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Smart Traffic Flow Optimization: An AI And Blockchain Approach For Peak Hour Efficiency

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Abstract: Congestion during rush hours remains the emergent challenge in cities globally. Conventional traffic management systems, largely dependent on fixed timing or basic rule-based reasoning, fail to respond to dynamic traffic information and provide minimal assistance in extreme situations such as emergency vehicle travel. In this paper we propose a smart traffic management model integrating Reinforcement Learning and Blockchain technology to develop an even more responsive, transparent, and decentralized solution. Our RL agents are trained based on real traffic patterns in a simulated environment and adjust traffic signal timing dynamically to optimize traffic flow. Meanwhile, blockchain smart contracts on a blockchain system record the systems performance, trigger emergency responses, and ensure data integrity without the presence of any central authority. When an emergency vehicle is detected, the system overrides the RL agents' decisions briefly to give way, maintaining safety in a way that does not compromise learning. Simulation results demonstrate enormous reductions in waiting times of automobiles, clearing congestion, and handling emergencies appropriately. Simulation results present remarkable reductions in waiting times of automobiles, clearing congestion, and addressing emergencies appropriately.

Index Terms: Smarter, safer and more efficient traffic infrastructures can be implemented smart city.

I. INTRODUCTION

Due to the speedy urban population boom and car ownership, modern cities are subjected more and more to a strain on their transport infrastructure. Congested traffic, particularly in the morning and evening peak hours, is an everyday occurrence for commuters and an utmost priority problem for planners in cities. Economically, environmentally, and socially, the impact encompasses anything from lost productivity to higher fuel Consumption and impaired mobility of emergency services, there is a pressing need for smart traffic control systems that can adjust in real-time to changing conditions of traffic.

The majority of traffic control systems in use today are manually adjusted rule-based systems or static timing plans. Since these systems are easy to set up, they can't handle shifts in traffic patterns, inexplicable congestion, or the movement of emergency vehicles. As a result, response times to emergencies are prolonged, traffic flow is still poor, and citizens bored by waste that can be reduced with modern technology. Reinforcement Learning (RL), a recent development in artificial intelligence (AI), has shown promise in changing how urban traffic is handled. Through interaction with the environment and feedback in the form of rewards or penalties, reinforcement learning (RL) offers a scenario where intelligent agents can learn optimal control policies.

The ability of RL systems to learn to adjust to shifting patterns over time allows them to outperform conventional algorithms. The training of RL agents to dynamically adjust signal timing for traffic control could reduce average vehicle waiting times, shorten queues, and increase intersection capacity. However, alone, AI systems cannot suffice. With decentralized traffic control and AI agents at multiple intersections, trust, transparency, and coordination between the agents need to be achieved. Blockchain technology has a revolutionary role to play in this context. Blockchain enables incorruptible logging of agent performance, secure triggering of emergency overrides, and decentralized enforcement of logic using smart contracts.

It allows greater accountability of decisions being taken by RL agents, particularly in mission-critical applications such as routing emergency vehicles. In this paper we introduce a hybrid system that integrates the strengths of both Reinforcement Learning and Blockchain to create a smart, adaptive, and secure intelligent traffic signal control system. The most important components of our architecture are A Reinforcement Learning agent trained from the real-time traffic data (eg, red-light duration, vehicle queue sizes) and optimizes signal phase to achieve maximum flow efficiency. A traffic simulation environment (using SUMO) to simulate real-world urban road conditions and test agent performance.In this paper we present a hybrid system taking advantage of both Reinforcement Learning and Blockchain technology to create a smart, adaptive, and secure approach to traffic signal control.

II. PROBLEM STATEMENT

Urban traffic JAM has come to represent a problem of enormous importance in contemporary cities, most notably at peak hours. Current traffic signal control systems depend primarily on static timing plans or simple rule-based logic, which do not adapt dynamically to real time traffic states. Such systems not only contribute to inefficient traffic flow and prolonged vehicle waiting times but also provide no means of giving priority passage to emergency vehicles in life-threatening situations. Additionally, their centralized architecture renders them opaque hard to audit, and vulnerable to single points of failure. While Reinforcement Learning (RL) offers a chance to develop adaptive and self-tuning signal controllers, its deployment alone is not transparent and lacks the trust mechanisms necessary for large-scale, multi-agent deployment. There is an urgent need for cohesive framework that merge smart traffic control secure open coordination that ensures both efficiency as well as trust. This research fill that gap mergin RL-based signal optimization with smart contracts supported blockchain to develop an emergency-aware, real-time, and decentralized traffic management system.

