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Research Review Presentation

Dynamic Traffic Controller System

Dynamic Traffic Signal Controller using YOLOv9 and MARL

Objective:

Develop a dynamic and adaptive traffic signal control system for a 4-way lane intersection, leveraging YOLOv9 for vehicle detection and Multi-Agent Reinforcement Learning (MARL) for signal optimization.

Tasks:

- To process the data such as Vehicle Density, Queue Length and presence of emergency vehicles from the YOLOV9 model.
- To initiate the data values to their respective agents and build the MARL model for TSC (Traffic Signal Controller)
- To develop and leverage scheduling algorithms to minimize the overall waiting time and lane prioritization

Literature Survey

How Well Do Reinforcement Learning Approaches Cope With Disruptions? The Case of Traffic Signal Control

- They compare two Reinforcement Learning (RL) methods (PressLight and GuidedLight) against other approaches like Analytic+ (self-organizing) and Random control.
- The algorithm being described is Q-learning, a type of Reinforcement Learning (RL) technique. Markov Decision Process (MDP), a mathematical framework, is also used.

Adaptive Traffic Signal Control to Reduce Delay Time at a Single Intersection Point

- This research tackles traffic congestion by proposing two new methods that leverage vehicle-to-infrastructure communication to gather real-time traffic data and dynamically adjust light timing or sequence. The goal is to minimize average wait times.
- Three signal control policies (SEQ, SEQDUR, and SEQ5) are being used which are designed to manage traffic light sequences and durations at a four-way intersection to minimize vehicle waiting times. The policies rely on monitoring the current state of traffic queues and making decisions accordingly.

Base Case: The fixed 30-second green light duration results in the highest average waiting times across all vehicle categories.
SEQ Policy: Reduces overall average waiting time by 16%.
SEQDUR Policy: Reduces overall average waiting time by 63%.
SEQ5 Policy: Reduces overall average waiting time by 80%.

Exploiting Stage Information for Prediction of Switching Times of Traffic Actuated Signals Using Machine Learning

This research explores using machine learning to improve traffic light switching time prediction for GLOSA systems. They test if including an estimated traffic light state (like a simplified picture of current signal combinations) as a feature improves prediction accuracy compared to just using signal data. They use XGBoost and Bayesian Networks to see if this additional information helps, and also investigate whether the actual next state or an estimated one works better, considering traffic patterns and volume.

- They use two intersections with different traffic volumes and analyze data points including current signal state, time since last green light, detector data, and public transport information.
- The baseline model uses only signal state and time information.
- An additional model incorporates the actual current traffic light stage based on the intersection's control system logic.
- To predict future stages, they use a combination of XGBoost (for predicting the next stage) and Bayesian Networks (for predicting the following two stages).
- The accuracy of these different models is then compared using statistical tests.

The compromised signal states and stages significantly enhance the prediction quality of switching time estimation of traffic lights. Whether the feature of the actual or following signal states respectively stage is best it depends on the individual signal group.

Traffic sign recognition based on deep learning

In this paper, an experiment to evaluate the performance of the YOLOv5 is implemented, based on the custom dataset for Traffic Sign Recognition, which unfolds how the model for visual object recognition in deep learning is suitable for TSR through comparison with SSD as the objective of this paper.

- YOLOv5 model and single shot multibox detector (SSD) are compared.
- The dataset of road signs was trained in both models and the TSR experiment was implemented in Google Colab.

YOLOv5 model has an excellent visualization function in the result. The values for all the classes are all over 90.00%, which indicates the excellent TSR performance of YOLOv5. For SSD, The accuracy of TSR in almost all classes reaches nearly 90.00%. Both YOLOv5 and SSD show good capabilities, but YOLOv5 performs a bit better.

Boosted Genetic Algorithm Using Machine Learning for Traffic Control Optimization

To optimize the traffic signal timings in signalized urban intersections, under non-recurrent traffic incidents.

- The optimization framework proposed combines the strengths of Genetic Algorithms (GA) and Machine Learning (ML) to improve traffic network management.
- This research proposes a hybrid approach for traffic signal control. It combines a Genetic Algorithm (GA) with a machine learning model (XGBT) to optimize traffic light timing. The GA searches for the best signal timings (decision variable) to minimize travel time (objective function), while the XGBT model predicts travel time efficiently.

This BGA-ML approach outperforms the original GA, significantly reducing travel time, especially during traffic disruptions.

