Multiple Intelligent Control Strategies for Travel-Time Reduction of Connected Emergency Vehicles

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***Abstract*— Travel-time reduction is a primary objective for managing connected emergency vehicles (CEVs) to save people's lives or put out a fire. With the integrity of internet of things (IoT) and connected autonomous vehicles (CAVs), it has been a research challenge to find a safe, reliable, and optimal strategy that not only minimizes the CEV's travel time but also lessens the undesirable side-effects on other road users. This article introduces multiple intelligent control strategies in one framework to boost the potential of CEVs traveling via multiple traffic intersections. The framework includes a path-planning mechanism adapting to sudden traffic delays, traffic signal preemption controller adapting to the urgency level associated with the emergency event, and a deep-learning model for CAVs to predict the time required for giving way to the CEV. All modules are implemented through a microscopic traffic simulation environment (PTV-VISSIM). This article holds significant implications for various scenarios involving CEVs and intelligent transportation systems (ITS). The path planning approach showcased notable improvements, reducing average path travel time by 9% when compared to existing benchmarks. The regression error for predicting the merging time of CAVs is minimized to be 0.4 second. Furthermore, the signal preemption controller demonstrated an important trade-off analysis between the level of intrusive preemption signal control and the undesired impacts on the traffic network. This finding enables traffic management authorities to make informed decisions regarding signal preemption strategies, considering both the travel time optimization for CEVs and the potential network-wide traffic impacts.**

***Index Terms*— Intelligent transportation, emergency vehicles, CAVs, signal preemption, dynamic path planning.**

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I. Introduction

Along with the recent advances in intelligent transportation systems (ITS) and connected autonomous vehicles (CAVs), one of the most important road users is connected emergency vehicles (CEVs) [1], [2], [3]. CEVs play a crucial role in saving lives by minimizing post-shock impacts and preventing cascading effects. The operation of the emergency vehicle requires safe passage, minimum response time, and least undesired traffic impacts. The probability of crashes occurrence is higher for CEVs due to the high speed and rush behavior they perform [4]. Travel time is a dominant key for a CEV to reach its destination on time. For instance, in London, an ambulance saves about 250 patients' lives per year due to the fast response to reach destinations [5]. Due to its vital role, some governments have set ambitious plans to make the arrival time of CEVs within a specific amount of time (e.g. 10 minutes) [6]. Therefore, novel control designs that utilize the potential features of ITS environment are required to improve the performance of CEVs.

The field of ITS is constantly evolving [7], and there are several recent techniques aimed at reducing travel time for CEVs [8], [9]. For example, the traffic signal preemption technique allows emergency vehicles to request priority at signalized intersections involving vehicle-to-infrastructure (V2I) technology, where CEVs can communicate with traffic signals to receive green light prioritization [6], [10], [11], [12]. Moreover, dynamic route guidance systems use real-time traffic information to dynamically adjust the route of CEVs based on traffic conditions [13], [14]. Considering congestion levels and identifying the fastest available route, CEVs can be directed to the most efficient route. Another novel technique is to design exclusively dedicated lanes for CEVs that can greatly speed up their travel time [15]. These lanes can be physically separated from regular traffic or temporarily allocated during emergency situations, allowing CEVs to bypass congestion and reach their destinations more quickly [16]. Furthermore, advanced machine learning techniques are employed to predict traffic patterns and optimize emergency vehicle routes accordingly [17]. By analyzing historical and real-time traffic data, these techniques can identify the most favorable routes and adjust them in real-time to avoid congestion and reduce travel time.

The primary aim of dynamic path planning for CEVs is to minimize travel time, making it a time-dependent problem that can be solved using many approaches [13], [14], [18]. Many scholars have formulated the problem as a directed graph search problem such as [18], [19], and [20]. To our knowledge, most algorithms are based on Dijkstra [21] or even other versions of it [22], [23]. Another common graph search algorithm is A* [24], which utilizes a heuristic function to accelerate the path-search process. Most of these search algorithms rely only on historical data [13] of the traffic they receive from web mapping platforms such as Google maps [25]. However, these data are not real-time data and expose the CEV to inaccurate information which could lead to undesirable delays. Consequently, there is a need for the integration of planning and real-time response for emergency medical services (EMS) within an ITS environment, utilizing V2I and vehicle-to-everything (V2X) technologies for event detection and data sharing to receive immediate traffic data, allowing the generation of adaptive plans for CEVs. In contrast, navigation apps such as Google Maps rely on crowdsensing data, resulting in longer estimation times until correct estimations are obtained.

In addition, traffic signal preemption for emergency vehicles is a system that allows them to override normal traffic signal operation and gain the right of way at intersections, ensuring their swift and safe passage to respond to emergencies such as the approaches proposed in [10], [26], and [27]. The effectiveness of these algorithms improved the operation of the CEV travel time. The algorithms are classified into two types, intrusive [10] and non-intrusive [28]. The intrusive signal preemption is the one that gives priority to the CEV regardless of the undesired impacts on the traffic network. The other type, namely non-intrusive signal preemption, tries to modify the traffic cycle length to smooth the traffic when the green phase is given to the CEV. Although these algorithms achieved the desired performance, a gap arises due to the lack of a soft technique that selects a proper preemption technique depending on the emergency level. For instance, if the emergency level is very high, then an intrusive technique can be utilized. If the emergency level is low, then a non-intrusive technique will be desired. However, if the emergency level is moderate, then a new technique is required to generate an amount of intrusiveness relevant to the emergency level.

Additionally, the cooperation between CAVs and emergency vehicles involves leveraging the capabilities of CAVs to facilitate the rapid and safe movement of emergency vehicles through traffic and improve emergency response times [29], [30]. The "give-way" behavior requires the cooperation of the road vehicles to give way to the CEV. In [31], the authors proposed a mathematical model for platooning vehicles to give way to the CEV. Nguyen et al. [18] proposed a macroscopic approach to give way by lanes merging to keep a lane empty for the CEV. One research problem is that the time required for vehicles to execute the merging behavior might be too long and worsen the other vehicles' performance. Consequently, there is a mandate for developing a predictive tool capable of making proactive decisions regarding the execution of lane merging. This tool would utilize information pertaining to the positions and conditions of road vehicles to determine whether it is appropriate or safe to proceed with the merging maneuver.

The literature gaps can be summarized as follows 1) Although most graph search algorithms for the CEV have relied on historical data from mapping platforms that may not always be real-time, advances in communication technologies now allow the integration of real-time traffic data. Despite these capabilities, there is an ongoing need to develop approaches that can fully utilize real-time data to minimize the CEV's travel time and adapt more dynamically to sudden changes in traffic conditions. 2) Traffic signal preemption still requires better designs that relate the urgency of an event with the intrusiveness level of the preemption technique. 3) To make the CAVs give way to the CEV, there is a mandate for a predictive tool that provides a prior decision on whether to execute the lane merging or not based on the location and state of the vehicles. Table I summarizes the gaps in the state-of-the-art relevant literature on optimizing CEV's travel time compared with our proposed solution.

The integrated system presented in this article addresses the CEV problem through the incorporation of dynamic path planning, signal preemption, and give-way strategies. Leveraging recent advances in ITS, the contributions of this study can be summarized as follows.

1) A dynamic path planning algorithm is developed, utilizing both historical and real-time traffic data to adaptively respond to sudden traffic conditions and delays.
2) A preemption signal technique is introduced that incorporates a selection mechanism for the appropriate controller based on the emergency level. A novel controller is proposed that combines intrusive and non-intrusive signal preemption within a single module.
3) A deep learning system is employed to accurately predict the merging time required for vehicles to create an empty lane for the CEV.

These contributions collectively improve the efficiency and effectiveness of CEV operations in the ITS environment.

The rest of the article is organized as follows. Section II introduces the problem description associated with the solution architecture. Section III formulates and solves the queue discharge time model. The dynamic path planning algorithm is proposed and analyzed in Section IV. Section VI formulates the intrusive and non-intrusive signal preemption control and validates the signal preemption control in a case study. Section V presents the deep learning model for predicting the merging time of CAVs. Finally, the article is concluded in Section VII.

II. Problem Statement and Solution Overview

In this research problem, there is a CEV such as an ambulance, police car, or fire truck in a smart traffic network where there are multiple connected traffic intersection nodes [3], [18]. The CEV belongs to a starting node and aims to reach a destination which may be a hospital or a fire station, as seen in Fig. 1. Each traffic intersection node in the traffic network is connected to the Traffic Control Center (TCC), which receives the instant location of the CEV and its destination. Then,

TABLE I
STATE-OF-THE-ART RESEARCH WORK IN OPTIMIZING THE TRAVEL TIME OF CEVS COMPARED WITH OUR PROPOSED FRAMEWORK[1]

Ref.	Dynamic path planning	Adaptive queue discharge	Signal preemption	Give-way	Consider network impacts	Research Gap
[18]	✓	✗	✓	✓	✗	Gap 3 & Gap 4
[10]	✗	✗	✓	✗	✓	Gap 1 & Gap 2 & Gap 4
[32]	✗	✗	✓	✗	✓	Gap 1 & Gap 4
[31]	✗	✗	✗	✓	✓	Gap 1 & Gap 2
[28]	✗	✗	✓	✗	✓	Gap 1 & Gap 4
[3]	✗	✓	✓	✗	✗	Gap 1 & Gap 4
[33]	✓	✓	✗	✗	✗	Gap 3 & Gap 4
						Main Contributions
Ours	✓	✓	✓	✓	✓	Dynamic path planning tailored with urgency-adaptive signal preemption mechanism considering traffic network impacts in addition to the give-way model for CAVs.

[1] Gap 1: Dynamic path planning is not tailored with adaptive signal control in an ITS environment, Gap 2: The signal preemption mechanism is not adaptive to multiple urgency levels, Gap 3: Not considering the undesired traffic network impacts, and Gap 4: The give-way prediction time is not included and is not integrated with all other modules.

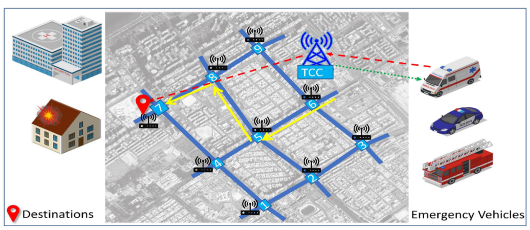

Fig. 1. Illustration of typical multiple intersections with CEVs.

the TCC generates a comprehensive plan that minimizes the travel time of the CEV with the least undesired traffic network impacts depending on the emergency level.

Initially, the CEV proposed research problem is divided into multiple sub-problems, which results in three primary modules, namely, path planning, traffic signal preemption, and give-way. The path planning module receives the current location of the CEV, the destination of the CEV, and the traffic intersection map in a graph format where the graph nodes are traffic intersections. Then, the shortest-time path is computed considering traffic delays and congestion of each path utilizing a queue discharge prediction model. The research gap we are addressing concerns the integration of planning and real-time response for EMS within an ITS environment where events can be detected from roadside units or traffic cameras, leveraging V2I and V2X technologies. In this domain, traffic data are shared with the proposed TCC, enabling the generation of an immediate adaptive plan for the CEVs. By focusing on the integration of planning and real-time response within the ITS environment, this research aims to optimize EMS operations by harnessing the benefits of the V2I and V2X technologies. The TCC plays a crucial role in the rapid generation of adaptive plans for CEVs based on real-time traffic data, ensuring a more efficient and timely response to emergencies.

