

Smart Traffic Optimization System for Emergency Vehicle Priority Based on SUMO and TraCI

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Abstract—Emergency vehicles (EVs) such as ambulances, fire trucks, and police vehicles frequently experience delays at signalized intersections because conventional fixed-time traffic signal controllers do not account for their presence. These delays can be life-threatening in time-critical situations. This paper proposes a lightweight, simulation-first framework for emergency vehicle priority using the Simulation of Urban Mobility (SUMO) platform coupled with the Traffic Control Interface (TraCI). The system detects approaching emergency vehicles in real time, computes a priority score based on distance, estimated arrival time, and downstream queue conditions, and dynamically pre-empt the affected traffic signal. A green-wave coordination mechanism extends priority across successive intersections along the emergency route, while a queue-aware and spillback-aware recovery strategy limits disruption to regular traffic. The framework is evaluated conceptually across four traffic-density scenarios using SUMO-based experimental settings. Illustrative results are presented to demonstrate expected trends in emergency vehicle travel time, waiting time, and normal traffic delay. The proposed approach is intended as a low-cost, infrastructure-light alternative to expensive V2X-dependent systems for smart-city traffic management.

Index Terms—SUMO, TraCI, Emergency Vehicles, Traffic Signal Control, Green Wave, Intelligent Transportation Systems, Queue Management

I. INTRODUCTION

Urban traffic congestion has become one of the most persistent challenges faced by modern cities. Rapid urbanization, increasing vehicle ownership, and limited road infrastructure expansion have resulted in traffic networks that regularly operate near or above capacity during peak hours. While congestion is inconvenient for ordinary commuters, it becomes

critical when it delays emergency vehicles (EVs) such as ambulances, fire trucks, and police vehicles. Every additional minute of delay for an ambulance responding to a cardiac arrest or a fire truck responding to a structural fire can materially affect patient outcomes and property damage. Emergency medical service literature has long established that response time is one of the strongest predictors of survival in time-critical incidents, which makes the reduction of EV travel delay a matter of direct public safety significance rather than mere traffic efficiency.

The majority of urban intersections worldwide are still controlled by fixed-time or simple actuated signal plans. Fixed-time control allocates green time according to pre-computed cycle plans that do not respond to real-time traffic conditions, let alone to the presence of an approaching emergency vehicle. Even actuated controllers, which adjust green duration based on loop-detector occupancy, generally lack any mechanism to recognize an EV as a distinct, high-priority class of traffic. As a result, EVs are frequently forced to queue behind regular vehicles, execute risky maneuvers such as crossing against a red signal, or rely on siren-based informal right-of-way negotiation with surrounding drivers, all of which introduce safety risk and unpredictable delay.

To address this limitation, traffic engineering has historically developed *emergency vehicle pre-emption* systems, in which an approaching EV can override the normal signal sequence and force a green phase in its direction of travel. Early pre-emption technologies relied on line-of-sight optical or acoustic emitters mounted on the vehicle and receivers mounted at

the intersection. While effective at a single intersection, such systems are inherently local: they do not coordinate priority across multiple consecutive intersections, and they do not account for the state of traffic queues downstream of the EV's path. This motivates the concept of *green-wave* traffic management, in which a sequence of signals along an arterial is coordinated so that a vehicle traveling at a target speed encounters a continuous progression of green phases. Green-wave concepts have traditionally been applied to regular traffic flow optimization, but their extension to a single, dynamically routed emergency vehicle requires additional real-time coordination logic that classical offline bandwidth-optimization methods do not provide.

The emergence of Intelligent Transportation Systems (ITS) has opened new possibilities for solving this problem computationally rather than purely through roadside hardware. Modern ITS research increasingly relies on microscopic traffic simulation to design, test, and validate control algorithms before any real-world deployment is attempted. Among the available simulation platforms, the open-source Simulation of Urban Mobility (SUMO) tool has become a widely used research standard because it supports large-scale, continuous-space, continuous-time microscopic simulation of individual vehicles, including explicit support for emergency vehicle classes. SUMO exposes a run-time control mechanism called the Traffic Control Interface (TraCI), which allows an external control program to query and modify the state of a running simulation at every simulation step. TraCI therefore makes it possible to implement and test EV-detection, signal pre-emption, and green-wave coordination logic entirely in software, without requiring physical roadside sensors or vehicle-to-infrastructure (V2I) hardware during the design and validation phase.