Deep Reinforcement Learning based Approach for Traffic Signal Control

A novel method for the TCS problem using AI (Reinforcement learning) is discussed. This paper proposes a new abstraction for the TSC problem: a combination of state representation, a brand new rewarding concept, and simplified action space.

- RL training is formulated as a Markov Decision Process.
- Control task is done using the Policy Gradient algorithm.
- The training environment is modeled in SUMO.

The agent is tested in scenarios where one lane has traffic and the other doesn't; and the agent successfully provides more greenlight to the former lane - even though this a new scenario for it. Similarly, when both lanes had traffic, it alternated green light time between the lanes to keep the traffic symmetry.

Emergency Vehicle Detection in Heavy Traffic using Deep ConvNet2D and Computer Vision

In this paper, a new method for detecting and classifying emergency cars is proposed. The Deep ConvNet2D Algorithm is implemented instead of ANN. The proposed system is implemented in real-time and features high accuracy.

- Data set is taken from Kaggle for the car.
- CNN is used for model creation and training.

The comparison of accuracy between CNN and shows CNN has better accuracy (90%) compared to ANN (84%). So, it is better to use CNN

Scheduling algorithm for adaptive traffic light under VANET scenario , 2022

In this paper, a scheduling algorithm based on the VANET scenario is proposed to analyze an isolated intersection as a case study. The proposed algorithm (STL) aims to increase traffic flow by utilizing the excess green signal time to reduce the waiting time for mobile vehicles at the intersection.

- A ‘MaxGreen’ value is set, and TrafficSpeed for each direction is read. ‘DistanceGreenArea’ (= MaxGreen/ TrafficSpeed) for each direction is calculated and all vehicles in the ‘DistanceGreenArea’ are read. Compute ‘LastVehicleDistance’ in each direction inside the ‘MaxGreen’ area and compute ‘BestGreen’ (=LastVehicleDistance / TrafficSpeed) for each direction. Schedule the current phase time by the lesser one among BestGreen and MaxGreen.

The total delay time of all vehicles in the traditional fixed algorithm is compared with the proposed STL algorithm. The results show a significant improvement in the delay time when the algorithm is implemented.

Toward A Thousand Lights: Decentralized Deep Reinforcement Learning for Large-Scale Traffic Signal Control

In the paper, the problem of multi-intersection traffic signal control is tackled, especially for large-scale networks, based on RL techniques and transportation theories. MPLight is proposed as a solution.

- For coordination, the concept of ‘pressure’ (derived from max pressure control theory) is used.
- FRAP architecture is used as the base model. FRAP specially design a network architecture for learning the phase competition in traffic signal control problems. Following the base model, DQN is used to solve the multi-intersection signal control problem.

The proposed MPLight consistently outperforms all the other methods in the four different scenarios tested, leading to both the least travel time of passengers and the maximum throughput. MPLight can handle traffic signal control for thousands of lights effectively and efficiently.

Real-time Emergency Vehicle Event Detection Using Audio Data

In this paper, the focus is on detecting emergency vehicles using only audio data. Improved and quick detection can help in faster preemption of these vehicles at signalized intersections thereby reducing overall response time in case of emergencies. ELMs have been used in this work because of its simplicity and shorter run-time.

- The audio data is segmented into fixed lengths since the number of input features of the model needs to be consistent. Then the data is balanced using SMOTE. Two features were extracted such as MFCC and ZCR which were merged and then fed into ELM.

Five different models were trained alongside ELM such as K-Nearest Neighbors (KNN), Random Forest (RF), Support Vector Machine (SVM), Multilayer Perceptron (MLP) and CNN. In the time required by the models, ELM is 10 times better than the next-best performing model. The model with the highest here is ELM with an accuracy of 94.5%. For quick and reliable emergency vehicle siren sound detection, it is reasonable to use 10 or 100 neurons in an ELM.

Ambulance detection using image processing and neural networks

Ambulance Detection using Image Processing and Neural Networks is a vehicle detection and tracking system, which recognizes ambulance amidst traffic congestion. Over past few years, vehicle usage on road is growing each day that results in traffic congestion. Hence making it hard for the emergency vehicle to pass through the traffic at the earliest possible time.