The traffic signal preemption controller deals with the traffic intersection controllers. It preempts the traffic signal for the CEV follows specific criteria that will be mentioned later. Finally, the give-way module controls the CAVs exist in a

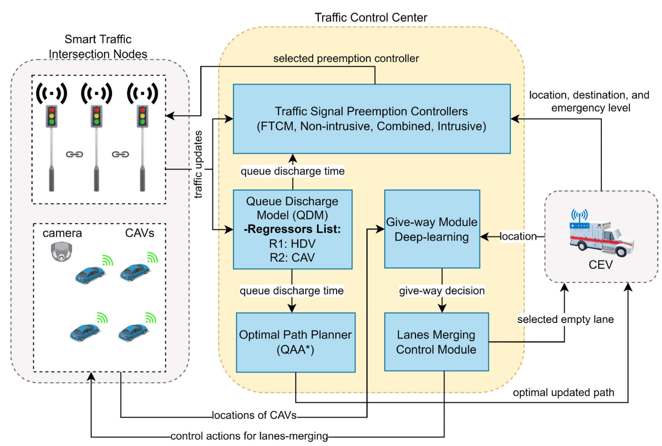

Fig. 2. Proposed architecture for optimizing the operation of CEVs in an intelligent transportation system.

road segment to merge in one lane and reserves an empty lane for the CEV only if the predicted merging time, which is computed from a deep learning model, is feasible.

The overall system architecture is illustrated in Fig. 2. The main blocks in the proposed system are:

- Smart traffic intersection nodes: In this block, multiple connected nodes send and receive data with the TCC (TCC). They send traffic updates such as the lengths of the traffic queue, the signal timings, and the IDs of the CAVs connected to each node.
- Traffic Control Center (TCC): This block has numerous modules that have controllability in the intersection nodes, the CEV, and the CAVs in the traffic network. The modules are: 1) Traffic signal preemption controllers: This module selects the optimal preemption technique based on various parameters such as queue discharge times, CEV location, destination, and emergency level. 2) The queue discharge time module: It selects the linear regression model based on the type of vehicles on the road link. Two types are introduced, HDVs and CAVs. 3) The optimal path planner: It receives the queue discharge

time and generates the optimal path in terms of arrival time. 4) The give-way model: It receives the location of vehicles on one road link. Then, a deep learning-based system predicts the merging time for the CAVs in that link. 5) Lanes merging control module: It receives the decision from the give-way model and executes the merging behavior on the CAVs. This research aims to integrate the unique capabilities of CAVs and CEVs to enhance the effectiveness of TCC-based optimization, specifically in the context of emergency response and traffic management. By leveraging the capabilities of CAVs and integrating them into the optimization process, our goal is to improve the efficiency, safety, and response time of emergency vehicles.
- CEV: It sends its current location, destination, and emergency level and it receives the optimal path from the TCC.

In the proposed framework, we assume the availability of V2I and V2X communication technologies to enable real-time data exchange between CEVs and the TCC. This allows for efficient real-time monitoring and optimization of traffic signals based on the dynamic locations of the CEVs. We recognize the challenges in deploying a large-scale communication network, but assume that a robust infrastructure is in place to support these needs effectively. The choice of technology depends on the communication range, data requirements, reliability, and availability of the infrastructure. For instance, some specific technologies can be established to achieve the connectivity purpose such as Dedicated Short-Range Communications [34], Cellular Vehicle-to-Everything [35], 5G technology [36], or Wi-Fi protocols such as IEEE 802.11p for high data rates [37].

A. Configuring Driving Behavior Parameters

In this subsection, an explanation is provided for the driving behavior parameters used to represent the vehicles in the proposed environment setup within the PTV-Vissim microscopic traffic simulation. In particular, three different vehicle types are introduced, namely HDVs, CAVs, and CEVs, each characterized by different driving behaviors.

To gain insight into the overall performance of a traffic network that could include HDVs, CAVs, and CEVs, it is crucial to evaluate the performance on a macroscopic level. This requires utilizing a driving behavior model that can capture the behavior of all vehicle-types together but with differentiated levels of features in a high-level fashion. To simulate these driving behaviors, the Wiedemann-74 model, as described in [38], is adopted, as this model successfully mimics human driving behavior by making use of perceptual thresholds concerning relative distance and speed between pairs of vehicles in leader-follower scenarios, with the driver taking action only when these thresholds are reached. The reason for choosing the Wiedemann-74 model as a base for simulating other vehicle types is that it is a well-established car-following model extensively validated against real-world traffic data [39]. In addition, it has the ability to realistically simulate driver behavior through different driving regimes such as free driving, approaching, following, and braking, and

TABLE II
THE CONFIGURED PARAMETERS AND FEATURES FOR HDVs, CAVs, AND CEVs

Driving behavior parameters	HDVs	CAVs	CEV
Average standstill distance	2 (m)	1 (m)	1 (m)
Multiplicative component of safety distance	3 (m)	0 (m)	0 (m)
Additive component of safety distance	2 (m)	1.5 (m)	1.5 (m)
Reaction time	(2 ± 0.3) (s)	0 (s)	0 (s)
Vehicle-to-Infrastructure (V2I)	x	✓	✓
Give-way ability	x	✓	x
Dynamic path planning	x	x	✓

its consideration of factors such as driver reaction time and vehicle dynamics. All these enabling features make it suitable for adaptation and utilization in traffic simulation purposes. In PTV-Vissim, we initialize three distinct vehicle types using the Wiedemann-74 driving behavior model, incorporating the calibrated ranges and values outlined in [39]. Then, modified versions of the model are employed for CAVs and CEVs to differentiate them from HDVs and to accommodate the different driving behavior parameters as depicted in Table II. This distinction relates primarily to their standstill distance and reaction time, leveraging the assumption that CAVs and CEVs are equipped with advanced communication and computational systems, making them intelligent vehicles.

To address different levels of connectivity and intelligence, both CAVs and CEVs are equipped with V2I communication capabilities, while HDVs lack this feature. CAVs have the ability to receive TCC directives, allowing them to give way to CEVs, which is an exclusive feature of CAVs. In contrast, CEVs continuously share their location, destination, and urgency level with the TCC and receive updates to optimize their travel routes. Our solution incorporates dynamic path planning specifically tailored for CEVs, a unique feature of our architecture. This customization ensures that CEVs can navigate traffic efficiently and reach their destinations quickly.

In the proposed framework, we have explored scenarios where CEVs share the road with CAVs and HDVs, illustrating two distinct traffic paradigms and highlighting the impacts of CAVs' give-way process alongside traffic signal control. Additionally, in mixed-traffic scenarios where all vehicle types coexist on the same road, detailed and specific modeling becomes crucial. For instance, the study in [40] examines the market penetration rate (MPR) of CAVs and its impact on driving behavior when these vehicles share the road with HDVs. Furthermore, to understand how interactions between CAVs and HDVs influence traffic flow, a stability analysis, conducted in [41], demonstrates that these interactions can significantly affect traffic flow stability.

III. QUEUE DISCHARGE MODEL

A. Queue Discharge Problem Formulation

When the traffic signal is red, a queue of vehicles is formed behind the signal head, waiting for the green signal to discharge (clear the intersection) as seen in Fig. 3. The

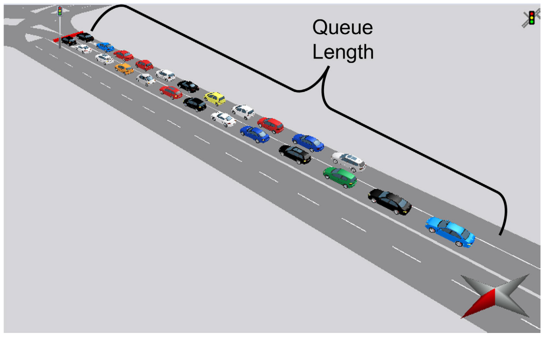

Fig. 3. Queue of vehicles on a two-lane road at a red traffic signal.

prediction of the queue discharge time is required, as it is a delay component of the CEV. As a result, a queue discharge model is introduced. In [42], the authors proposed a queue discharge model based on queue length and traffic flow; however, when this model is deployed in the proposed environment, the prediction outcome did not fit the real-time simulation. Therefore, a new regression model is developed to predict the queue discharge time.

Consider an edge defined by (e_i, e_{i+1}) where e_i is an intersection node and e_{i+1} is an adjacent intersection node. The edge is occupied by a queue of vehicles $\mathcal{Q}_{(e_i,e_{i+1})}$. Since the start time of the green phase, the relation between the number of vehicles per lane and the discharge time of the queue can be described using the following regression model.

$$\hat{\mathfrak{t}}^{-}(\mathfrak{n}_{s\in S}) = \hat{\beta}_1 \mathfrak{n}_{s\in S} + \hat{\beta}_0 \tag{1}$$

where $\mathfrak{t}^{-}(\mathfrak{n}_{s\in S})$ is the queue discharge time for queue $\mathcal{Q}_{(e_i,e_{i+1})}$ and vehicle type $s \in \{S : S = \{HDVs, CAVs\}\}$. The coefficients β_1 and β_0 are determined by a statistical method based on regression. In this work, we considered the perception-reaction time of both CAVs and HDVs in simulating their behaviors as the CAVs have less perception reaction time than the human-driven vehicles (HDVs) which consume longer time. While HDVs typically have an average perception-reaction time of around 1 ± 0.5 seconds on average [43], CAVs can have much quicker response times, often in the range of milliseconds. Thus, we incorporated these factors into our queue-discharge model to reflect the behavior of CAVs and distinguish it from the HDVs. PTV-Vissim microscopic simulation is utilized to develop a data-driven solution that estimates the relationship between the number of vehicles in the queue and the queue discharge time. Several experiments with different scenarios are generated, and the measurements of both vehicles' numbers per lane, types of vehicles, and the time consumed after the start of the green signal until the queue discharges are obtained. To find the model parameters, the following statistical equations are used:

$$\hat{\beta}_1 = \frac{\sum_{i=1}^{k}(\mathfrak{n}_i - \bar{\mathfrak{n}}_i)(\mathfrak{t}_i - \bar{\mathfrak{t}}_i)}{\sum_{i=1}^{k}(\mathfrak{n}_i - \bar{\mathfrak{n}}_i)^2} \tag{2}$$

$$\hat{\beta}_0 = \bar{\mathfrak{t}} - \hat{\beta}_1 \bar{\mathfrak{n}} \tag{3}$$

where $\bar{\mathfrak{t}} \equiv \frac{1}{k}\sum_{i=1}^{k}\mathfrak{t}_i$ and $\bar{\mathfrak{n}} \equiv \frac{1}{k}\sum_{i=1}^{k}\mathfrak{n}_i$ are the sample means. The accuracy of the estimated parameters is evaluated

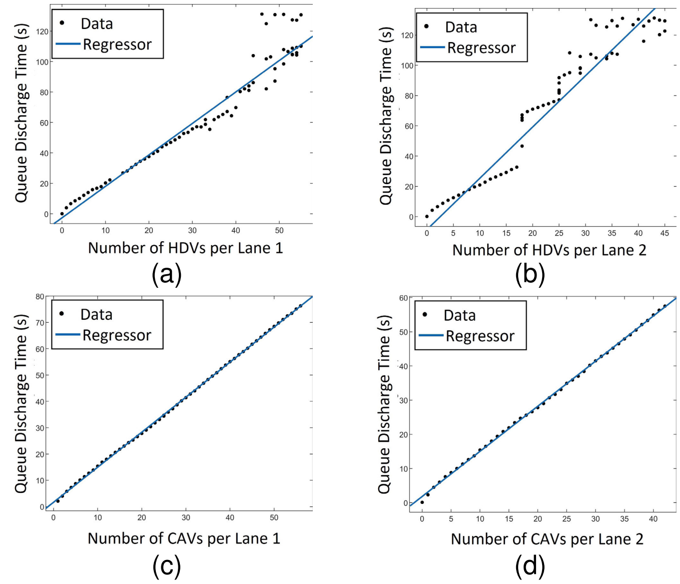

Fig. 4. The regression results of HDVs in (a,b) for lanes (1,2) respectively, and CAVs in (c,d) for lanes (1,2) respectively.