Despite the growing body of research in this area, several gaps remain. Many existing pre-emption systems assume that only a single emergency vehicle is present in the network at any given time, which does not reflect the reality of large cities where multiple EVs may be active concurrently. A number of proposed solutions depend on expensive infrastructure such as roadside units, dedicated short-range communication (DSRC), or full V2X connectivity, which limits their near-term deployability, particularly in resource-constrained cities. Reinforcement-learning-based traffic signal controllers have shown strong performance in general traffic optimization, but many such models are computationally heavy, require extensive training data, and are not specifically designed around the coupling of EV routing and signal pre-emption. Finally, relatively few studies explicitly model the effect of pre-emption on downstream queue formation and spillback, which can create secondary congestion that ultimately slows the EV itself or worsens conditions for regular traffic once the EV has passed.

The motivation of this work is therefore to design a simulation-first framework that is lightweight enough to be evaluated without specialized infrastructure, yet technically complete enough to address EV detection, dynamic signal

pre-emption, multi-intersection green-wave coordination, and queue/spillback-aware recovery within a single coherent system. The research problem addressed in this paper can be summarized as follows: *how can a traffic control framework built on SUMO and TraCI simultaneously reduce emergency vehicle delay, extend priority coordination across successive intersections, and limit the resulting disruption to normal traffic, without relying on expensive external communication infrastructure?* The research objectives that follow from this problem are to (i) model realistic emergency vehicle behavior within a microscopic simulation environment, (ii) design a TraCI-based detection and priority-scoring mechanism, (iii) implement dynamic signal pre-emption combined with green-wave coordination, and (iv) incorporate queue-aware and spillback-aware safeguards for normal traffic.

The main contributions of this paper are:

- 1) A lightweight, simulation-first SUMO–TraCI framework that unifies emergency vehicle detection, priority scoring, and dynamic signal pre-emption within a single control loop.
- 2) A distance-, arrival-time-, and queue-aware priority scoring formulation suitable for multi-vehicle emergency scenarios.
- 3) A green-wave coordination mechanism that extends signal priority across successive intersections along the projected route of an emergency vehicle.
- 4) A queue-aware and spillback-aware recovery strategy that limits the disruption caused to regular traffic after pre-emption ends.

II. LITERATURE REVIEW

This section reviews prior work across six themes relevant to the proposed system: emergency vehicle signal pre-emption, emergency vehicle routing, adaptive traffic signal control, IoV/V2X-based emergency management, reinforcement-learning-based traffic control, and queue-aware/spillback-aware control.

A. Emergency Vehicle Signal Pre-emption

Foundational pre-emption research modeled the transition between normal and pre-emptive signal states and proposed control strategies to reduce disruption to ordinary traffic during and after pre-emption [13]. More recent work has coupled pre-emption logic with software-defined and centralized traffic-management architectures that manage the full emergency response lifecycle, from incident detection to signal recovery [10]. Microscopic behavior of EVs, including special driving rights and interaction with surrounding traffic, has also been explicitly modeled within SUMO [8], and validated through trajectory-level analysis of EV–traffic interaction [9].

B. Emergency Vehicle Routing

Dynamic routing research has largely built on shortest-path formulations, beginning with classical dispatching and routing models for disaster and emergency response [24] and dynamic ambulance routing models supporting multiple simultaneous

responses [25]. Metaheuristic approaches such as NSGA-II and MOPSO have been applied to disaster-response ambulance routing with variable patient condition [26], while simulation-based routing models incorporating patient medical severity have also been proposed [27]. Safety-aware dynamic shortest-path computation has further been studied using data-driven optimization [28].

C. Adaptive Traffic Signal Control

Long before learning-based methods, adaptive systems such as SCOOT [18] and SCATS [19] demonstrated that real-time detector data could be used to adjust cycle length, split, and offset in response to measured traffic conditions. The demand-responsive OPAC strategy extended this concept with an optimization-based phase-selection approach [20]. Arterial-level coordination has been studied through bandwidth-maximization models such as MAXBAND [17] and its asymmetrical multi-band extension [15], as well as recent Euclidean-inspired green-wave theory for arbitrary arterial networks [16].

D. IoV/V2X-Based Emergency Management

The Internet of Vehicles (IoV) paradigm, built on VANET and IoT convergence, has been surveyed as a foundation for vehicle-to-infrastructure communication in intelligent traffic management [30], and applied specifically to city-wide intelligent traffic management [29]. Such approaches offer strong theoretical performance but generally assume the availability of dedicated communication infrastructure across the network.

