HyFURE - Hybrid Fuzzy Reinforcement for Adaptive Class-based Traffic Control

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***Abstract*—The rapid surge in the number of vehicles per household places immense pressure on urban transportation networks, leading to severe congestion, time loss, and adverse environmental impact. The basic drawback in most of the traffic control systems is the lack of adaptiveness in the signal control, as the signal timings are mostly fixed and operate in a repeating loop. This is followed by the issue of ”vehicle blindness”, where all vehicles are treated the same, giving no priority to vehicles like an ambulance carrying patients amid regular traffic. This limitation poses a direct risk to public safety, where seconds saved in commute can be crucial in determining the outcome of an emergency that requires an intelligent transportation system. To bridge the current gap, HyFURE, a two-layer Artificial Intelligence (AI) framework, adaptively prioritizes vehicles acting as an Adaptive Traffic Management System (ATMS). The first layer acts as a strategic controller using fuzzy logic to determine the priority depending on the vehicle type (ambulance, trucks, buses, etc.) present at the intersection. This strategy is then communicated to the second layer, a Reinforcement Learning (RL) agent, which effectively learns the optimal real-time sequence of signal changes that best satisfies the priority set by the strategic controller to reduce the waiting time of ambulances and the overall congestion by approximately 88% and 70% respectively compared to the traditional system. The implementation and validation of the proposed model were done in SUMO, a simulated real-life environment, as it eliminates the risk or the cost element of a live implementation. SUMO is a microscopic traffic simulator used to model and analyze large-scale urban transportation systems.**

***Index Terms*—Fuzzy Logic, Reinforcement Learning, Adaptive Traffic Management System, Priority Vehicle Management, Intelligent Transportation System, SUMO.**

I. Introduction

Nowadays, traffic bottlenecks have become a common occurrence, leading to stress, time loss, and even missed appointments. Adding to the problem, urban areas have a large number of vehicles consuming fuel, resulting in high carbon emissions. Traffic congestion has been predicted to result in a loss of approximately 14660 crores per year in New Delhi by 2030. In addition, the vehicular population in New Delhi, which surpassed 10 million in 2020, is predicted to increase exponentially due to the rise in population. However, existing traffic signals use fixed time limits and do not adapt according to real time conditions, leading to inefficiencies and delays [1], [2]. To prevent these problems, ATMS should be adopted to optimize traffic flow, reducing delay and congestion [3].

Due to congestion, it takes a lot of time for emergency vehicles to pass through an intersection. ATMS optimizes emergency vehicle response in smart cities by dynamically adjusting traffic controls, increasing coordination, and ensuring safety [4]. A priority based signal management system dynamically adjusts signal timing based on vehicle density and importance, aiming to optimize traffic flow and reduce congestion [5]. SUMO, a microscopic traffic simulation suite for modeling, analyzing, and managing urban mobility and vehicular communication, is used to replicate real world traffic [6].

The critical gap in current traffic management research lies in the fact that general optimization techniques are 'vehicle-blind', failing to convey the strategic priority of a real-time situation. The contribution of this paper is to fill this gap by proposing Hybrid Fuzzy-Reinforcement (HyFURE), a new framework that fuses the powers of fuzzy logic and RL. The proposed system aims at enhancing the representation of traffic flow states and the learning process by embedding human-like reasoning based on priorities directly into the decision-making of the agent.

When understanding the state of the traffic network, the number of vehicles, congested lanes, and the waiting time of vehicles act as the input to the system. The data is passed through a fuzzy inference system, which uses human-like logic to give a better understanding of the priority. Fuzzy logic picks out complex relationships that could be missed by analyzing raw numbers, highlighting the priority in a traffic situation. The state space passed to the RL agent is composed of the raw inputs and the scores produced by the fuzzy logic.

The RL agent fine-tunes the traffic signal timings and transition phases based on its understanding of the state space during the learning phase. Therefore, by incorporating fuzzy outputs, the agent obtains a more comprehensive representation of traffic congestion, enhancing the accuracy and efficiency of its decision-making. The signal processing unit is responsible for these decisions to regulate network traffic flow. Using reinforcement learning paradigms, this process enables the agent to continuously elaborate its policy, thereby contributing to reducing congestion and delays across the network.

The fuzzy priority scores are blended with typical measures of traffic performance, such as average wait times, queue reduction, and throughput, when defining the reward function for the HyFURE framework. This reward engineering brings high-priority traffic into the picture, making the goals of the agent perfectly in sync with the real world, and sends back valuable feedback to the system, enabling it to learn and grow. With its dynamic approach, the HyFURE framework fixes all the shortcomings of static, one-trick pony control systems.