TABLE III
QUEUE DISCHARGE MODEL PARAMETERS AND THE ACCURACY CALCULATIONS

Type	$\hat{\beta}_1$	$Conf.(\hat{\beta}_1)$	$\hat{\beta}_0$	$Conf.(\hat{\beta}_0)$	R^2
HDV L1	2.066	(1.962, 2.17)	-2.595	(-6.272, 1.082)	0.9381
HDV L2	3.388	(3.202, 3.575)	-8.555	(-12.96,-4.152)	0.9277
CAV L1	1.32	(1.315, 1.326)	1.813	(1.666, 1.96)	0.9995
CAV L2	1.332	(1.328, 1.336)	1.649	(1.52, 1.779)	0.9997

through 1) the standard error as in Eqs. 4, and 5, and 2) the confidence interval (95%) is given by Eq. 6. The overall accuracy of the model is represented by the R-squared as in Eq. 7.

$$SE(\hat{\beta}_1)^2 = \frac{\sigma^2}{\sum_{i=1}^{k}(\mathfrak{n}_i - \bar{\mathfrak{n}}_i)^2} \tag{4}$$

$$SE(\hat{\beta}_0)^2 = \sigma^2\left[\frac{1}{k} + \frac{\bar{\mathfrak{n}}^2}{\sum_{i=1}^{k}(\mathfrak{n}_i - \bar{\mathfrak{n}}_i)^2}\right] \tag{5}$$

$$\hat{\beta}_1 \pm 2.SE(\hat{\beta}_1) \tag{6}$$

$$R^2 = \frac{\sum_{i=1}^{k}(\mathfrak{t}_i - \bar{\mathfrak{t}}_i)^2 - \sum_{i=1}^{k}(\mathfrak{t}_i - \hat{\mathfrak{t}}_i)^2}{\sum_{i=1}^{k}(\mathfrak{t}_i - \hat{\mathfrak{t}}_i)^2} \tag{7}$$

The data generated from PTV-VISSIM is utilized for the statistical prediction method to predict the time required for the queue to discharge in terms of a given number of vehicles per queue. Each queue consists of two lanes. As a result, two models are developed for each queue. Fig. 4 illustrates the outcome of the regression models. A summary of the model parameters and the accuracy assessments are presented in Table III.

The outcome of the regression model predicts the queue discharge time in terms of queue length with high accuracy, especially if the vehicles are CAVs. The value of R^2 refers to the goodness of fit, which is 0.99 for CAVs and 0.93 for HDVs. These values indicate that the model fits the data well. The queue discharge model plays a vital role and is utilized in the following sections to find the optimal path planning for the CEV and the optimal traffic signal preemption controller.

Although existing research works and resources such as the Highway Capacity Manual (HCM) [44] provide directions on modeling queue discharge, we opted to develop a customized model for several reasons. First, the proposed framework incorporates specific features and requirements that may not be fully captured by existing models. By developing this model, we were able to tailor it to the unique characteristics of CAVs and HDVs and their behavior in the context of the proposed framework. Furthermore, we acknowledge that simulation-generated data may be considered synthetic in nature. However, in this research, simulation-based experiments allowed to systematically evaluate and validate the performance of the proposed framework in a controlled environment. In addition, the insights and findings derived from the experiments contribute to a better understanding of the impacts and effectiveness of our framework.

Although the focus of this study is on scenarios where the intersection's edge is occupied either by HDVs or CAVs, we recognize the importance of mixed-traffic scenarios. In our implementation, we consider two distinct cases: one where the edge is fully occupied by HDVs, and the other where it is fully occupied by CAVs. For the HDV case, the control is only over the signal timing, whereas, for the CAVs case, we have control over both the signal timing and the possibility of executing a give-way behavior. The QDM developed in this work helps optimize signal timing, as detailed in Section VI, by considering vehicle types {CAVs, HDVs}. For a mixed-traffic scenario, the discharge time of HDVs can serve as an upper bound due to their typically longer perception-reaction times and less efficient discharge rates compared to CAVs. To fully address mixed traffic conditions, we refer to our earlier study in [40], where the impact of the market penetration rate (MPR) of CAVs on the average network delay and intersection discharge time was analyzed. The MPR parameter significantly affects the mixed-traffic environment, influencing both network's average delay and queue discharge times.

IV. Dynamic Path Planning for CEVs

The CEV path planning problem is solved by finding the least-cost path from the origin point to the destination in terms of arrival time, which is constrained by many arguments such as traffic densities, traffic queue lengths, and the distance of each road segment in the path. The investigated research problem is from the time-invariant path planning problem in which the underlying costs in the graph can change over time. Thus, it is required to design a graph search technique that would be adapted to such dynamic environment to provide an automatic updated path. These approaches, namely, re-planning graph search algorithms or incremental path planning, are widely used in the literature [45], [46], [47]. In this Section, the proposed approach for solving the dynamic path planning for the CEV subject to sudden queue changes is presented.

A. Dynamic Path Planning and Proposed Solution

First, we define the proposed approach nomenclature as follows.

N	Set of intersection nodes in the graph.
n_i	Intersection node i where $n_i \in N$.
n_s	Starting intersection node where $n_s \in N$.
n_g	Goal intersection node where $n_g \in N$.
$succ(n_i)$	The set of successor nodes from node n_i.
E	Set of edges between nodes.
G	Traffic network graph representation.
Q	Set of queues discharge time in G.
e_{ij}	Edge from node n_i to node n_j and $\{e_{ij} \in E\}$.
q_{ij}	Queue discharge time at edge e_{ij}.
C_{ij}^h	The historical cost of the edge between node n_i and node n_j.
C_{ij}^*	The real-time cost for the edge between node n_i and node n_j.
C_{ij}^d	The travel distance cost for node n_i and node n_j.
$h(n_i)$	The heuristic cost of the path from node n_i to n_g.
$UCS(n_i, n_g)$	The optimal path from node n_i to n_g based on uniform cost search algorithm that utilized the edges fixed costs (travel distance).
$g(n_i)$	The actual cost from node n_s to node n_i.
$f(n_i)$	The approximated cost of node n_i to n_g where $(f(n_i) = g(n_i) + h(n_i))$.

The traffic network is composed of intersection nodes that are modeled as a graph $G = (N, E)$. The set of all feasible paths from the origin location to the destination is $\mathcal{P}$. Every path $P_i \in \mathcal{P}$ is defined by a sequence of nodes $P_i = \langle n_1, n_2, \ldots, n_g \rangle$. Given the length of an edge as $\mathcal{L}_{(n_i,n_{i+1})}$ and the desired speed of the CEV as v, the mean travel time of a CEV crossing an edge can be expressed by:

$$\mu_{(n_i,n_{i+1})} = \begin{cases} \dfrac{\mathcal{L}_{(n_i,n_{i+1})}}{v} + \mathcal{T}_{delay}^{(n_i,n_{i+1})} & \text{give-way is infeasible} \\ \dfrac{\mathcal{L}_{(n_i,n_{i+1})}}{v} & \text{otherwise} \end{cases} \tag{8}$$

where the $\mathcal{T}_{delay}^{(n_i,n_{i+1})}$ is the possible delay time that could result from queue discharge time or the give-way option being infeasible. The calculations of that delay time are computed according to the type of control of the traffic signal preemption method control and the discharge time of the queue. The expected time of arrival (ETA) for a generated path is expressed as:

$$\text{ETA}(P_i) = \sum_{i=1}^{n} \mu_{(n_i,n_{i+1})} \tag{9}$$

The path is evaluated by its ETA. The optimal path is the one with the minimum ETA. We define three types of costs in that transportation problem.

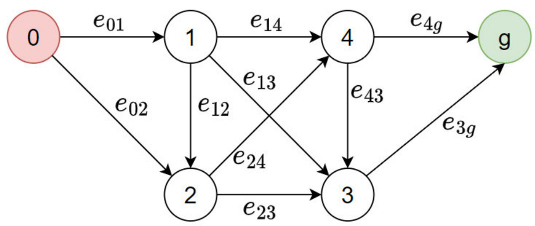

Fig. 5. A graph representation of multiple traffic intersections network.

- Travel distance cost C^d_{ij}: This is the cost of crossing an edge without any delays.

$$C^d_{ij} = \frac{\mathcal{L}_{(n_i, n_{i+1})}}{v} \tag{10}$$

- Historical cost C^h_{ij}: This cost depends on the traffic hour and the traffic density level, and this is measured based on crowdsensing techniques.
- Real-time measured cost C^*_{ij}: This cost is based on the ITS based technology such as cameras at the intersection node, then detects the vehicles at their cells, then predicts the queue discharge time from the number of vehicles per edge as mentioned in the article Section (III). We define the real-time cost as follows:

$$C^*_{ij} = C^d_{ij} + q_{ij} \tag{11}$$

In this work, we combine real-time data and historical traffic data on a traffic network to develop an optimal path planning technique for emergency vehicles. It is worth mentioning that the historical data is used for global planning, while real-time traffic data (one- step look ahead) is utilized for local planning. To explain well the proposed approach without losing generality, we provide an example of a traffic network composed of 5 intersection nodes as shown in Figure 5. The starting node is n_0 and goal node is n_g and the edges are e_{ij}. The ultimate objective is to keep the CEV updated with the optimal path of minimum travel time until reaching the goal node.

In order to initialize the heuristic values of $h(n_i)$, we use the uniform cost search (UCS) algorithm, which computes the optimal path and its cost from node n_i to n_g based on the historical costs of the paths C^h_{ij}. They are assumed to be fixed and correct until a delay event is detected. The pseudocode of the employed UCS is shown in Algorithm 1. The sudden delay event is detected through a condition applied to the measurement of the real-time cost of an edge. We define constraint of delay event as follows:

$$C^*_{ij} \geq C^h_{ij} + \delta_{max} \tag{12}$$

We depend on the historical costs of traffic for an edge C^h_{ij} in addition to a predefined variable δ_{max} to give tolerance for not considering small delays and only big delays are counted.

The sequence of steps for the algorithm is shown in Figure 6a. The corresponding progression flowchart of the heuristic values is shown in Figure 6b.

The proposed approach initializes the heuristic values of each node with $h(n_i) = UCS(C^h_{ij})$. Only, $h(n_s)$ is given by $UCS(C^*_{ij})$. The main reason for giving the real-time delay measurement for the start node (current node) is that traffic changes randomly with time, so one step ahead is adequate to keep informed about the path. Then, the process is repeated by checking after every step if there is a delay event to reinitialize the algorithm. Otherwise, it continues on its path as shown in Figure 6a.