- The only piece of hardware used is the surveillance camera. YOLOv3 and CNN are used as they make work much more compatible with countries where road width is irrelevant for separate ambulances

Preparing a dataset for the program to train and assess was done, and it was used by the program to identify the Ambulance among all the vehicles. Upon sensing that the captured vehicle was an ambulance, the program successfully turned that traffic light into green, while others were turned red.

Deep Reinforcement Learning for Traffic Light Control in Intelligent Transportation Systems

In this paper, deep reinforcement learning to control traffic lights is investigated, and both theoretical analysis and numerical experiments show that the intelligent behavior “greenwave” emerges naturally from a grid road network, which is proved to be the optimal policy

- Two DL algorithms are analyzed in different scenarios - In a single road intersection, the DQN algorithm is verified to deliver a thresholding policy; and in a grid road network, the deep deterministic policy gradient (DDPG) algorithm is adopted. Optimality for ‘greenwave’ policy in grid networks is also achieved.

In the comparisons of the policies derived by the DQN algorithm, the fixed-cycle policy, and the optimal policy, the result of the DQN policy coincides with that of the optimal policy. The training time using DQN is very short. As the car arrival/passing ratio increases, the queue length also increases. The policy learned by DQN shows better effects than the fixed-cycle policy.

DDPG demonstrates emergent "greenwave" patterns, showcasing its ability to learn beneficial traffic flow structures from passive observations.

A Comparative Study of Algorithms for Intelligent Traffic Signal Control

In this paper, methods have been explored to effectively optimize traffic signal control to minimize waiting times and queue lengths, thereby increasing traffic flow.

- Round Robin Scheduler, a Feedback Control mechanism and two Reinforcement Learning techniques - Deep Q Network(DQN) and Advantage Actor-Critic (A2C) are compared.

The results of testing the different traffic light agents in the three traffic scenarios for a time period of 5400 timesteps are compared.
In RR, the agent performs well in uniform traffic scenarios and the queue length is above half only 33% of the time, but in non-uniform scenarios , it is above half ~80% of the time.
The performance of MONOPOLY in uniform traffic scenarios displays a similarity in behavior to RR. However, under non-uniform traffic densities, the agent performs significantly better than the RR agent.
The results of testing the DQN agent on the uniform traffic agent show no major improvement over RR and MONOPOLY. However, its performance in non-uniform traffic densities are improved.
The plots of queue length of A2C over time were observed to be similar to DQN in all three scenarios. Though the queue lengths were the same, the training time was significantly lesser than DQN.
The major advantage of A2C is the performance improvement (reduction in total wait times) achieved with lower training times, as the number of processes was increased.

Single Intersection Traffic Light Control by Multiagent Reinforcement Learning

In this paper, a traffic signal of an intersection is divided into four independent phases and then controlled by DQN(Revised QMIX) models respectively. Models can receive observations from their own angle of view instead of extracting features from the whole scene. It is supposed that it is beneficial for learning better policy if agents could sense the environment more precisely.

- Deploy QMIX to co-train the four DQN agents. Each agent receives the observation of its own phase. The observation scope is 200 meters from the intersection.
- The global immediate reward is set as the difference between two vehicle queues of adjacent steps.
- If the queue at the current step is shorter than the last one, the immediate reward is positive and vv. The agents of the four phases share the same global reward but have their own actions. Action=1 denotes that the light turns green and 0 vv.
- Add a constraint to TD error to prevent collision.
- For execution, a method to compare the Q-value of action=1 of all agents and select the maximum Q-value's action is designed.

After 100 epochs of training, plot the average rewards of each episode, which clarifies the superior performance of method (revised QMIX for cycle decomposition) compared to DQN (for the whole cycle). The rewards increase rapidly as training progresses. During the whole process, this method gets higher rewards than DQN.

Dynamic Traffic Control System with Reinforcement Learning Technique

This research proposes a new Deep Reinforcement Learning (DRL) model for traffic light control that adapts to real-world traffic patterns. Unlike prior research focused on simulations, this model is trained on a massive real-world traffic dataset from cameras. The authors plan to further improve performance by incorporating a feature extraction algorithm, with the ultimate goal of creating a practical DRL system to optimize traffic flow and reduce congestion in real-world transportation networks.

- The agent uses four features (queue length, waiting time, phase, and vehicle count) to represent traffic conditions and a reward function to measure how well an action improves traffic flow.
- Q-Network with Phase Gates: The agent uses a special Q-network architecture to learn the best action for each traffic light phase. This network separates features into two convolutional layers and then combines them with additional traffic data. A "phase gate" controls which process is active depending on the current phase.
- Feature Extraction: The system uses Speeded-Up Robust Features (SURF) object recognition to extract additional features from camera data.