II. LITERATURE SURVEY

Urban mobility has been challenged by traffic congestion over the years, and its temporary solution has been using fixed-time signals. These systems do not tend to traffic fluctuations, accidents, or unpredictable demand because they depend on historical data and fixed cycles, resulting in the environment's under performance and delays. To overcome these challenges, early adaptive systems like Split Cycle and Offset Optimization Technique (SCOOT) and Sydney Coordinated Adaptive Traffic System (SCATS) were developed to adapt timings to real-world traffic flows. However, they were confined to simple models and heuristic optimizations.

AI, machine learning, and RL are used for the development of ATMS as an effective strategy. RL learns iteratively in real-world traffic situations to increase its responsiveness in conditions that are stochastic. Frameworks prefer the use of fuzzy logic, predictive modeling, and deep RL over traditional methods. They reduce delays and avoid inefficient cycle patterns. The benefits include reductions in waiting times, reduction of fuel use, and lower CO_2 emissions, supporting goals of sustainability [7]–[9].

Management of traffic effectively is not only for the convenience of commuters but also important for public safety, as traffic conditions can adversely affect the response times of emergency vehicles. The major drawback of traditional traffic management is its "vehicle-blind" nature, treating all vehicles with equal priority. Simulation-based studies demonstrate that priority-aware systems can reduce the waiting time of emergency vehicles by 50% without adversely affecting regular traffic. However, more studies argue that a truly intelligent system must also include the severity of the incident to assign appropriate priority levels and calculate the optimal number of signal interruptions to minimize the adverse impact on surrounding traffic. This establishes the need for systems that are not just adaptive but also context-aware and strategically efficient in managing emergency scenarios. [10], [11]

Fuzzy logic provides a framework for carrying out complex decisions based on vague real-world data. A Fuzzy Logic Controller can effectively optimize signal timings by evaluating multiple inputs, such as the number of vehicles, queue length, and road width, against a set of semantic rules. This approach avoids the issue of unnecessary green signals and allows for dynamic and context-aware adjustments, making the system more efficient than the conventional time-based system [12]. A significant drawback in most of the Reinforcement Learning (RL) applications for the control of traffic is the dependence on the fixed intervals for the signal phases, which is inefficient in dynamic traffic environments. Fuzzy Logic Controller (FLC) is an effective method to overcome this rigidity. FLC is well suited to provide in-depth adaptive control over the duration of each signal phase based on real-time traffic volume. In such a hybrid architecture, the FLC can work in collaboration with an RL agent, where the optimal sequence of signal phases is determined by the agent and the calculation of the accurate and dynamic duration is done by the FLC. This combination of RL and FLC results in a system that is more robust and efficient than an RL only approach [13].

Reinforcement learning is a stream of machine learning where agents take action in an environment to increase the combined rewards. This agent interacts with the traffic environment and provides feedback in the form of rewards or penalties, adjusting its actions accordingly to improve the environment's goals. RL has become a strong approach for improving traffic signal control in urban areas. In comparison, traditional methods like Webster's deterministic formula, dynamic programming, and genetic algorithms provided early solutions that were adaptive, but their scalability and real-time responsiveness were questioned. RL, by using the Markov Decision Processes, allows agents to learn the protocol that reduces congestion and wait times through interactions created from trial and error. Q-learning, which is an earlier RL method, drew upon table representations of state-action pairs. Although

TABLE I
LITERATURE SURVEY OF EXISTING METHODOLOGIES

Author	Methodology (Keywords)	Key Limitations
Ali et al. [7], Zrigui et al. [8], Othman et al. [9]	AI, ML, RL-based Adaptive Traffic Management Systems (ATMS)	Poor scalability; limited adaptiveness
Carvalho et al. [10], Karmakar et al. [11]	Emergency vehicle prioritization in simulation	No context-based severity handling
Chabchoub et al. [12]	Fuzzy Logic Controller (FLC) for adaptive timing	Static rules; no learning ability
Tunc et al. [13]	Hybrid Fuzzy–RL architecture	Complex tuning; coordination overhead
Roz et al. [14], Park et al. [15], Kondratov et al. [16]	Q-learning, Deep Q-Network (DQN) for signal control	High computation; slow convergence

its mechanism is valid for small problems, this approach becomes infeasible due to its nature of instability and the curse of dimensionality in large traffic networks when integrated with naive function approximators. To solve this problem, Deep Q-Network (DQN) is implemented by integrating a deep neural network for a high-dimensional state space by approximating Q-values. Key innovations like "experience replay" and "target networks" regulated training, enhanced convergence, and decreased the amount of correlations between samples. In traffic signal systems, DQN-based controllers showcased major diminutions in waiting times and congestion in comparison with fixed-time and dynamic methods. [14]–[16]