Algorithm 1 Traffic Network-Based Uniform Cost Search

Data: Graph G, start node n_s, goal node n_g
Result: Shortest path from n_s to n_g
Function `UniformCostSearch`(G, s, g)**:**
  $Q \leftarrow$ priority queue $cost \leftarrow$ dictionary with initial values of C^h_{ij} $parent \leftarrow$ dictionary with initial values of *null*
  Q.enqueue(n_s, 0) $cost[n_s] \leftarrow 0$
  while Q *is not empty* **do**
    $v \leftarrow Q$.dequeue()
    if $v = n_g$ **then**
      break
    end
    for *each* $succ(v)$ **do**
      $new\_cost \leftarrow cost[v] + weight(v, succ(v))$
      if $new\_cost < cost[succ(v)]$ **then**
        $cost[succ(v)] \leftarrow new\_cost$ $parent[succ(v)] \leftarrow v$ Q.enqueue($succ(v)$, $cost[succ(v)]$)
      end
    end
  end
  if $parent[n_g]$ *is null* **then**
    return "No path found"
  end
  $path \leftarrow$ empty list $v \leftarrow n_g$
  while v *is not null* **do**
    $path$.prepend(v) $v \leftarrow parent[v]$
  end
  return *path*

To explain in detail Figure 6, initially, the TCC generates the optimal path $P_1 : \{n_0 \rightarrow n_1 \rightarrow n_3 \rightarrow n_g\}$ (as shown in the blue highlighted path in step 0 in Figure 6a) regarding an initial belief in the traffic conditions. Before the CEV moves, the present heuristic values are computed. The real-time costs of the starting node ($n_s = n_0$) namely C^*_{01} and C^*_{02} are included as shown in the first step in the Figure 6b. This path is evaluated and the delay event detector has captured a delay in that path P_1, so the algorithm moves to step 2 in Figure 6b and generates the path $P_2 : \{n_2 \rightarrow n_3 \rightarrow n_g\}$. Thus, the CEV moves to node n_2 as the road segment e_{02} is selected (as shown in the highlighted yellow path in step 1 in Figure 6a). Now, the starting node is updated to ($n_s = n_2$) and again the path P_2 is evaluated and updated as there is a detection of delay-event. To recap, the CEV continues in the optimal path until a delay event is detected. Then, it utilizes the real-time measurement of that delay to be updated with the optimal path until reaching the goal node.

In general, the heuristic function is a crucial component of replanning search algorithms, as it allows the algorithm to quickly adapt to changes in the search space and efficiently find an optimal path to the goal node. To recap, the CEV continues in the optimal path until a delay event is detected,

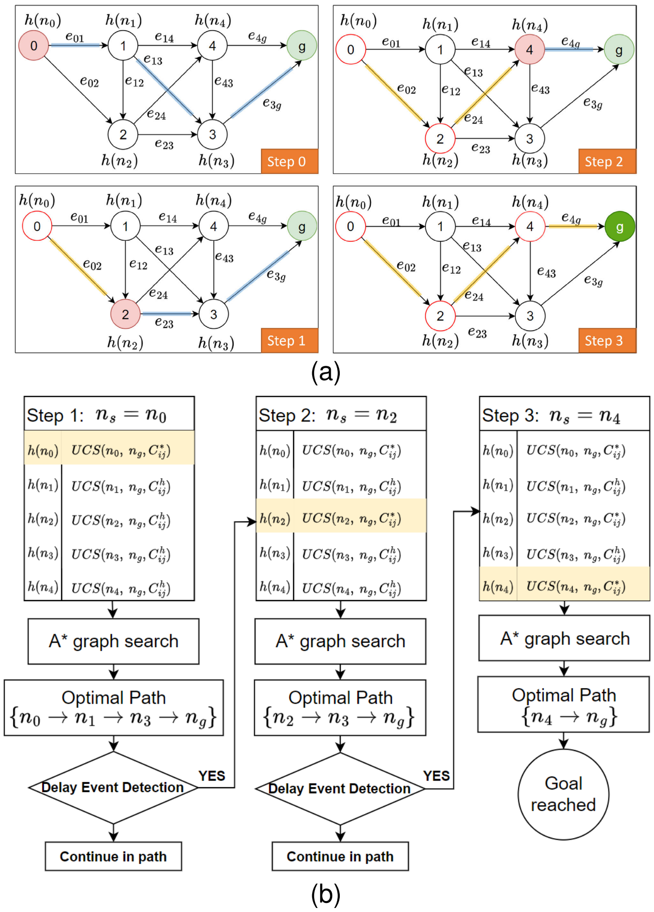

Fig. 6. A demonstration of the steps and flowchart for the proposed dynamical path planning approach. (a) Iterative steps until reaching the goal node. (b) A flow chart to represent the progression of the heuristic values for each node when there is a series of delay events.

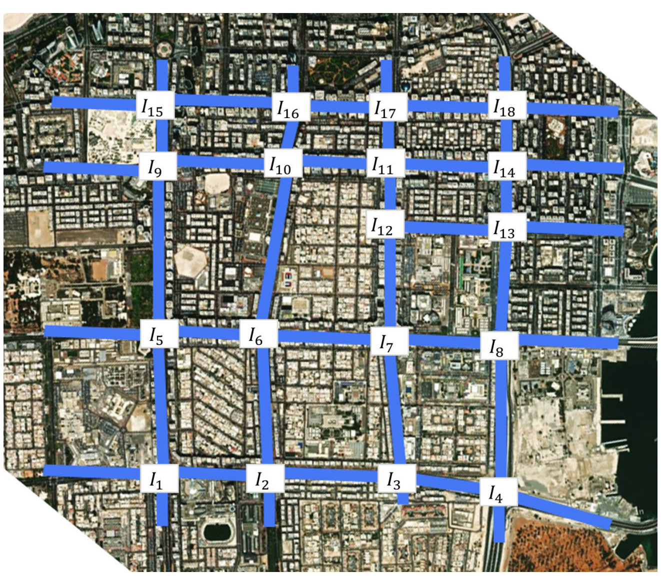

Fig. 7. Multiple traffic intersections in Abu Dhabi city in UAE. The snapshot is from PTV-VISSIM microscopic traffic simulation. The intersection nodes are labeled from 1 to 18.

then it utilizes the real-time measurement of that delay to be updated with the optimal path until reaching the goal node.

Algorithm 2 AQA* Heuristic Graph Search for Optimal Path

Function `initialize`(G, n_s, n_g):
- openList = PriorityQueue()
- openList.push($\{n_s\}$)
- closedList = {}
- $g(n_s) = 0$
- $h(n_s) = UCS(n_s, n_g, C^*_{ij})$
- $h(n_i) = UCS(n_i, n_g, C^h_{ij})$
- $f(n_s) = g(n_s) + h(n_s)$

while *openList* **do**
- n_i = openList.Pop()
- **if** $n_i == n_g$ **then**
  - return
- **end**
- remove n_i from openList
- add n_i to closedList
- **for** $n \in succ(n_i)$ **do**
  - **if** *n in closedList* **then**
    - continue
  - **end**
  - $cost = g(n_i) + h(n)$
  - **if** *n in openList AND cost < g(n)* **then**
    - remove n from openList
  - **end**
  - **if** *n in closedList AND cost < g(n)* **then**
    - remove n from closedList
  - **end**
  - **if** *n not in openList AND n not in closedList* **then**
    - add n to openList
    - g(n) = cost
    - $h(n) = UCS(n, n_g, C^h_{ij})$
    - $f(n) = g(n) + h(n)$
  - **end**
- **end**

end

The overall algorithm pseudocode of the proposed approach is shown in Algorithm 2.

B. Path Planning Evaluation and Testing

The proposed algorithm is validated on a scenario based on real-time microscopic simulation in Abu Dhabi city in an area where there are multiple intersections as shown in Fig. 7. Table IV shows the actual distances between every couple of adjacent vertices.

During the evaluation of the proposed dynamic path planning approach, the proposed queue discharge model discussed in Section III and the combined intrusive and non-intrusive signal preemption controller shown in Section VI are employed. To explore the performance of the proposed approach, we compared it against the algorithms in the literature such as A* and UCS. The scenario is as follows: the starting node is any of the nodes, and it is assumed that the goal node is node I_{17}. To clarify the contribution of the proposed algorithm, random traffic delays are inserted into the paths where their initial states range from I_1 to I_6. Fig. 8 illustrates the algorithms' performances, which are evaluated in terms of

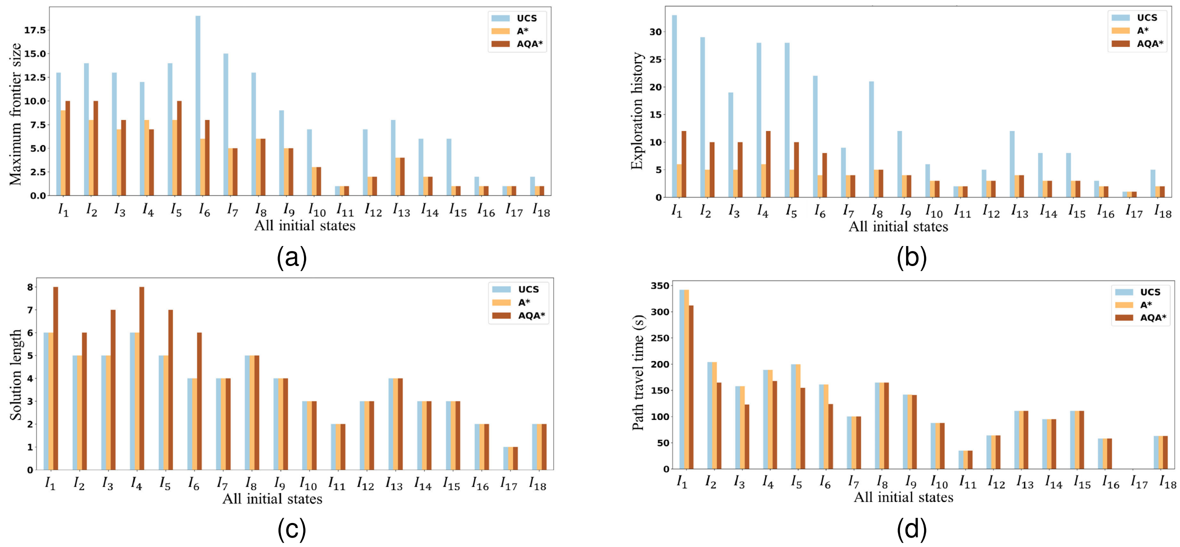

Fig. 8. The performance of the proposed algorithm AQA* against the baseline algorithms when the first 6 initial states are exposed to sudden traffic changes. The comparison is conducted in terms of (a) maximum frontier size, (b) exploration history, (c) solution length, (d) path travel time for the CEV.

TABLE IV
The Edges Between Every Two Nodes and Their Corresponding Costs

e_i	d_i	e_i	d_i	e_i	d_i	e_i	d_i
I1-I2	614	I5-I6	590	I9-I10	756	I12-I13	573
I1-I5	840	I5-I9	1022	I9-I15	335	I13-I14	333
I2-I3	812	I6-I7	780	I10-I11	630	I14-I18	322
I2-I6	847	I6-I10	1080	I10-I16	318	I15-I16	822
I3-I4	560	I7-I8	685	I11-I12	360	I16-I17	560
I3-I7	848	I7-I12	666	I11-I14	685	I17-I18	690
I4-I8	950	I8-I13	675	I11-I17	312		

1) the maximum frontier size, which refers to the maximum size of the priority queue data structure in each algorithm, 2) the solution length, which is the number of nodes in the generated path, 3) the exploration history, which is the number of expanded nodes, and 4) the path travel time for the CEV. Although path travel time is indeed the priority metric for CEVs, the inclusion of exploration history, solution length, and maximum frontier size provides a comprehensive evaluation of the proposed algorithm's performance in terms of efficiency, optimality, and exploration capabilities.

The scenario setting defined in Subsection VI-E is utilized to conduct a comparative study among the optimal path cost algorithms. In normal operation, seen in the initial states from I_7 to I_{18}, all algorithms are optimal as they generate the optimal paths. In addition, it can be noticed that the proposed AQA* has a similar performance in terms of computation (maximum frontier size, exploration history) such as the A* algorithm, since it inherits its optimality and completeness. However, the UCS, which is a variant of the Dijkstra algorithm, has a lower performance in terms of computation. In abnormal circumstances, where sudden traffic delays are introduced, the proposed AQA* has an obvious improvement in terms of path travel time, which is a dominant key for the CEV to save people's lives. Although the other algorithms have better values in terms of the computation during the first six initial states, their outcomes are worse when the comparison is held in terms of the path travel time. In total, the proposed algorithm saved about 201 seconds in the first six initial states, which is important for the application of emergency vehicles, and on average it improved the travel time by 9%.