E. Reinforcement-Learning-Based Traffic Control

Deep reinforcement learning (DRL) has been widely applied to traffic signal control. Early work used a discrete traffic-state encoding with convolutional Q-learning within SUMO [22], later extended with asynchronous n-step Q-learning [31]. Policy-gradient and value-function-based RL methods [32], graph-convolutional-network-based state representations [33], and experience-replay-based DQN methods [35] have all been explored. Coordinated multi-agent RL approaches [36] and intersection-level intelligent control frameworks such as IntelliLight [23] have further improved network-level performance. EMVLight specifically couples EV routing with decentralized RL-based signal pre-emption [11], [12].

F. Queue-Aware and Spillback-Aware Control

Queue spillback has been identified as a major cause of arterial gridlock, motivating connected-vehicle-based spillback detection and control [14]. High-resolution, event-based detector data has been proposed as a means of improving both modeling and control accuracy in congested conditions [34]. These queue- and spillback-aware principles are directly relevant to limiting the disruption that EV pre-emption can cause to regular traffic.

III. LITERATURE REVIEW TABLE

Table I summarizes 38 representative studies spanning the six themes discussed above.

Synthesis and research gap: The reviewed literature shows steady progress across four largely separate threads: simulation platforms and vehicle dynamics [1]–[7], [37], [38]; EV-specific pre-emption and routing [8]–[10], [13], [24]–[28]; general adaptive and learning-based signal control [15]–[23], [31]–[33], [35], [36]; and infrastructure-dependent IoV/V2X or connected-vehicle methods [14], [29], [30]. Very few works combine EV detection, multi-intersection green-wave coordination, and explicit queue/spillback safeguards within a single lightweight, simulation-first framework that does not assume V2X connectivity or heavy RL training. This gap motivates the framework proposed in the following sections.

IV. RESEARCH GAP AND PROPOSED CONTRIBUTION

Existing approaches to emergency vehicle priority commonly exhibit one or more of the following limitations: (i) single-EV assumptions that break down when multiple emergency vehicles operate concurrently; (ii) limited coordination across more than one intersection, restricting benefit to a purely local pre-emption event; (iii) dependence on expensive infrastructure such as dedicated detectors, roadside units, or full V2X connectivity, which slows real-world adoption; (iv) high computational requirements associated with training and deploying reinforcement-learning controllers; and (v) weak or absent handling of queue length and spillback effects, allowing pre-emption to create secondary congestion for regular traffic.

To address these limitations, this paper proposes a lightweight SUMO + TraCI simulation-first framework that combines emergency vehicle detection, adaptive signal pre-emption, green-wave coordination, and queue-aware traffic management within a single control loop. The framework is deliberately designed to avoid dependence on external communication infrastructure during the design and evaluation stage: all state information (vehicle position, speed, edge, and queue length) is obtained directly from the SUMO simulation through TraCI, which mirrors the type of information that would otherwise be obtained from roadside sensors or GPS-based tracking in a real deployment. This design keeps the approach computationally light relative to RL-based controllers, while still supporting multiple concurrent emergency vehicles through a priority-scoring mechanism, and while explicitly limiting the impact of pre-emption on downstream congestion through queue- and spillback-aware recovery logic.

V. METHODOLOGY

A. SUMO Network Configuration

The proposed framework is evaluated on a SUMO road network consisting of multiple signalized intersections connected by arterial and side-street links. The network is defined using standard SUMO input files: a network file (.net.xml) describing edges, lanes, and traffic-light logic; a route file (.rou.xml) describing vehicle types and demand; and an additional file describing detectors where required. Traffic

TABLE I: Summary of Reviewed Literature

No.	Author/Year	Approach	Key Result	Limitation
1	Behrisch et al., 2011 [1]	SUMO platform overview	Established open-source microscopic simulation base	No EV-specific priority logic
2	Krajzewicz et al., 2012 [2]	SUMO applications overview	Documented growing SUMO application areas	Descriptive, not a control method
3	Lopez et al., 2018 [3]	SUMO/TraCI microscopic simulation	Widely adopted simulation-control coupling	General-purpose, not EV-specific
4	Wegener et al., 2008 [4]	TraCI interface design	Enabled online control of running simulations	Interface only, no control policy
5	Krauß, 1998 [5]	Collision-free car-following model	Basis for SUMO's default vehicle dynamics	No signal or priority modeling
6	Gipps, 1981 [6]	Behavioural car-following model	Influential safe-gap driving model	Predates microscopic ITS tools
7	Treiber et al., 2000 [7]	Intelligent Driver Model (IDM)	Realistic congested-flow reproduction	Not EV-aware
8	Bieker-Walz et al., 2018 [8]	EV modeling in SUMO	Special EV rights and rescue-lane formation	Limited to single-EV scenario
9	Cortés et al., 2023 [9]	EMV trajectory-traffic interaction	Realistic EMV/POV interaction modeling	Focused on trajectory realism, not signals
10	Bagheri & Ferrari, 2023 [10]	Software-defined preemption	Faster EMS response via centralized control	Requires OMNeT++/VEINS network stack