Summary of the literature survey is provided in the table I. Thus, existing methodologies suffer from limited scalability and lack of smart prioritization in complex urban networks. Therefore, a hybrid, context-aware and adaptive framework is needed, which is addressed by the proposed system HyFURE, which integrates fuzzy logic and reinforcement learning for intelligent and priority-based traffic control validated using SUMO.

III. METHODOLOGY

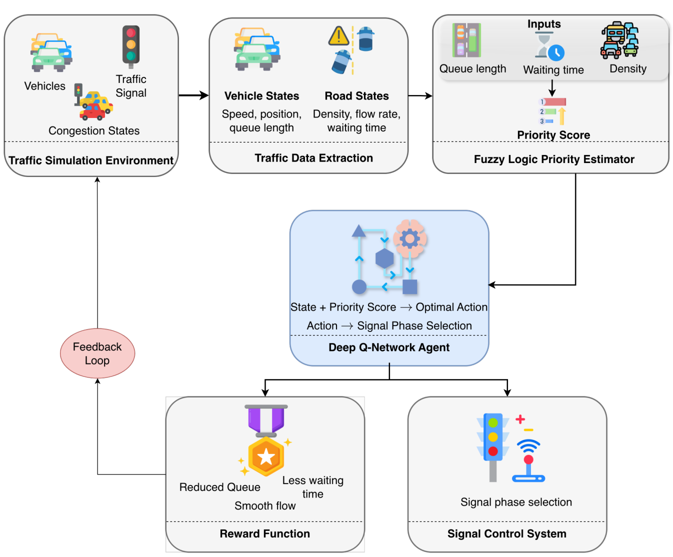

Fig. 1. Reinforcement Learning with Fuzzy Logic for priority vehicles

A. Environmental setup and Data acquisition

The traffic intersection is created using SUMO (Simulation of Urban MObility), an open-source software where lanes and vehicles are simulated in a virtual environment. A four-way intersection is created where each road has three lanes along with a traffic signal. Vehicles like cars, bikes, trucks, buses, and ambulances are created. The frequency of each vehicle is based on a probability value. Bikes have a higher value, and an ambulance has the least value. The priority value is inversely proportional to the probability score. This means that traffic is cleared first where the ambulance is present. This is then simulated using TraCl. At each simulation the environment provides the count of vehicles and the waiting time. This acts as an input for the reinforcement learning agent. This data is collected to simulate a dynamic traffic condition.

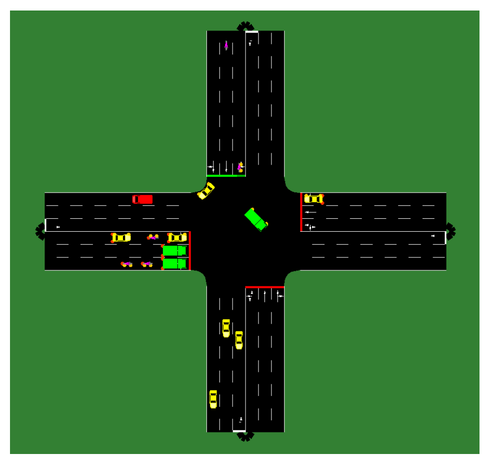

Fig. 2. Virtual Simulation of a Junction in SUMO

B. Fuzzy Logic

A Mamdani-style fuzzy logic system uses lane counts and waiting time to figure out the importance of each incoming direction. Lanes with a high vehicle count and a long waiting time are given higher priority as they contribute more to congestion. However, in the event that an ambulance or other emergency vehicle arrives, the ambulance's safe and efficient passage is given even more priority. Using piecewise linear membership functions, inputs are categorized into three groups: low, medium, and high. Fuzzy rules are directly proportional to the priority of a lane. The fuzzy output is normalized to the range of [0,1] and is then added to the reinforcement learning state vector. The fuzzy module gives the agent understandable advice by combining quantitative and qualitative traffic data.