V. Give-Way Approach for CAVs in Emergency

The CEVs are driven at high speed to reach the emergency scene in the shortest time. To optimize the CEV travel time, a give-way process is needed. If a two-lane road is considered, then the give-way process requires all CAVs to merge in one lane and leave the other lane to be empty for the CEV. Some research work in the literature proposed mathematical techniques [31] and approaches to do the merging process. However, the proposed approach in this study is based on deep learning models specifically trained to facilitate the merging process when it is deemed advantageous and time-efficient. If the merging time exceeds a certain threshold and offers no significant benefits, the merging process is considered redundant. To achieve this, a collaborative mechanism is developed to enable CAVs to change lanes. Subsequently, the TCC assesses the lanes and identifies the one with fewer vehicles. Before instructing the CAVs to clear the lane for the approaching CEV, the TCC utilizes a novel deep learning model, developed in this research, to predict the merging time based on the initial positions of the CAVs.

In recent years, the ITS has leveraged advanced technologies to accurately count vehicles in traffic queues. One of the most widely used methods is video-based vehicle detection based on advanced computer vision techniques combined with surveillance cameras. These technologies offer a huge amount of data, such as the number of vehicles per lane and their accurate locations. In this article, we utilized these data to train deep learning models to predict the time required for the merging process.

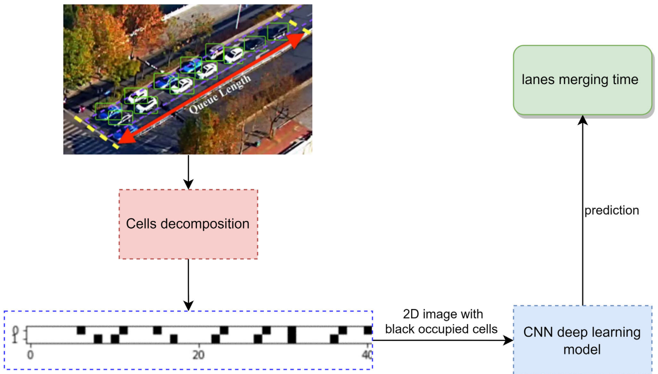

Fig. 9. The block diagram of the proposed give-way module.

TABLE V
LANE-CHANGE PARAMETERS IN THE SIMULATION FOR THE MERGING PROCESS

parameter	own vehicle	trailing vehicle
maximum deceleration	-4.00 m/s^2	-3.00 m/s^2
-1 m/s^2 per distance	100 m	100 m
accepted deceleration	-1.00 m/s^2	-1.00 m/s^2

The proposed solution architecture is shown in Fig. 9. To train the deep learning model, a dataset is needed. For this reason, a dataset is generated using Python scripting and the microscopic traffic simulation PTV-VISSIM [48]. The simulation is used to run 4000 scenarios leading to a generated dataset size of 4000 samples. Each sample contains the initial locations of vehicles on lane 1 and lane 2, which are selected randomly. In every simulation run, the lane with fewer vehicles is merged with the other one. The merging process is implemented by making the vehicles with the fewer-vehicles lane do a lane change behavior with the simulation parameters mentioned in Table V. If the number of vehicles in both lanes is equal, then the left lane is selected and reserved for the CEV.

A. Deep Learning Model

Deep-learning models based on convolutional neural network (CNN) have demonstrated the capability to capture complex patterns and relationships through multiple layers of non-linear transformations, potentially leading to better performance and predictive accuracy in scenarios where complicated data representations are present. In our case, the deep learning model was designed to complement the detection and localization of CAVs on the road, which is assumed to be performed by traffic cameras and an ITS. Using this model, the TCC can make informed decisions based on the location of the vehicles received.

To predict the merging time utilizing the dataset mentioned above, two deep learning models are proposed: 1) the regression model and 2) the classification model. The regression model is used to predict the time required for the merging process. The classification model is used to perform a macroscopic analysis on the time length level. The dataset is labeled and split into three levels {green, yellow, red}. The labeling

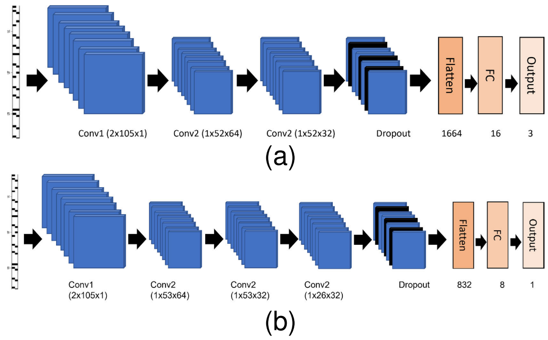

Fig. 10. The deep learning convolution neural network (CNN) models for predicting the vehicles merging time for (a) classification model and (b) regression model.

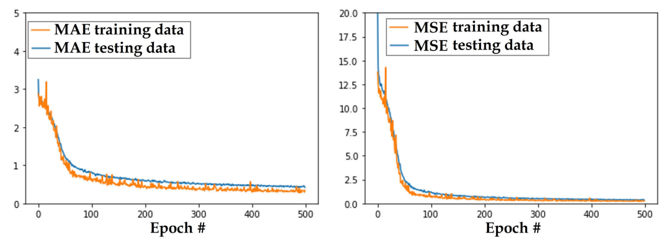

Fig. 11. The performance of the proposed deep learning regression model in terms of the mean absolute error (MAE) (in the left figure), and the mean square error (MSE) (in the right figure) for the training and testing data.

TABLE VI
THE CLASSIFICATION PERFORMANCE SUMMARY OF THE PROPOSED DEEP LEARNING CLASSIFICATION MODEL

#	Precision	Recall	F1-score	Support	Accuracy
green	0.99	1.00	1.00	306	
yellow	0.99	0.99	0.99	391	0.99
red	1.00	0.99	0.99	497	

is based on the following formula:

$$label = \begin{cases} green & t_{merge} < 7 \\ yellow & 7 \leq t_{merge} \leq 10 \\ red & t_{merge} > 10 \end{cases} \quad (13)$$

The architectures of the regression and classification models are shown in Fig. 10.

The performance of the deep learning model to predict the time it takes for the vehicles to merge is presented. As mentioned before, two models are introduced, so there are two evaluation criteria to be used. For the regression model, the mean square error (MSE) and the mean absolute error (MAE) are used as means to define the prediction error for training data and validation data, as shown in Fig. 11. For the classification model, the accuracy and F1-score shown in Table VI and the confusion matrix shown in Fig. 12 are used to depict the classification performance.

Fig. 11, Fig. 12, and Table VI show that both regression and classification models correctly predict the time required for vehicles to do the lanes merging behavior. In the regression model, the MSE and MAE are below 0.4, and it should be noticed that 0.4 second could be acceptable in the context of time prediction for the vehicles to merge since the

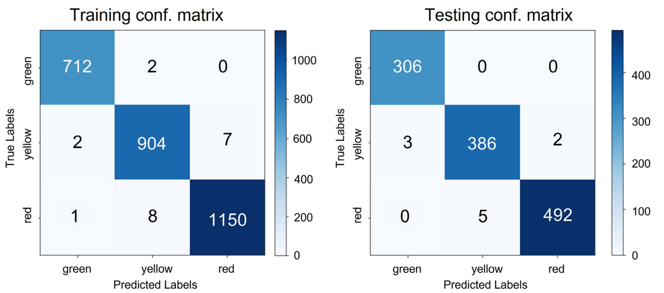

Fig. 12. The performance of the proposed deep learning classification model in terms of confusion matrix for the training data (in the left figure) and testing data (in the right figure).

complex behavior is not deterministic. Hence, a window of error less than 1 second is acceptable. On the other hand, the classification model achieved a high accuracy of 99% to predict in which class the merging will be {green, yellow, red}. It is important to note that the give-way process or merging of lanes should be performed prior to the arrival of the emergency vehicle. Merging after the emergency vehicle has already entered the road segment would render the process ineffective. To ensure proper timing, we have established the following rules:

- If the merging time is classified as red, the give-way process is deemed infeasible due to its extensive time consumption.
- In the case where the merging time is classified as yellow or green, we measure the distance between the last CAV and the CEV. Subsequently, we assess the time required for the CEV to reach this CAV.
- If the merging time is shorter than the travel time of the emergency vehicle, the merging process is considered valid. Conversely, if the merging time exceeds the travel time of the emergency vehicle, the merging process is deemed invalid.

By establishing these rules, we ensure that the give-way process is conducted in a timely manner, maximizing the efficiency of lane merging for emergency vehicles.

In conclusion, the proposed model is valid for the real-time prediction of the merging time of vehicles. Although learning-based models have been explored in existing studies, the proposed study extends the existing literature by incorporating the lane-merging-time prediction module into a broader framework specifically designed for optimizing traffic signal preemption for CEVs during emergency situations. This integration in the context of preemption of traffic signals is a unique aspect of the proposed work.

It is important to note that within the proposed framework, the lane module is specifically integrated for the highest emergency level scenario and when the road segment e_{ij} is fully occupied with CAVs. In order to achieve this, the intrusive signal preemption control is employed in addition to the give-way module. Furthermore, in the proposed framework, we primarily applied the give-way module to CAVs due to their ability to send and receive signals from the traffic infrastructure. Since CAVs are computerized and more deterministic compared to traditional vehicles, they can effectively respond to signal preemption instructions. However, in scenarios where the emergency level is high, the framework includes the use of intrusive signal control. This strategy involves giving a green signal to all road users, including HDVs, to evacuate the area for the emergency vehicle. In such cases, the proposed framework focuses solely on the implementation of intrusive signal preemption control. It is worth noting that requesting HDVs to give way to CEVs might not yield optimal results, as not all HDV drivers may comply with traffic instructions or may exhibit a low response, introducing uncertainty into the system.

VI. Traffic Signal Preemption for Emergency Response

Traffic signal preemption is a common technique used by state-of-the-art research to shorten the travel time of the CEV while clearing the traffic intersection [6], [10], [49], [50]. A CEV requires a green signal to pass the intersection safely. Otherwise, a crash might occur because other vehicles might not consider the sudden passage of the CEV. There are multiple ways of preempting the traffic signal for the CEV such as 1) phase preemption and 2) phase skipping. Both methods may confuse other vehicles' drivers, and they might think that there is a malfunction to the traffic signal controller.

Consequently, a soft technique based on optimization, namely "non-intrusive control" is introduced in [6] and [28]. It is achieved by manipulating the signal cycle length and the green phases before the CEV reaches the signal head to provide the green signal for the CEV. The other method, namely "intrusive control", which is mainstream now in the industry, forces the signal phase to be green until the CEV crosses the intersection. Then, the traffic intersection controller restores the normal operation as in [10] and [51].

Both methods have been developed and introduced in state-of-the-art research work. The problem with non-intrusive signal preemption control is that it is not always finding the optimal solution because sometimes the waiting time, until the start of next cycle, is too long. In addition, there is no well-defined prediction model for the queue discharge time of the road segments. That means that the method is not always beneficial for the CEV. Furthermore, the disadvantage of intrusive signal control is that it always gives the right to the CEV regardless of the delay time of other vehicles in the traffic network.

Consequently, a moderate novel technique is proposed to reduce CEV travel time with less unwanted traffic impacts. This proposed version of signal control preemption tries to find a moderate way to deal with the preemption problem corresponding to a moderate emergency level. The proposed combined intrusive and non-intrusive signal preemption with the integrity of the queue discharge model gives another level of controllability that permits the CEV to clear the intersection in a green phase even when the non-intrusive preemption technique is not valid. If the non-intrusive method results in an infeasible solution, the system seamlessly transitions to intrusive preemption, which may involve overriding the current signal state to immediately clear the path for the CEV, thus ensuring that emergency vehicles are not delayed at intersections even when less disruptive methods fail to provide feasible solutions. This strategy strikes a balance between minimizing traffic disruption and avoiding delays in emergency responses.