Peak hour vs Non-peak hour:

On the given day, there is more traffic on WE bearing than SN, during which a perfect traffic light control strategy is relied upon to provide a longer time for WE. And during top hours, the policies gained from our technique give a longer time for the green light on WE. In the early morning, the vehicle appearance rates on SN are larger, and the strategy consequently gives a longer time to SN.

Weekday versus Weekend:

The policy gives fewer green lights on WE during weekend daytime than it gives on weekdays. This is on the grounds that there is more traffic on SN than on WE during weekend daytime.

CycLight: learning traffic signal cooperation with a cycle-level strategy

This study introduces CycLight, a novel cycle-level deep RL approach for network-level adaptive traffic signal control system. CycLight adopts a cycle-level strategy, optimizing cycle length and splits simultaneously using Parameterized DQN algorithm.

- PAMDP is utilized to accurately capture key traffic flow features while minimizing computational load. CycLight adopts the cycle-level TSC logic, leveraging PDQN agents to perform discrete-continuous hybrid actions.
- Given an environmental state, a hybrid action is obtained so as to interact with the environment. Then the collected transition sample is stored in the replay buffer, after which the policy learning is performed using the data sampled.

The average waiting time values extracted the training curve reveals that CycLight and Advance CycLight demonstrate standard deviations of 25.65 and 26.97, respectively. While single PDQN and MAADDPG exhibit standard deviations of 34.03 and 42.54, respectively. It is evident that both CycLight and Advance CycLight converges to the most optimal and stable policy with a narrow deviation range.