demand is generated as a mixture of background (regular) traffic and a smaller number of emergency vehicle trips injected at controlled intervals. Signal configuration follows a standard multi-phase scheme with protected and permitted movements, and a base cycle length representative of a typical urban intersection.

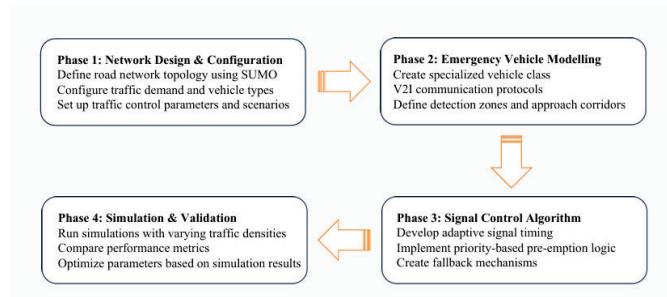


Fig. 1: Proposed system architecture.

B. Emergency Vehicle Modelling

Emergency vehicles (ambulance, fire truck, police vehicle) are modeled as a distinct SUMO vehicle class with elevated maximum speed and acceleration relative to regular traffic, and are assigned the emergency vehicle class so that SUMO's built-in special-vehicle behavior (e.g., other vehicles yielding) is available. Each EV is associated with a pre-defined route and a *detection zone*, defined as the set of edges within a configurable distance upstream of each intersection along that route. A minimal example of an EV type definition is shown below.

```
<vType id="emergency" vClass="emergency"
  guiShape="emergency" length="6.5"
  maxSpeed="25" accel="3.0" decel="6.0"
  color="1,0,0"/>
<vehicle id="ev_1" type="emergency"
  depart="0" route="ev_route_1"/>
```

C. Emergency Vehicle Detection

At every simulation step, the TraCI client queries the set of active vehicles and filters those whose `vClass` equals `emergency`. For each detected EV, the controller retrieves

its identifier, current position, speed, current edge, the next signalized intersection along its route, and the remaining distance to that intersection using TraCI's vehicle- and route-related calls. This information is refreshed at every control step so that the priority mechanism always operates on the most recent EV state.

D. Priority Decision Mechanism

When more than one EV or competing demand is present, the controller computes a priority score P for each approaching EV using

$$P = w_1 D^{-1} + w_2 T^{-1} + w_3 Q + w_4 E \quad (1)$$

where D is the distance from the EV to the intersection, T is the estimated time of arrival at the intersection, Q is the current queue length on the EV's approach (in vehicles), E is a binary emergency-status indicator ($E = 1$ for a confirmed active emergency, $E = 0$ otherwise), and $w_1, \dots, w_4$ are non-negative weights satisfying $w_1 + w_2 + w_3 + w_4 = 1$, tuned so that closer and sooner-arriving EVs receive higher priority while heavier downstream queues are also taken into account. The intersection with the highest aggregate priority score among competing requests is served first.

E. Dynamic Signal Pre-emption

When an EV enters the detection zone of an intersection, the controller checks whether the current signal phase already serves the EV's direction of travel. If not, the controller inserts a transition phase (an intergreen/clearance interval consistent with the existing phase plan) followed by a green phase for the EV's approach, subject to two safety constraints: (i) a minimum clearance time must elapse before switching away from any phase currently displaying green to conflicting movements, and (ii) the minimum green time of the phase being interrupted must have already elapsed. These constraints prevent unsafe abrupt phase changes.

