantly reduces the duration of the evacuation process. The second main finding of this study is that we can benefit from the capacity of the traffic network by using dynamic shelter allocation (Figure 3).

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

Several research directions will guide our future proposals. First, we aim to evaluate our framework performance in different real network evacuation scenarios. Second, we plan to extend the current framework to include safety instructions and objectives based on different types of hazards. Finally, we consider addressing multiple hazard zones by mimicking the hazard evolution.

TABLE 7. Convergence iterations.

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

APPENDIX

IMPACT OF THE MAXIMUM DEVIATION ON RESULT

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

$$a = \frac{\sum_{o\in O}\sum_{s\in S}\sum_{p\in\pi_{os}} t_{tr,\pi}}{\sum_{o\in O}\sum_{s\in S} n(\pi_{os})} \tag{15}$$

$$CV = \frac{\sigma(a)}{E(a)} = \frac{\sqrt{\frac{1}{Nr}\sum_{i\le Nr}(a_i - \sum_{i\le Nr}\frac{a_i}{Nr})^2}}{\sum_{i\le Nr}\frac{a_i}{Nr}} \tag{16}$$

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

Table 7 shows the time difference between the tree solution calculated. Having better results in terms of deviation requires surely more iteration calculation and more consumed resources. We have set 50 iterations as the maximum number of iterations to find the result, and we attain this limit while having the maximum deviation of 0.004. In addition, Table 7 demonstrates no linear relation between the amount of computation time needed for solution finding and the deviation measure. Results shown by Table 7 are only for the last time interval of the evacuation process.

CONFLICT OF INTEREST

The authors declare no potential conflict of interests.

AUTHOR CONTRIBUTION STATEMENT

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

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