Proposed methodolgy

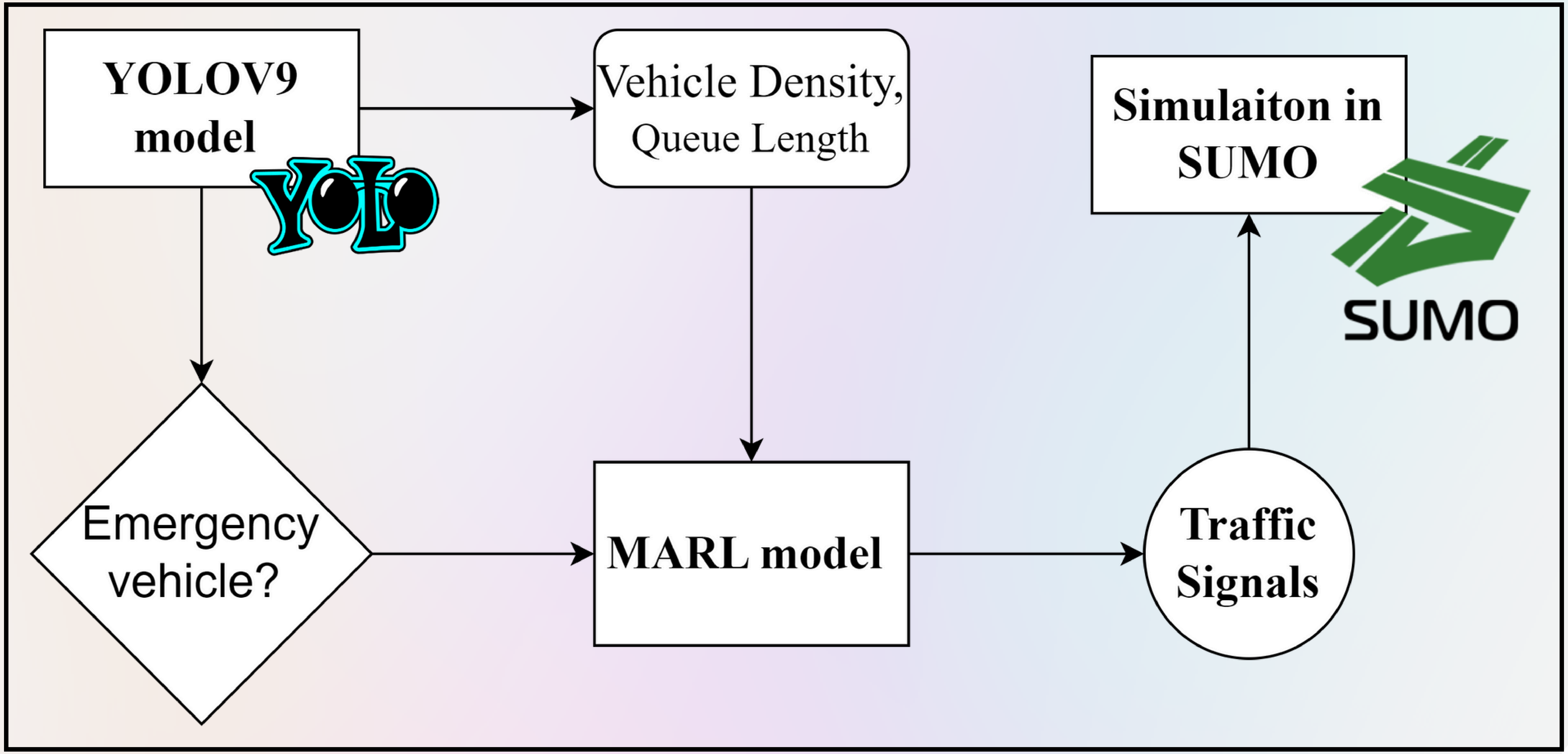


Fig : Block Diagram of the complete process

Proposed methodolgy - Desciption

System Architecture

- **Components:** YOLOv9 for vehicle detection, MARL for policy optimization, SUMO for traffic simulation.
- **Functionality:** YOLOv9 monitors traffic, detects vehicles, identifies emergency vehicles, provides traffic density and queue length data. MARL uses this data to optimize traffic signal policies.

Proposed methodolgy - Description

Implementation Steps

- **Deployment of YOLOv9:** Installed at the intersection for continuous traffic monitoring and data collection.
- **Data Aggregation:** Collected data includes vehicle density, queue length, and emergency vehicle presence.
- **MARL Agent Setup:** Agents per lane optimize signal timings based on real-time data using Q-learning.
- **Training in SUMO:** MARL agents trained and refined in SUMO for effective policy development.

Proposed methodolgy - Desciption

Scheduling Strategies and Algorithm Selection

- **Evaluated Strategies:** Fixed-Time Control, Actuated Control, Adaptive Control.
- **Chosen Strategy:** Q-learning-based Adaptive Control for real-time adjustments and emergency vehicle prioritization.