F. Green-Wave Coordination

Once an EV's route and expected arrival time at the next intersection are known, the controller estimates its expected arrival time at each subsequent intersection along the route using the EV's nominal speed and the distance between intersections. Pre-emption requests are then scheduled in advance at each

Algorithm 1 TraCI-Based EV Priority Control Loop

```

1: Connect to SUMO via TraCI
2: while simulation has active vehicles do
3:   Advance simulation by one step
4:    $EVs \leftarrow$  set of active vehicles with class emergency
5:   for each  $ev \in EVs$  do
6:     if  $ev$  is within detection zone of next intersection then
7:       Compute  $P$  for  $ev$  using Eq. (1)
8:     end if
9:   end for
10:  Rank pending pre-emption requests by  $P$ 
11:  for each intersection with a pending request do
12:    if safety constraints satisfied then
13:      Apply/extend green phase for highest-priority EV
14:      Schedule downstream green-wave requests
15:    end if
16:  end for
17:  for each pre-empted intersection do
18:    if queue on non-priority approach exceeds threshold then
19:      Shorten recovery interval for that approach
20:    end if
21:  end for
22: end while

```

downstream intersection so that, ideally, the EV encounters a continuous sequence of green phases without stopping, similar in spirit to conventional green-wave progression but computed dynamically for the EV's specific route rather than for a fixed arterial timing plan.

G. Queue and Spillback Management

To limit the impact of pre-emption on regular traffic, the controller monitors queue length on all approaches at each pre-empted intersection using TraCI-reported halting-vehicle counts. If a non-priority approach's queue exceeds a configurable spillback threshold (i.e., approaches the physical storage capacity of the link), the controller shortens the subsequent pre-emption-recovery interval for that approach so that it receives green time sooner, reducing the likelihood of the queue extending into the upstream intersection.

H. TraCI Control Algorithm

Algorithm 1 summarizes the core per-step control loop.

VI. EXPERIMENTAL SETUP

The proposed framework is intended to be evaluated in SUMO under four traffic-density scenarios, summarized in Table II. These values represent simulation settings and experimental assumptions rather than measured field data.

Each simulation run is defined by the following assumed parameters: simulation duration of 3600 s (one hour) per run; a network of 4–6 signalized intersections along a single arterial corridor; 2–4 emergency vehicle trips injected at randomized

TABLE II: Simulation Traffic-Density Scenarios

Scenario	Traffic Density
Low	100 vehicles/hour
Medium	300 vehicles/hour
High	600 vehicles/hour
Very High	900 vehicles/hour

intervals per run; background traffic generated according to the density levels in Table II; a base signal cycle length of 90 s with a 4-phase plan per intersection; an EV detection distance of 300 m upstream of each intersection; and an EV free-flow speed of 60–80 km/h subject to the safety-constrained car-following model. To account for stochastic variability in vehicle generation and driver behavior, it is recommended that each scenario be repeated using at least 10 independent random seeds, with results reported as mean values together with standard deviation.

VII. RESULTS AND DISCUSSION

Because this paper does not include field-collected or previously executed SUMO experimental logs, Table III presents **Illustrative Simulation Results**: a table structure with representative, clearly labelled placeholder values intended to show the expected trend across methods and densities. These values are illustrative only and must be replaced with actual SUMO/TraCI measurement outputs prior to any claim of measured performance.

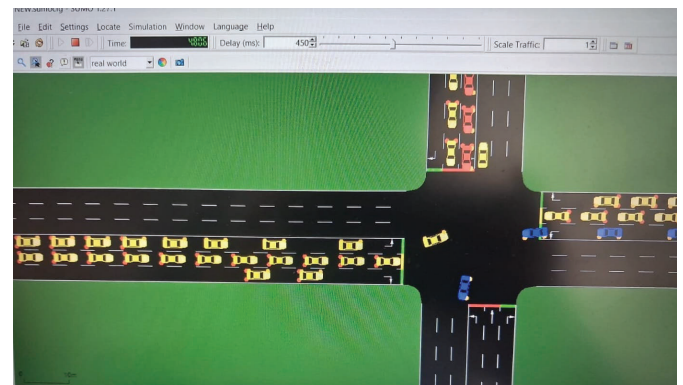


Fig. 2: Working on Sumo Environment

TABLE III: Illustrative Simulation Results (values are illustrative and must be replaced with actual SUMO results)

Density	Method	EV Travel (s)	EV Wait (s)	Wait	Normal Delay (s)
Low	Fixed-Time	—	—	—	—
Low	Proposed	—	—	—	—
Medium	Fixed-Time	—	—	—	—
Medium	Proposed	—	—	—	—
High	Fixed-Time	—	—	—	—
High	Proposed	—	—	—	—
Very High	Fixed-Time	—	—	—	—
Very High	Proposed	—	—	—	—