For each direction $d \in \{N, S, E, W\}$, the fuzzy utility score U_d is computed as a weighted aggregation of fuzzy rule strengths:

$$U_d = \frac{r_1 \cdot U_{\text{high}} + r_2 \cdot U_{\text{med}} + r_3 \cdot U_{\text{low}}}{r_1 + r_2 + r_3} \tag{1}$$

where $U_{\text{high}}, U_{\text{med}}, U_{\text{low}}$ are predefined fuzzy scores that correspond to the high, medium, and low congestion, respectively. The rules r_1, r_2, r_3 are defined as:

$$r_1 = \max\Big(\mu_{\text{high}}(\text{count}_d),\ \mu_{\text{high}}(\text{wait}_d)\Big) \tag{2}$$

$$r_2 = \max\Big(\mu_{\text{med}}(\text{count}_d),\ \mu_{\text{med}}(\text{wait}_d)\Big) \tag{3}$$

$$r_3 = \min\Big(\mu_{\text{low}}(\text{count}_d),\ \mu_{\text{low}}(\text{wait}_d)\Big) \tag{4}$$

where $\mu_{\text{low}}, \mu_{\text{med}}, \mu_{\text{high}}$ are piecewise linear membership functions where the parameters (a,b,c) were empirically tuned based on observed congestion.

C. Reinforcement Learning Agent

The reinforcement learning agent is implemented with the DQN (Deep Q-Network) model, where the state vector s_t is composed of lane vehicle counts, waiting times, and fuzzy priority scores that together capture the current traffic situation.

$$s_t = \big[\ \text{counts},\ \text{waits},\ U_N,\ U_S,\ U_E,\ U_W\ \big] \tag{5}$$

The action space consists of four discrete traffic signal phases, representing possible green light allocations at the intersection. At each decision step, the agent observes the current state and selects an action using the epsilon-greedy exploration policy, followed by applying it to the SUMO environment. The environment then transitions to a new state, and a reward is computed based on improvements in traffic flow and waiting time reduction. These experiences are stored in a replay buffer, and the DQN is trained by sampling from this buffer, while a target network ensures stable learning. In particular, experience replay stores past traffic interactions in memory and samples them randomly for training, which breaks correlations between consecutive states and makes learning more efficient. To ensure realistic switching behavior, a minimum green time constraint is enforced. The DQN has two fully connected hidden layers with 128 and 64 neurons each along with ReLU activation function. The adam optimizer with learning rate 0.001 is used for smoother convergence and momentum decay of 0.95 for reward balance. The Epsilon-greedy policy involves epsilon decaying from 1 to 0.05. Through repeated interaction with the SUMO environment, the agent gradually learns how to optimize traffic flow, minimize waiting times, and dynamically prioritize congested or high-priority lanes.

D. Reward Calculation

The reward function helps the agent to manage traffic effectively while looking at priority lanes. It has four main components: minimizing the change in cumulative waiting time for all vehicles, awarding additional points to lanes with high congestion based on a fuzzy priority function, optionally rewarding prioritized vehicles such as an ambulance, and heavily penalizing teleportation of cars in the simulation where teleportation is an inbuilt mechanism present in SUMO but it is countered using the heavy penalization as it does not occur in reality. Thus, the agent is trained to optimize global traffic flow as well as busy or congested lanes.

$$R(s_t, a_t, s_{t+1}) = \Delta W_t + \lambda\, U_{a_t} + \sum_{v \in V} \tau_v - P_{\text{teleport}}, \tag{6}$$

where:

- $\Delta W_t = W_{\text{prev}} - W_{\text{curr}}$ is the reduction in total waiting time across all lanes. Positive if waiting time decreases, negative otherwise.
- $U_{a_t} \in [0, 1]$ is the fuzzy urgency score of the chosen action (direction), scaled by $\lambda > 0$ to encourage serving urgent lanes.
- τ_v is a small reward associated with high-priority vehicles (e.g., ambulances, buses), summed over all vehicles $v \in V$ present at the junction.
- P_{teleport} is a penalty applied for vehicles that teleport due to excessive waiting in SUMO, discouraging undesirable states.

E. Feedback Loop

In the reinforcement learning framework, the agent perceives the current traffic state, leading to the selection of an optimal signal phase followed by the application to the simulation environment. The reward function is now computed and fed back to the agent, which, when repeated continuously, results in improvement and reduced traffic congestion along with optimized traffic management.

$$\begin{aligned} Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \Big[& R(s_t, a_t, s_{t+1}) \\ & + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \Big], \end{aligned} \tag{7}$$

- $Q(s_t, a_t)$ represents the current action-value estimate for state s_t and action a_t.
- $R(s_t, a_t, s_{t+1})$ represents the reward obtained after taking action a_t in state s_t and reaching state s_{t+1} (see Eq. (6)).
- $\alpha \in [0, 1]$ represents the learning rate which controls how much the new information overrides the old Q-value.
- $\gamma \in [0, 1]$ represents the discount factor, determining the importance of future rewards.
- $\max_{a'} Q(s_{t+1}, a')$ represents the maximum predicted Q-value for the next state s_{t+1} over all possible actions a'.