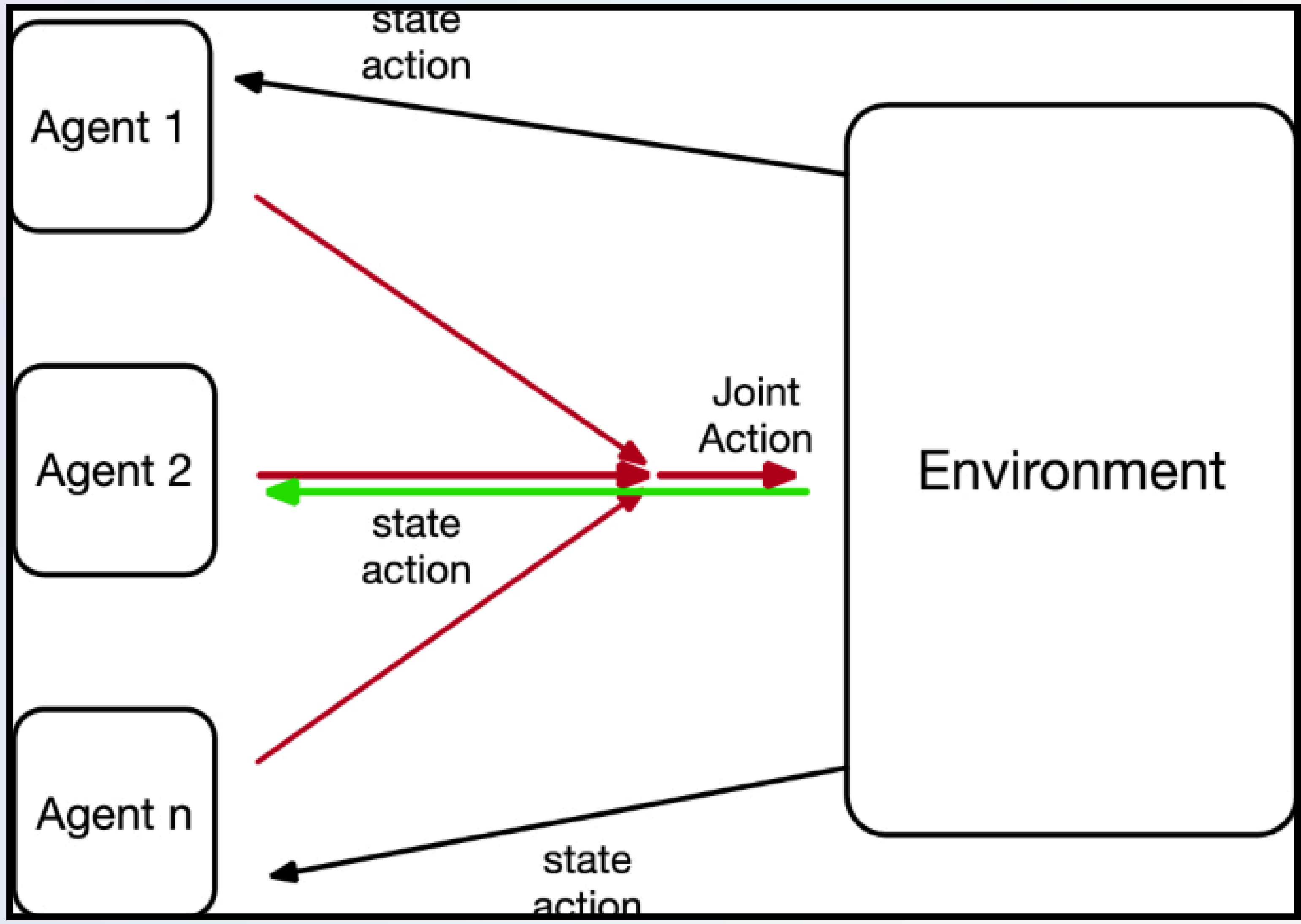


Fig: A pictorial representation of MARL

Proposed methodolgy - Desciption

System Simulation and Evaluation

- **Performance Metrics:** Waiting time, queue length, emergency vehicle response time evaluated against traditional methods.
- **Simulation Environment:** SUMO used to validate and optimize MARL policies under varied traffic conditions.

Deployment and Real-World Adaptation

- **Deployment:** MARL-based system deployed at the intersection for continuous monitoring and adjustment.
- **Real-Time Optimization:** System adjusts based on real-world feedback to optimize traffic flow and safety.
- This structured approach ensures robustness, adaptability, and efficiency in managing dynamic traffic conditions.