Moreover, effective coordination among multiple intersections is essential to ensure efficient and safe routing for CEVs. As introduced in Section II, the TCC plays a crucial role in this process. The TCC addresses optimization challenges on two distinct scales. At the intersection level, optimization focuses on determining optimal signal timings and preemption strategies for individual intersections, tailored to the current local traffic conditions as explained in this Section VI. This involves adjusting the signals in real time to facilitate the smooth passage of CEVs, thus minimizing delays caused by regular traffic flows. At the multiple intersection level, the TCC constructs a graph with dynamically weighted edges, which represent the varying traffic conditions and the potential delays at multiple intersections, as emphasized in Section IV. Furthermore, the TCC enhances the flexibility of signal preemption control by employing multiple signal preemption controllers. These controllers are designed to be adaptive, adjusting their strategies based on traffic conditions and the emergency level of the CEV. This adaptability allows for a more nuanced approach to managing intersection signals, ensuring that the urgency of the situation is matched by an appropriate level of response. The effectiveness of this technique will be thoroughly evaluated and discussed later in this Section.

A. Non-Intrusive Signal Control Problem Formulation

Non-intrusive signal preemption control can be particularly useful for CEVs in situations where maintaining the flow of regular traffic is essential while still providing priority to the CEV. This approach minimizes disruptions to the normal traffic pattern and reduces the potential for congestion or delays for other vehicles. It can be beneficial in scenarios where the emergency vehicle response time is critical, but the traffic volume is relatively low or manageable. By utilizing non-intrusive signal preemption control, CEVs can navigate through intersections more efficiently without significantly impacting the overall traffic flow. It is worth mentioning that the non-intrusive preemption signal control involves the queue discharge model built in Section III.

The initial formulation of non-intrusive signal preemption control is found in [6]. In this proposal, some constraints are modified and the proposed queue discharge model is utilized. To illustrate the idea of non-intrusive traffic signal preemption control, Fig. 13 shows the traffic signal before and after the preemption technique.

As seen in Fig. 13, the moment when the CEV is detected at the road link is t_{in}, and the moment when the CEV arrives at the intersection is t_{arr}. The old cycle length is C, and the new cycle length is C'. The remaining time of the old cycle length C is R. The cycle of the traffic signal consists of four splits, namely $\{g_1, g_2, g_3, g_4\}$ corresponding to the four entry points at the traffic intersection. The target phase is the signal phase that corresponds to the intersection entry where the CEV exists. There are also a number n of cycles C

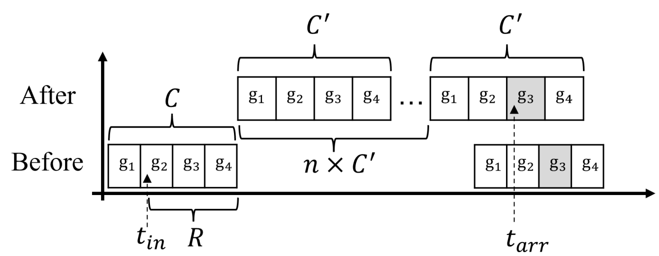

Fig. 13. The illustration of the non-intrusive signal control.

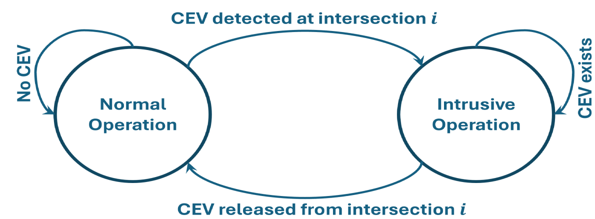

Fig. 14. State machine model represents the behavior of the intrusive control.

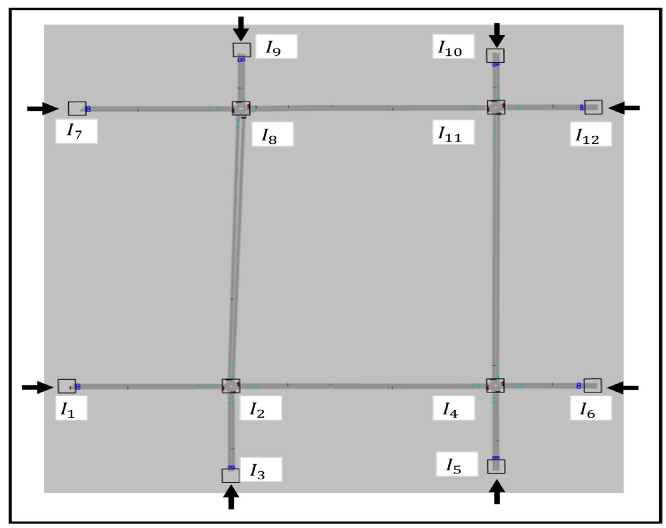

Fig. 15. Multiple intersections map used to validate the proposed framework.

remaining until the CEV reaches the intersection. The main idea of the non-intrusive signal preemption control is to change the old cycle length to a new one that enables the CEV to arrive at the intersection at its needed phase. The problem is formulated as a quadratic programming optimization problem as the objective function is the error squared of the new cycle length and the new phase splits for the new cycle as expressed in Eq. 14. β is a hyperparameter that is tuned for the optimization process. The objective function is subject to the constraints in Eq. 15 which are selected cautiously to enable the CEV to reach the signal head at the green time with minimal impacts on other road users. The first constraint (15a) ensures that the sum of signal splits in the cycle length remains the same, as in the new cycle. Moving to the second constraint (15b), P represents the duration in the new cycle C' until the arrival of the CEV at time t_{arr}. In addition, the queue discharge time is represented in Δg. To accommodate slight delays in CEV arrival, a tolerance window of $\pm\delta_t$ is provided. Additional constraints are then imposed to limit signal splits and cycle lengths, which completes the set of constraints. The Gurobi solver [52] with Python is utilized to find the optimal solution in a short time.

$$\underset{G'}{\arg\min}\left((C'-C)^2+\beta\sum_{i=1}^{I}(g_i'-g_i)^2\right) \tag{14}$$

$$\text{subject to}\begin{cases} C=\sum_{i=1}^{I}g_i,\quad C'=\sum_{i=1}^{I}g_i' & \text{(15a)}\\ P=t_{arr}-t_{in}-R-n\times C' & \text{(15b)}\\ n=\lfloor\frac{t_{arr}-t_{in}-R}{C'}\rfloor & \text{(15c)}\\ \sum_{i=1}^{k-1}g_i'<P-\delta_t<\sum_{i=1}^{k}g_i' & \text{(15d)}\\ \sum_{i=1}^{k-1}g_i'<P+\delta_t<\sum_{i=1}^{k}g_i' & \text{(15e)}\\ C_{min}\le C'\le C_{max} & \text{(15f)}\\ \forall i\in I,\quad \tau_i^{min}\le g_i'\le\tau_i^{max} & \text{(15g)}\\ n\times(g_k'-g_k)+P-\sum_{i=1}^{k-1}g_i'\ge\Delta g & \text{(15h)}\end{cases}$$

B. Intrusive Signal Control Problem Formulation

The formulation of the intrusive signal preemption control is straightforward, as seen in Fig. 14. There are two state machines that represent the normal operation and the intrusive operation in which the system preempts the signal to allow the CEV to cross in a green signal phase.

To clarify the point, the non-intrusive preemption technique is a soft technique, and it may not work in all cases due to the failure in satisfying all the constraints (e.g. at high-density traffic). However, the intrusive method is a greedy technique, and it forces road users to evacuate the area for the CEV. Consequently, a combined intrusive and non-intrusive mechanism is proposed. The combination process works by switching between the controllers and maximizing the utilization of non-intrusive preemption technique when it is available, as it has lower impacts on the road users than the other methods.

C. Testing and Validation

The proposed signal preemption controllers are tested on a scenario map of intersections as seen in Fig. 15. The proposed scenario consists of four intermediate traffic intersection nodes with signal controllers $\{I_2, I_4, I_{11}, I_8\}$ and eight entry nodes $\{I_1, I_3, I_5, I_6, I_{12}, I_{10}, I_9, I_7\}$ from which the CEV might enter the traffic network.

To test traffic preemption signal controllers on all scenarios, every node in the entry node set is defined to be a starting node, and all other nodes are defined as goal nodes. Two types of vehicles are used, namely CAVs and HDVs. In addition, three density levels are tested, low, medium, and high. The total number of scenarios is

$$\begin{aligned}\text{Total Scenarios}&=\text{number of starting nodes}\\&\quad\times\text{number of goal nodes}\\&\quad\times\text{number of vehicle types}\\&\quad\times\text{number of density levels}\\&=8\times7\times2\times3\\&=336\text{ scenarios}\end{aligned}\tag{16}$$

Every scenario of the 336 scenarios corresponds to a path trajectory generated from the path planning module from a starting node to the goal node.

The evaluation methods are divided into two types, 1) local impacts, which refer to the CEV path travel time, and 2) the traffic network performance, which covers the impacts on the other vehicles in the traffic network. The performance of the traffic network is evaluated using the following evaluation methods: 1) Total stops: The overall count of vehicles' stops whether inside the traffic network or have left it. A stop is considered when the speed changes from a value greater than zero to zero. 2) Total delay: The total count of delays for vehicles that were in or out of the network. A delay is considered when the actual speed of the vehicle is less than the desired driver-behavior speed. For example, stop times on a red signal are taken into account as a delay.

TABLE VII
SELECT THE TYPE OF CONTROLLER ACCORDING TO THE EMERGENCY LEVEL

Emergency Level	Controller Type
Low	-Non-intrusive signal preemption control -Dynamic path planning
Medium 1	-Non-intrusive signal preemption control -Dynamic path planning
Medium 2	-Combined intrusive and Non-intrusive signal preemption control -Dynamic path planning -Give-way if fully occupied with CAVs
High	-Intrusive preemption signal control -Dynamic path planning -Give-way if full occupied with CAVs

D. Signal Preemption Results

The traffic network map seen in Fig. 15 is tested in the scenarios mentioned above and evaluated using the travel time of the CEV path and the network performance mentioned in subsection VI-C. The performance of the proposed algorithm, namely combined intrusive and non-intrusive preemption signal control, is investigated against 1) Fixed-time control method (FTCM), 2) Non-intrusive preemption signal control, and 3) Intrusive preemption signal control The performance in terms of the CEV travel time is shown in Fig. 16, and the network performance is shown in Fig. 17.