F. Signal Control System

The control logic of the system works on a dynamic priority basis. When the system identifies an approaching emergency vehicle, it takes over, giving green to that particular lane and stopping the rest of the lanes. Under normal conditions, the system allows priority traffic depending on real-time congestion levels, distributing the green time to the lane that has the greatest density of vehicles. During periods of low traffic, it operates in demand-based mode to provide a green signal to incoming cars to reduce unnecessary halts. In the absence of any cars, the system reverts to upholding the previous green phase.

IV. RESULTS

The performance of the proposed framework, HyFURE, is tested against the two baseline systems, existing and reinforcement learning based traffic control. The analysis focuses on both overall congestion and the congestion faced by the priority vehicles.

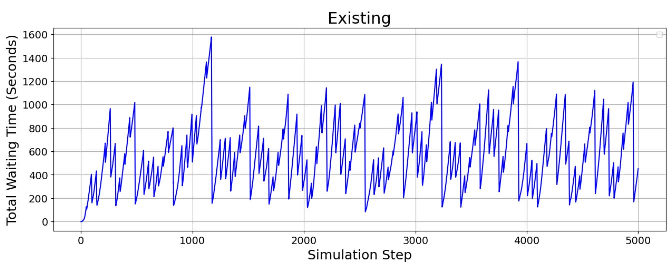

Fig. 3. Existing traffic control

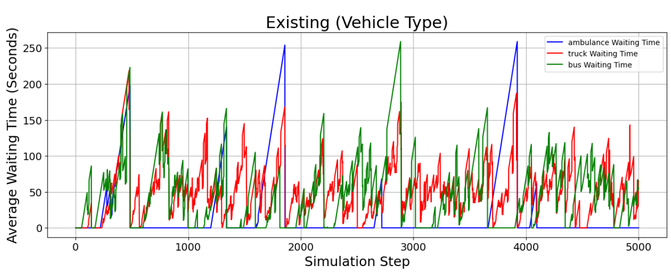

Fig. 4. Existing traffic control for priority vehicles

The conventional fixed time system as shown in Fig. 3 and Fig. 4 established a baseline of extreme inefficiency, with overall network waiting time being highly volatile and often peaking above 1500 seconds, making the treatment of vehicles uniform. Inference from priority classes shows that ambulances experience delays approaching 20.5 seconds, while trucks & buses face extreme wait times of about 52 seconds & 47 seconds, respectively, exhibiting a fundamental failure to manage traffic, as it is both vehicle blind and there is no adaptiveness. The system will only work in the ideal case of vehicles coming to the junction at the time of the green light.

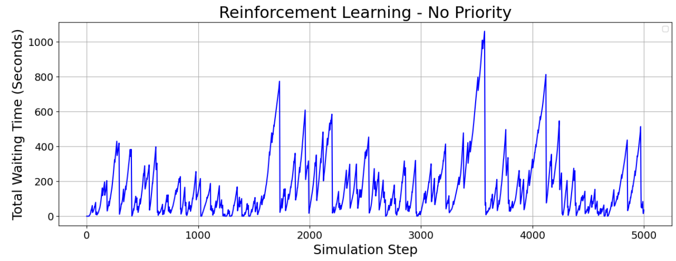

Fig. 5. Reinforcement Learning

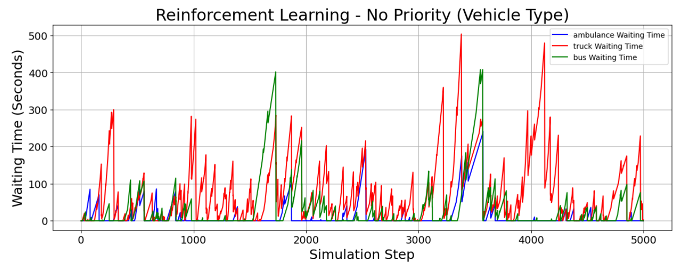

Fig. 6. Reinforcement Learning - No priority (Vehicle Type)

The RL approach in Fig. 5 & Fig. 6 shows a clear capability for ATCS, reducing the average waiting time from the baseline. Despite the irregular congestion spikes & peaks surpassing 700 at times, the agent showcased strong reactive abilities, constantly dissipating these surges. The critical limitation is "vehicle blindness", as it fails to recognize priority vehicles, leading ambulances to a delay of 14.5 seconds and trucks to a peak wait time of 500 seconds and beyond. This proves that even though it is effective in reactive control, a RL only approach is a limitation in executing priority based objectives.