SIMULATION

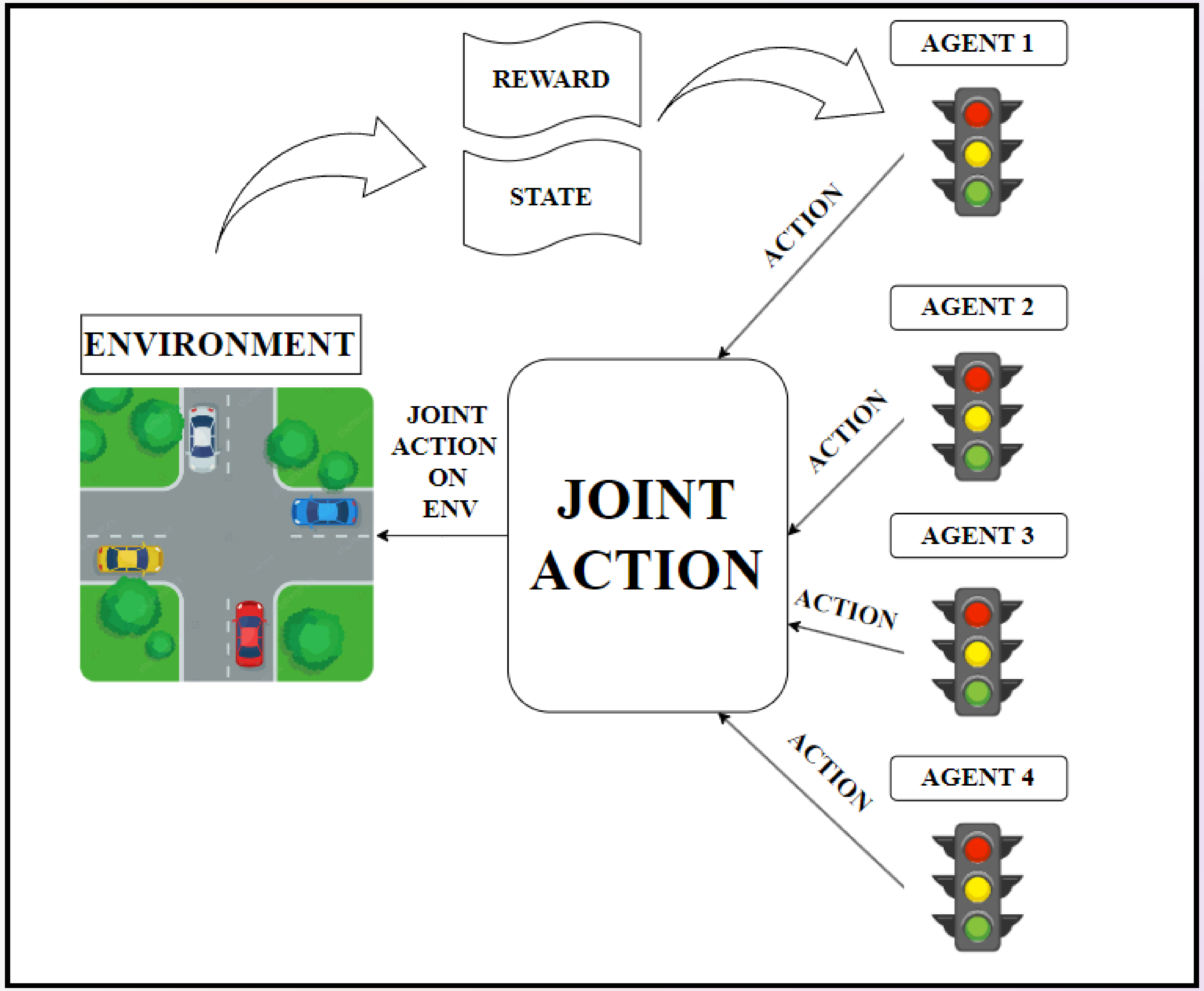
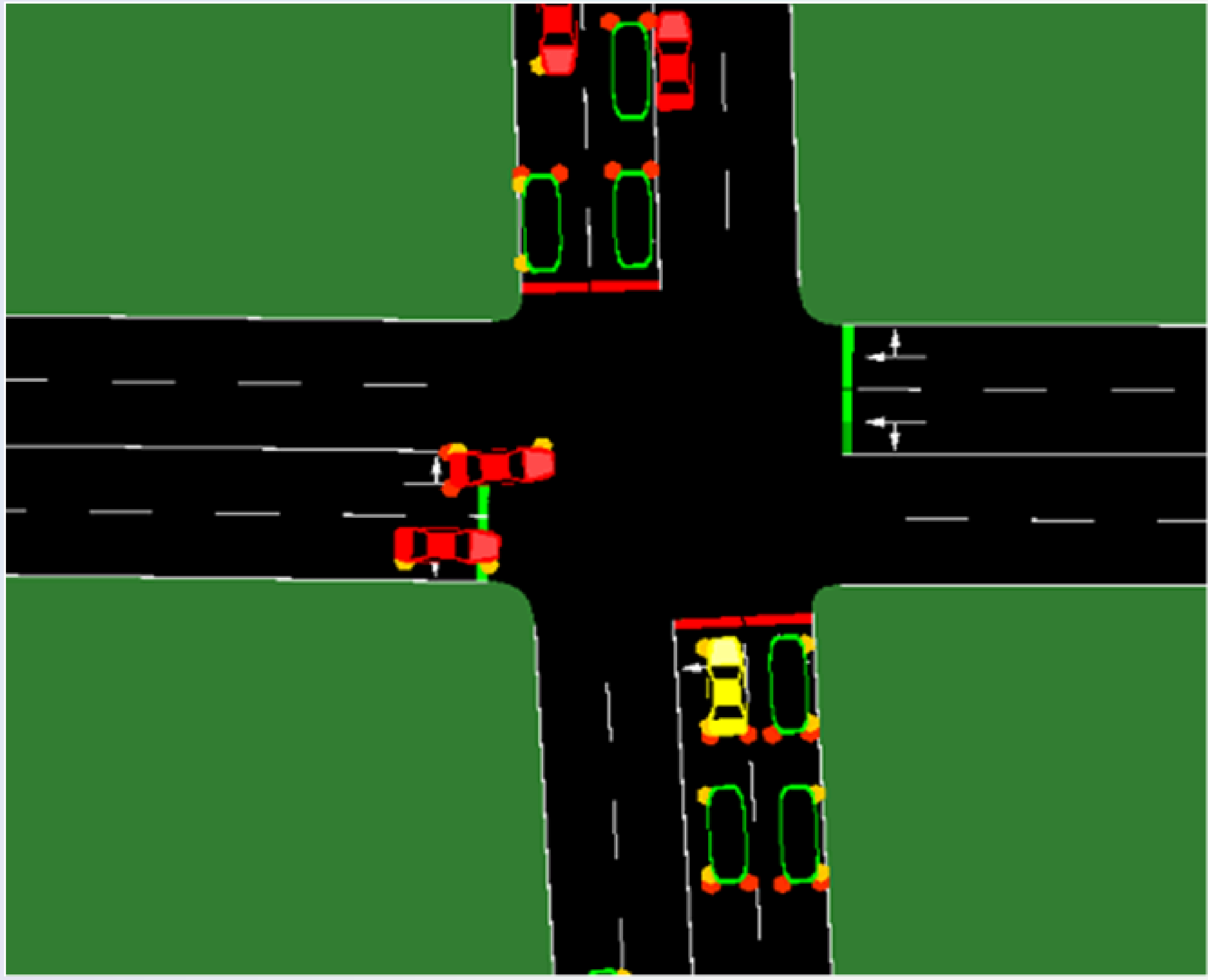