First, in Fig. 16, every element on the x-axis represents the optimal path corresponding to a scenario set in the 336 scenarios mentioned above. The y-axis represents the travel time of the path. Second, in Fig. 17, there are 8 bar charts in which the proposed preemption signal control is compared with the

TABLE VIII
INTEGRATION ASSESSMENT RESULTS, '+' FOR IMPROVEMENT, '−' FOR NETWORK NEGATIVE IMPACT

ID	Scenario (urgency, vehicle type, density)	Avg. travel time (s) FTCM	Ours	Impact	Traffic network delay (Avg.) Intrusive	Ours	Impact
1	(M/HDVs/Low)	95.24	82.61	+13.2 %	24.52	22.189	+10.52 %
2	(M/HDVs/Mid)	163.39	108.10	+33.8 %	28.17	27.51	+2.4 %
3	(M/HDVs/High)	162.69	110.11	+32.3 %	29.46	28.03	+5.08 %
4	(H/HDVs/Low)	95.24	82.61	+13.2 %	24.52	22.189	+10.52 %
5	(H/HDVs/Mid)	163.39	108.10	+33.8 %	28.17	27.51	+2.4 %
6	(H/HDVs/High)	162.69	110.11	+32.3 %	29.46	28.03	+5.08 %
7	(M/CAVs/Low)	100.71	85.10	+15.5 %	20.35	18.84	+7.97 %
8	(M/CAVs/Mid)	137.07	82.90	+39.5 %	22.24	20.21	+10.04 %
9	(M/CAVs/High)	101.41	81.35	+19.7 %	23.01	22.62	+1.74 %
10	**(H/CAVs/Low)**	100.71	76.19	**+24.3 %**	20.35	21.35	**-4.91 %**
11	**(H/CAVs/Mid)**	137.07	72.90	**+46.8 %**	22.24	22.91	**-3.01 %**
12	**(H/CAVs/High)**	101.41	73.10	**+27.9**	23.01	24.81	**-7.74 %**

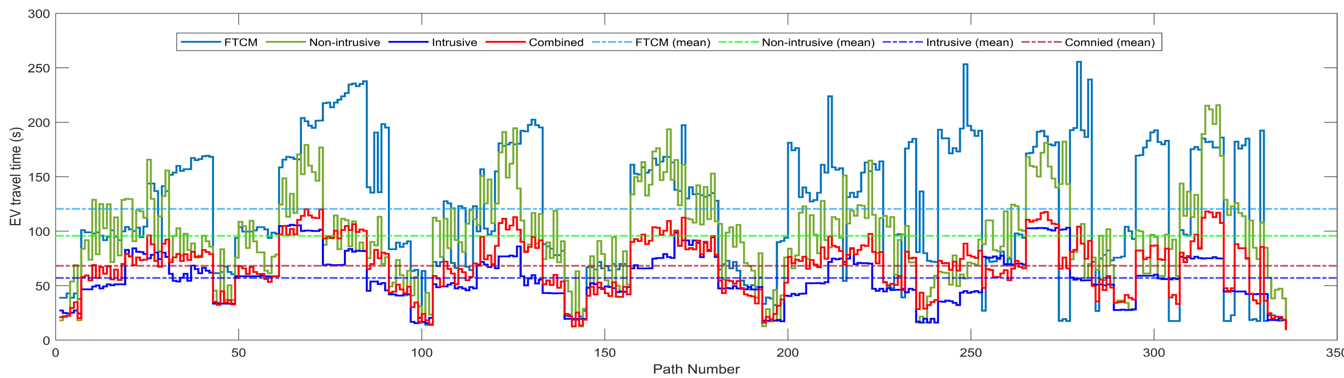

Fig. 16. Comparison of CEV path travel time using the proposed algorithm, which combines intrusive and non-intrusive preemption signal control, against benchmark traffic signal preemption controllers.

intrusive control and non-intrusive control. In every bar chart, the x-axis represents the goal nodes, and the title of the chart represents the starting node. Two evaluations are considered; the first row of plots represents the total network delays and the second row represents the total stops.

In Fig. 16, the FTCM on average achieved the lowest performance as it results in the maximum path travel time. It can be used when the emergency level of the CEV is very low and there is no need for traffic signal preemption. The non-intrusive signal preemption control improved the performance by reducing the travel time on average. The reason for not being always better than FCTM is that the optimization algorithm sometimes produces infeasible solutions. It can be used in situations where emergency levels are minor. The intrusive signal preemption control has clearly improved the performance of the travel time; however, it has a significantly poor performance when the network impacts are considered, as shown by the blue bars in Fig. 17. The proposed combined intrusive and non-intrusive control has enhanced the travel time performance against the non-intrusive method. Although the proposed method has a lower performance than the pure intrusive preemption signal control, it has outperformed the intrusive method in terms of traffic network impacts.

In practice, for clarification, the selection of the traffic signal preemption approach is determined based on the associated emergency level. In this research, we have developed a table that describes the selection process, considering the urgency level and the corresponding controller, as shown in Table VII. By categorizing emergency levels and associating them with specific controllers, our goal is to address the varying degrees of urgency and the appropriate response required. This approach allows us to tailor the traffic signal preemption strategy based on the severity of the emergency situation.

In conclusion, traffic signal preemption techniques have a trade-off behavior. The more intrusive they are associated with, the more undesired traffic network impacts are experienced. The intrusiveness levels are represented by the following order {intrusive method, combined method, non-intrusive, FTCM}. Consequently, the design of the proposed preemption signal controller selects the proposed preemption controller depending on the emergency lever. The higher the emergency level, the more intrusiveness required.

E. Integration Assessment

In this subsection, we evaluate the proposed framework by integrating modules to test the impact of optimizing and including give-way driving behavior of CAVs along with the combined traffic signal control method in terms of travel time and average network delay. This evaluation is carried out through 12 test cases, as shown in Table VIII, to cover the possible scenarios arising from different urgency levels (Moderate/High), vehicle types (HDVs/CAVs), and traffic densities (Low/Mid/High).

In each scenario, the proposed combined intrusive and non-intrusive signal control method was employed as a

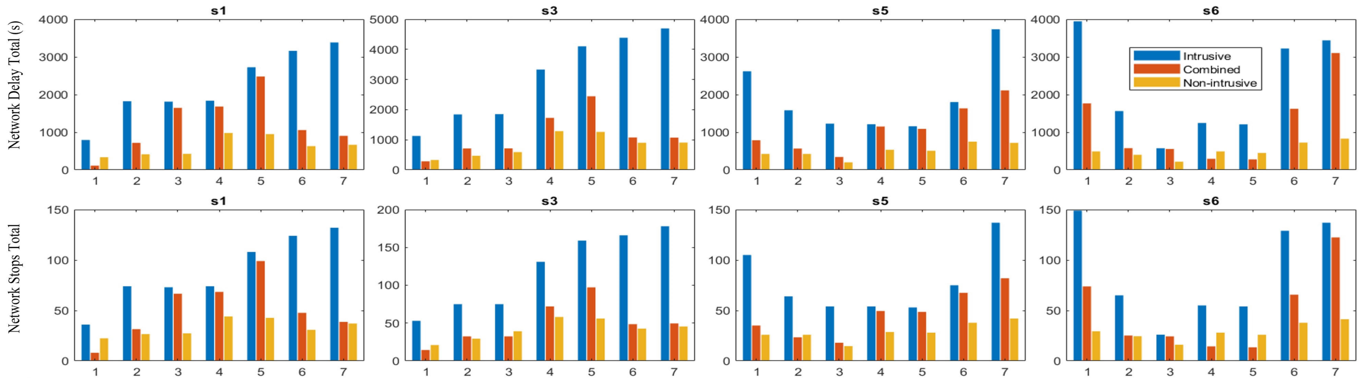

Fig. 17. Comparison of total network stops and total delay using the proposed algorithm, which combines intrusive and non-intrusive preemption signal control, against benchmark traffic signal preemption controllers.

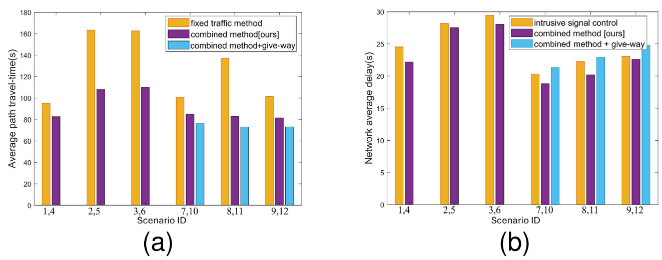

Fig. 18. Performance evaluation of proposed methods in terms of (a) Average CEV path travel-time and (b) Average network delay.

signal control method namely "ours" in Table VIII. Comparisons were conducted with the 1) FTCM to demonstrate the overall decrease in path travel time compared with the traditional method, and with 2) the intrusive signal control method to highlight the average impacts in traffic network delays. We demonstrate the cases when optimizing the driving behavior of the CAVs by enabling the give-way feature in conjunction with the optimized signal control method in high urgency level scenarios. The results, as shown in Figure 18 and Table VIII, illustrate the reductions in CEV travel time and their impact on the performance of the traffic network, proving that the integration of multiple intelligent control strategies can help optimize the operation of CEVs in an ITS environment.

In Figure 18(a), a clear reduction in the travel time of the CEV is evident when the combined signal control method is used in all scenarios. In particular, even greater improvements are observed when CAVs perform the give-way driving behavior during high-urgency levels of CEVs. In contrast, the network's average delay, as shown in Figure 18(b), experiences a reduction in all scenarios except those involving the give-way behavior executed by CAVs. This behavior results in a more significant reduction in travel time at the expense of average traffic network delays. Therefore, we opt to employ the give-way driving behavior when CEVs have a high urgency level.

VII. Discussion and Conclusion

In conclusion, this research aimed to address the critical issue of improving response times for emergency vehicles, particularly during pandemics or urgent situations that end users may face. The proposed intelligent framework presented a variety of effective strategies and mechanisms to minimize the travel time of CEVs. The introduction of a queue discharge model demonstrated a high predictive capability, achieving a high goodness of fit with an R-squared value of 0.99 for CAVs and 0.93 for HDVs. This regression model accurately estimated delay times caused by traffic queues, providing valuable insights for effective traffic management and congestion mitigation. Its application extends beyond emergency vehicle operations, providing insights for optimizing traffic flow and reducing delays.

The development of a dynamic path-planning algorithm, termed AQA*, showcased its adaptability to varying traffic congestion scenarios. Compared to benchmark algorithms (A*, UCS), the proposed AQA* outperformed by reducing travel times of the CEV by a 9% during sudden traffic delays. This algorithm demonstrated its effectiveness in enhancing emergency vehicle response times. Furthermore, this algorithm can be applied to other contexts, such as ITS, where dynamic routing is crucial to optimize travel time and improve efficiency.

Furthermore, the proposed traffic signal preemption control highlighted the trade-off relationship between intrusive preemption signal control and the undesired impacts on the overall traffic network. The technique presented a moderate approach that significantly reduced CEV travel time while minimizing adverse effects on other vehicles, striking a balance between efficient CEV travel and maintaining smooth traffic flow. Beyond its immediate application in emergency vehicle operations, this technique can be extended to other scenarios that require traffic signal optimization, such as public transportation systems or large-scale events, where the efficient movement of specific vehicles or groups is paramount.

Lastly, the utilization of a CNN-based deep learning model yielded promising results. The model achieved high accuracy in both regression with a mean absolute error of approximately 0.4 seconds, and classification tasks, boasting an accuracy of 99%. This model proved instrumental in predicting the merging time of CAVs operating in two lanes to facilitate the smooth passage of the CEV. Beyond predicting merging times for emergency vehicles, it can be employed for traffic lane-change behavior for CAVs, optimizing traffic signal timings, and enhancing overall traffic management. Additionally, the model can be adapted to other domains where real-time prediction and decision making based on complex data patterns are essential.

Overall, this research provides significant insights and advancements in the domain of improving emergency vehicle response times. The proposed intelligent framework and associated techniques demonstrate substantial potential for enhancing emergency vehicle operations, optimizing traffic management, and ultimately improving general public safety and well-being. In future work, multiple CEVs will be considered with different emergency levels corresponding to multiple priorities at the same time. It is important to consider that requesting HDVs to yield for CEVs may not produce optimal outcomes due to potential non-compliance by some HDV drivers or low response rates, which can introduce uncertainty into the overall system. This issue can be tackled in the future plan by developing an uncertainty-aware module that takes into account all road users in mixed-traffic and their respective responses to facilitate the passage of emergency vehicles. Besides, the effects of multi-priority aspects of scheduling the traffic signal and path planning will be studied under different traffic conditions.

References

[1] S. Choi, J. Kim, H. Yu, and H. Yeo, "Real-time prediction of arterial vehicle trajectories: An application to predictive route guidance for an emergency vehicle," in *Proc. IEEE Intell. Transp. Syst. Conf. (ITSC)*, Oct. 2019, pp. 4030–4036.