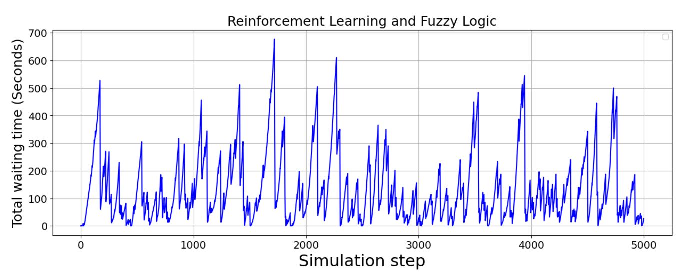

Fig. 7. Reinforcement Learning with Fuzzy Logic

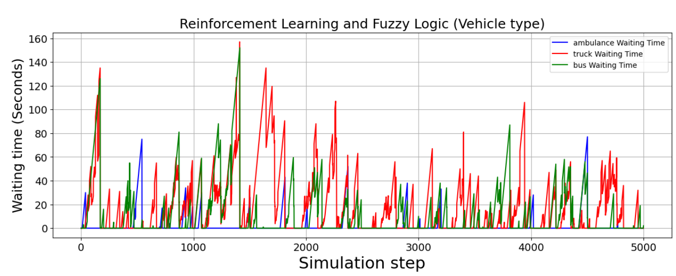

Fig. 8. Reinforcement Learning with Fuzzy Logic for priority vehicles

The HyFURE model in Fig. 7 and Fig. 8 demonstrated a high-level, multi-tiered system. The total network wait time spikes peaked at almost 700 seconds, still being intentional and narrow, indicating quick recovery after the priority events. The framework successfully handled priority vehicles, where the ambulances had an average waiting time of 2.5 seconds, while buses and trucks waited for 18.45 and 12.5 seconds, respectively. This approach proves the model's ability to make intelligent decisions.

TABLE II
COMPARISON OF MODELS

Metrics	% Improvement compared to Existing System	
	Reinforcement Learning	**HyFURE**
Overall Traffic	69.75	77
Ambulance	29	88
Bus	-46.35	64.5
Truck	30.75	74.66

The comparative analysis reveals a clear performance hierarchy. While the standard RL agent reduced overall congestion more effectively than the traditional system, its limitations led to irregular and unwanted spikes. In stark contrast, the proposed Fuzzy-RL model demonstrated superior intelligence. Its congestion peaks were narrower and intentional and the direct result of prioritizing traffic of emergency vehicles, successfully suppressing the ambulance's average wait times. This proves the framework's ability to execute strategic, life-saving objectives, not just optimize for general traffic flow.

V. CONCLUSION

The application of intelligent systems in urban traffic management is a crucial domain, yet it is full of challenges, particularly the need to prioritize emergency services within such dynamic environments. This paper introduced HyFURE, a novel hierarchical AI model proposed to address this challenge directly. By fusing a fuzzy logic strategist for priority assessment with a reinforcement learning agent for signal control, our approach creates a system that is both intelligent and socially aware. The feasibility of this method was validated through testing in the SUMO simulation environment. The results provide solid proof of the model's effectiveness. The HyFURE system achieved a remarkable 88% reduction in the average waiting time for ambulances, maintaining it at approximately 2.5 seconds. Moreover, it effectively managed other priority vehicles by reducing the average waiting time for buses by 64.5% and trucks by 74.66%, while decreasing the total traffic congestion by 77% when compared to existing systems. Further adding to these, the integration of real-time computer vision technologies like YOLO will enable the system to identify vehicles from live video feeds, facilitating real-world implementation. The main challenge for HyFURE is its inability to handle accidents or violations of rules, as SUMO represents a controlled environment, resulting in the model under-performing in the specified scenarios. The framework is designed to allow the superimposition of multi-agent reinforcement learning to control an entire city's road network. Ultimately, this paper contributes to a validated plan for creating intelligent systems that are not just efficient but also ethically responsible in addressing the community's urgent needs, giving way for safer, more intelligent urban centers of the future.

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