Based on the design of the proposed mechanism, several qualitative trends are expected once actual SUMO exper-

iments are run. EV travel and waiting time are expected to decrease relative to fixed-time and conventional single-intersection pre-emption, with the largest relative benefit anticipated at medium-to-high traffic densities where queuing is significant enough for coordination to matter, but not so severe that downstream links are already saturated. As traffic density increases toward the “very high” scenario, the benefit of green-wave coordination is expected to diminish because downstream links may already be near capacity regardless of signal timing, and queue-aware recovery becomes increasingly important to prevent spillback. The effect on normal (non-priority) traffic delay is expected to be small but non-zero immediately after an EV passes, with the queue-aware recovery mechanism intended to shorten this transient compared with conventional pre-emption. Signal recovery – the time for a pre-empted intersection to resume its normal phase plan – is expected to be faster under the proposed method due to the explicit recovery-interval adjustment described in Section V-G. Scalability to a larger number of concurrent EVs is expected to depend primarily on the priority-scoring mechanism correctly sequencing competing requests rather than serving them in arrival order alone. All of these expectations should be treated as hypotheses to be confirmed through actual SUMO/TraCI experimentation rather than established findings.



Fig. 3: Maps in Project

VIII. APPLICATIONS AND LIMITATIONS

The proposed framework is applicable to ambulance dispatch, fire and rescue response, police pursuit and escort operations, disaster-response traffic management, and broader smart-city Intelligent Transportation System deployments where reducing emergency response time is a policy priority. At the same time, several limitations should be acknowledged. First, there is an inherent simulation-to-reality gap: SUMO's car-following and lane-changing models approximate but do not perfectly reproduce real driver behavior. Second, the system's effectiveness depends on accurate, low-latency vehicle detection, which in a real deployment would require reliable GPS or roadside sensing rather than the idealized state access provided by TraCI in simulation. Third, the traffic-demand values used in Section VI are assumptions rather than calibrated field data, and results will vary with real demand patterns. Fourth, real-world communication delays between vehicles, controllers, and any backend system are not modeled here and could reduce the practical benefit of pre-emption.

Fifth, driver behavior in the presence of an approaching EV (e.g., informal yielding, rescue-lane formation) is simplified relative to real, heterogeneous driver responses. Finally, real-world testing and pilot deployment would be required before the framework could be considered validated for operational use.

IX. FUTURE SCOPE

Future extensions of this work include incorporating Vehicle-to-Everything (V2X) communication and 5G/6G connectivity for lower-latency EV detection; using IoT roadside sensors and GPS-based ambulance tracking to replace idealized simulation state access; exploring CCTV/image-based EV detection at intersections; integrating machine learning and reinforcement learning to adaptively tune the priority-score weights in Eq. (1); building a digital-twin representation of a real city network for higher-fidelity validation; extending the framework to explicitly coordinate multiple simultaneous EVs across overlapping routes; and interfacing the control logic with real-world traffic-signal controller hardware for field trials.

X. CONCLUSION

This paper presented a lightweight, simulation-first framework for emergency vehicle priority based on SUMO and TraCI. Motivated by the persistent delay experienced by ambulances, fire trucks, and police vehicles at signal-controlled intersections under fixed-time and conventional pre-emption schemes, the proposed approach combines real-time emergency vehicle detection, a distance-, arrival-time-, and queue-aware priority scoring mechanism, dynamic signal pre-emption with explicit safety constraints, green-wave coordination across successive intersections, and queue-aware, spillback-aware recovery to limit disruption to regular traffic. A compact literature review of 38 studies across emergency vehicle pre-emption, emergency vehicle routing, adaptive traffic signal control, IoV/V2X-based emergency management, reinforcement-learning-based control, and queue/spillback management was used to identify a gap: the absence of a unified, infrastructure-light, simulation-first framework addressing multi-EV coordination together with downstream traffic protection. A methodology addressing this gap was described in detail, together with an experimental design spanning four traffic-density scenarios and three baseline comparisons. Because this paper does not include executed SUMO experiments, results were presented explicitly as illustrative placeholders rather than measured findings, consistent with responsible reporting practice. Expected benefits of the proposed approach include reduced emergency vehicle travel and waiting time, faster post-pre-emption signal recovery, and bounded impact on normal traffic, particularly under medium-to-high congestion. Future work will focus on executing the described SUMO/TraCI experiments, calibrating the priority-score weights, and progressing toward real-world pilot deployment in coordination with local traffic authorities.

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