[2] C. L. González, J. J. Pulido, J. M. Alberola, V. Julian, and L. F. Niño, "Autonomous distributed intersection management for emergency vehicles at intersections," *Commun. Comput. Inf. Sci.*, vol. 1472, pp. 261–269, May 2021.

[3] E. Joelianto, K. Ramli, S. Sumaryo, and A. Halim, "Queueing theory based accelerated traffic discharging model in front of emergency vehicle on intersection," *Int. J. Vehicle Auto. Syst.*, vol. 14, no. 3, p. 213, 2019.

[4] L. Bieker-Walz, Y.-P. Flötteröd, and A. Sohr, "Modelling of emergency vehicles route choice with use of trajectory data," in *Proc. 6th Int. Conf. Models Technol. Intell. Transp. Syst. (MT-ITS)*, Jun. 2019, pp. 1–8.

[5] (2017). *NHS Ambulance Services*. Accessed: Oct. 14, 2022. [Online]. Available: https://www.england.nhs

[6] W. Min, L. Yu, P. Chen, M. Zhang, Y. Liu, and J. Wang, "On-demand greenwave for emergency vehicles in a time-varying road network with uncertainties," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 7, pp. 3056–3068, Jul. 2020.

[7] B. Singh and A. Gupta, "Recent trends in intelligent transportation systems: A review," *J. Transp. Literature*, vol. 9, no. 2, pp. 30–34, Apr. 2015.

[8] W. Yu, W. Bai, W. Luan, and L. Qi, "State-of-the-art review on traffic control strategies for emergency vehicles," *IEEE Access*, vol. 10, pp. 109729–109742, 2022.

[9] A. Alzubaidi, A. S. Al Sumaiti, Y.-J. Byon, and K. A. Hosani, "Emergency vehicle aware lane change decision model for autonomous vehicles using deep reinforcement learning," *IEEE Access*, vol. 11, pp. 27127–27137, 2023.

[10] X. Qin and A. M. Khan, "Control strategies of traffic signal timing transition for emergency vehicle preemption," *Transp. Res. Part C, Emerg. Technol.*, vol. 25, pp. 1–17, Dec. 2012.

[11] Y. Wang, Z. Wu, X. Yang, and L. Huang, "Design and implementation of an emergency vehicle signal preemption system based on cooperative vehicle-infrastructure technology," *Adv. Mech. Eng.*, vol. 5, Jan. 2013, Art. no. 834976.

[12] I. Silaghi, Z. Alssadi, and M. Silaghi, "Informed traffic signal preemption for emergency vehicles," in *Int. FLAIRS Conf. Proc.*, vol. 37, May 2024, pp. 1–26.

[13] J. Zhao, Y. Guo, and X. Duan, "Dynamic path planning of emergency vehicles based on travel time prediction," *J. Adv. Transp.*, vol. 2017, pp. 1–14, May 2017.

[14] C. Jose and K. S. Vijula Grace, "Optimization based routing model for the dynamic path planning of emergency vehicles," *Evol. Intell.*, vol. 15, no. 2, pp. 1425–1439, Jun. 2022.

[15] S. R. Rad, "Design evalution dedicated lanes for connected automated vehicles," Ph.D. dissertation, Dept. Transp. Planning, Delft Univ. Technol., Delft, The Netherlands, 2023.

[16] Z. Xin and P. Mingbao, "A control method of dedicated lanes for mixed use of special vehicles and cavs based on dynamic clear distance," *J. Transp. Inf. Saf.*, vol. 40, no. 3, pp. 118–126, 2022.

[17] A. Kherraki and R. El Ouazzani, "Deep convolutional neural networks architecture for an efficient emergency vehicle classification in real-time traffic monitoring," *IAES Int. J. Artif. Intell. (IJ-AI)*, vol. 11, no. 1, p. 110, Mar. 2022.

[18] V.-L. Nguyen, R.-H. Hwang, and P.-C. Lin, "Controllable path planning and traffic scheduling for emergency services in the Internet of Vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 8, pp. 12399–12413, Aug. 2022.

[19] C. Malandraki and M. S. Daskin, "Time dependent vehicle routing problems: Formulations, properties and heuristic algorithms," *Transp. Sci.*, vol. 26, no. 3, pp. 185–200, Aug. 1992.

[20] D. Delling and G. Nannicini, "Core routing on dynamic time-dependent road networks," *INFORMS J. Comput.*, vol. 24, no. 2, pp. 187–201, May 2012.

[21] E. W. Dijkstra, "A note on two problems in connexion with graphs," *Numerische Math.*, vol. 1, no. 1, pp. 269–271, Dec. 1959.

[22] S. Gao and I. Chabini, "Optimal routing policy problems in stochastic time-dependent networks," *Transp. Res. B, Methodol.*, vol. 40, no. 2, pp. 93–122, Feb. 2006.

[23] M. H. Olya, "Applying Dijkstra's algorithm for general shortest path problem with normal probability distribution arc length," *Int. J. Oper. Res.*, vol. 21, no. 2, pp. 143–154, 2014.

[24] P. E. Hart, N. J. Nilsson, and B. Raphael, "A formal basis for the heuristic determination of minimum cost paths," *IEEE Trans. Syst. Sci. Cybern.*, vols. SCS-4, no. 2, pp. 100–107, Jul. 1968.

[25] *Google Maps Google Maps API*. Accessed: Oct. 20, 2022. [Online]. Available: https://developers.google.com/maps

[26] L. Qi, M. Zhou, and W. Luan, "Emergency traffic-light control system design for intersections subject to accidents," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 1, pp. 170–183, Jan. 2016.

[27] L. Qi, M. Zhou, and W. Luan, "A two-level traffic light control strategy for preventing incident-based urban traffic congestion," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 1, pp. 13–24, Jan. 2018.

[28] L. Zhong and Y. Chen, "A novel real-time traffic signal control strategy for emergency vehicles," *IEEE Access*, vol. 10, pp. 19481–19492, 2022.

[29] Q. Lu and K.-D. Kim, "A genetic algorithm approach for expedited crossing of emergency vehicles in connected and autonomous intersection traffic," *J. Adv. Transp.*, vol. 2017, pp. 1–14, Jun. 2017.

[30] M. Haghani, A. Hosseinzadeh, and R. Kluger, "A lane-changing behaviour algorithm for connected and autonomous vehicles to facilitate emergency vehicle movements on urban arterials in microsimulation," *J. Simul.*, vol. 18, no. 3, pp. 413–427, May 2024.

[31] Z. Liu, H. Jia, R. Wu, J. Tian, and G. Wang, "IoV-based mathematic model for platoon give way to emergency vehicles promptly," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 9, pp. 16280–16289, Sep. 2022.

[32] M. Hosseinzadeh, B. Sinopoli, I. Kolmanovsky, and S. Baruah, "MPC-based emergency vehicle-centered multi-intersection traffic control," *IEEE Trans. Control Syst. Technol.*, vol. 31, no. 1, pp. 166–178, Jan. 2023.

[33] S. Wang, S. Djahel, Z. Zhang, and J. Mcmanis, "Next road rerouting: A multiagent system for mitigating unexpected urban traffic congestion," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 10, pp. 2888–2899, Oct. 2016.

[34] E. Paikari, S. Tahmasseby, and B. Far, "A simulation-based benefit analysis of deploying connected vehicles using dedicated short range communication," in *IEEE Intell. Vehicles Symp. Proc.*, Jun. 2014, pp. 980–985.

[35] X. Wang, S. Mao, and M. X. Gong, "An overview of 3GPP cellular vehicle-to-everything standards," *GetMobile, Mobile Comput. Commun.*, vol. 21, no. 3, pp. 19–25, Nov. 2017.

[36] C. R. Storck and F. Duarte-Figueiredo, "A survey of 5G technology evolution, standards, and infrastructure associated with vehicle-to-everything communications by Internet of Vehicles," *IEEE Access*, vol. 8, pp. 117593–117614, 2020.

[37] F. Arena and G. Pau, "An overview of vehicular communications," *Future Internet*, vol. 11, no. 2, p. 27, Jan. 2019.

[38] R. Wiedemann and U. Reiter, "The simulation system mission, background, and actual state," Commission Eur. Communities, Brussels, Belgium, Project ICARUS, Final Rep. V1052, 1992. [Online]. Available: http://eprints.soton.ac.uk/id/eprint/75517

[39] H. U. Ahmed, Y. Huang, and P. Lu, "A review of car-following models and modeling tools for human and autonomous-ready driving behaviors in micro-simulation," *Smart Cities*, vol. 4, no. 1, pp. 314–335, Mar. 2021.

[40] A. Ahmad, A. S. Al-Sumaiti, Y.-J. Byon, and K. Al Hosani, "Eco-driving framework for autonomous vehicles at signalized intersection in mixed-traffic environment," *IEEE Access*, vol. 12, pp. 85291–85305, 2024.

[41] X. Hu, M. Zheng, J. Zhao, B. Long, and G. Dai, "Stability analysis of mixed traffic flow considering personal space under the connected and automated environment," *Appl. Sci.*, vol. 13, no. 5, p. 3231, Mar. 2023.

[42] R. Akcelik and M. Besley, "Queue discharge flow and speed models for signalised intersections," in *Transportation and Traffic Theory in the 21st Century*. Bingley, U.K.: Emerald Group Publishing Limited, 2002, pp. 99–118.

[43] W. Hugemann, "Driver reaction times in road traffic," in *Proc. Annu. Meeting*, vol. 32, 2002, pp. 1–22.

[44] *Highway Capacity Manual 2010 (HCM2010)*, Transp. Res. Board. [Online]. Available: https://www.trb.org/Main/Blurbs/164718.aspx

[45] A. T. Le and T. D. Le, "Search-based planning and replanning in robotics and autonomous systems," in *Advanced Path Planning for Mobile Entities*. IntechOpen, 2018.

[46] J. R. Sánchez-Ibá nez, C. J. Pérez-del-Pulgar, and A. García-Cerezo, "Path planning for autonomous mobile robots: A review," *Sensors*, vol. 21, no. 23, p. 7898, Nov. 2021.

[47] X. Sun, S. Koenig, and W. Yeoh, "Generalized adaptive A*," in *Proc. AAMAS*, 2008, pp. 469–476.

[48] PTV Group, *PTV VISSIM 2022 User Manual*. Karlsruhe, Germany: PTV Planung Transport Verkehr AG, 2022. [Online]. Available: https://www.ptvgroup.com

[49] H. Mu, Y. Song, and L. Liu, "Route-based signal preemption control of emergency vehicle," *J. Control Sci. Eng.*, vol. 2, pp. 1–11, Aug. 2018.

[50] K. Shaaban, M. A. Khan, R. Hamila, and M. Ghanim, "A strategy for emergency vehicle preemption and route selection," *Arabian J. Sci. Eng.*, vol. 44, no. 10, pp. 8905–8913, Oct. 2019.

[51] H. Noori, L. Fu, and S. Shiravi, "A connected vehicle based traffic signal control strategy for emergency vehicle preemption," in *Proc. Transp. Res. Board 95th Annu. Meeting*, 2016, pp. 1–20.

[52] *Gurobi Optimizer Reference Manual*, Gurobi Optim., LLC, 2022. [Online]. Available: https://www.gurobi.com

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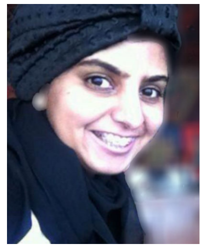

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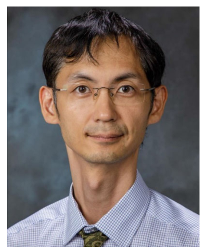

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