Fig: A pictorial representation of the complete process for TSC (Traffic signal controller).



SUMO Simulator

Why MARL Takes Traffic Management to the Next Level

Beyond Static Rules:

- Traditional fuzzy logic relies on pre-defined rules, limiting its adaptability to dynamic traffic situations. MARL, on the other hand, learns optimal behaviors "on the fly" through interactions with the environment and other agents. This allows it to handle unexpected events and changing traffic patterns more effectively.

Collaborative Power:

- Deep Q-learning, while powerful, struggles with coordinating multiple agents. MARL excels in this aspect. It enables agents (vehicles) to learn joint action policies that maximize collective rewards, promoting smoother traffic flow through coordinated lane changes and speeds.

Tackling High-Dimensionality:

- Genetic algorithms, useful for optimization, can get bogged down in high-dimensional problems like traffic management with numerous vehicles and actions. MARL's decentralized approach and communication protocols shine here, enabling efficient learning and collaboration even in complex scenarios.

Learning from Each Other:

- Unlike rule-based systems that offer limited adaptability, MARL allows agents to learn from each other's experiences. This fosters the emergence of collaborative strategies through interaction and even competition, leading to a more robust and adaptive traffic management system.

NOVELTY OF PROPOSED SOLUTION

Dynamic Lane Management (MARL):

- Our system utilizes Multi-Agent Reinforcement Learning (MARL).
- Vehicles act as intelligent agents, learning optimal behavior based on real-time traffic data.
- This enables dynamic lane adjustments, optimizing traffic flow across all lanes.

Secure Blockchain Communication:

- Secure blockchain technology safeguards data exchange between vehicles and infrastructure.
- This fosters trust and collaboration within the MARL framework.
- Secure communication promotes safe driving behavior.

Holistic Traffic Management:

- This combined approach addresses a wider range of traffic challenges:
- Reduced Congestion: MARL optimizes lane usage for smoother traffic flow.
- Improved Efficiency: Collaborative lane changes and coordinated speeds minimize bottlenecks.
- Enhanced Safety: Secure communication promotes safer driving behaviour.
- Emergency Vehicle Prioritization: The framework can prioritize emergency vehicles for faster passage.

Proposed Timeline

A brief of about our project work flow

30th June - 04th July

Data processing (Vehicle density, Queue length and presence of emergency vehicle Available Data from ***YOLOV9*** model and open-source datasets

04th July - 12th July

Building of ***MARL model*** and leveraging Scheduling algorithms using ***Q-learning algorithm***

- ***Lane Prioritization***
- ***Reduction in waiting time***

12th July - 16th July

TSC (Traffic Signal Controller) simulation in ***SUMO*** and building the real-time TSC

16th July - 18th July

Deployment, Documentation of the TSC

- Report submission
- Presentation of the results

THANK YOU