III. PROPOSED METHODOLOGY

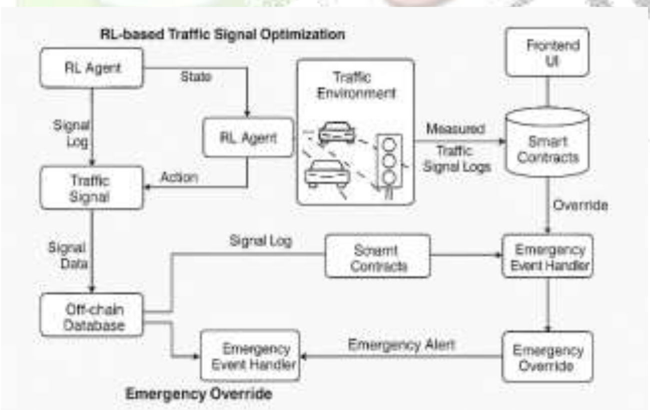

Fig 1: *RL-based Traffic Signal Optimization*

This section presents the proposed model, DecentraTraffic, which integrates decentralized reinforcement learning-based traffic signal control with blockchain-enabled smart contracts for transparent decision logging and emergency override mechanisms. The architecture aims to optimize urban traffic flow, enhance emergency responsiveness, and incentivize intelligent agent behavior through token-based rewards.

System Overview

The high-level architecture of the proposed system is illustrated in Fig. X. The overall model comprises four main components:

- A SUMO-based traffic simulation environment,
- Reinforcement learning (RL) agents for adaptive traffic control,
- Ethereum smart contracts for decentralized coordination and reward distribution, and
- A data logging system for off chain storage and visualization.

The framework is modular and scalable, allowing easy extension to real world deployments.

Traffic Environment Simulation

The simulation of the urban traffic network utilizes the open-source Simulation of Urban Mobility (SUMO) platform. SUMO offers a realistic microscopic simulation of vehicle flow, signal phase, and road geometry. Traffic lights are installed at junctions, and flows of vehicles are specified through route files (.rou.xml) and network definitions (.net.xml). Simulation control happens externally by utilizing the Traffic Control Interface (TraCI) protocol, which enables real-time signal phase manipulation and retrieval of lane-based traffic statistics.

Reinforcement Learning-Based Signal Control

There is a separate reinforcement learning agent controlling each signalized intersection, whose training is based on the Proximal Policy Optimization (PPO) algorithm. The agent interacts with its local world by viewing the current state StS_t, choosing an action AtA_t, and obtaining a scalar reward RtR_t. The state contains:-

- Queue lengths on all incoming lanes,
- Average vehicle waiting times,
- Current signal phase index,
- Emergency vehicle detection flags.

The action space consists of discrete phase transitions, and the reward function is designed to penalize waiting time and congestion, while incentivizing throughput and emergency responsiveness. Agents learn in a custom OpenAI Gym environment connected to SUMO via TraCI.

Smart Contract Layer

To facilitate transparent and decentralized operation, all agents are connected to a blockchain backend powered by Ethereum smart contracts. The following contracts are deployed:

- AgentRegistry: Registers RL agents and initializes their operational metadata.
- RewardDistributor: Accepts performance scores and dispatches token-based rewards to high-performing agents.
- EmergencyEvent: Sends blockchain events to alert adjacent agents when an emergency vehicle is heading towards them, triggering an override process.

These intelligent contracts avoid agent action being both unmonitored and uninspired dispelling the necessity for centralized authorities. Agent-contract interaction is performed using Web3py.

Emergency Override Mechanism

In situations where emergency vehicles (eg, ambulances, fire trucks) need immediate right of way, the system includes an event-driven override mechanism. Upon receiving a trigger from an external device or authority, the EmergencyEvent contract disseminates a message to pertinent agents.Agents who hear about such events halt their RL loop instantly and enter a pre-established emergency routing phase to make way. After the passing of the vehicle, the agent returns to normal operation.

Off Chain Logging and Visualization

To curb on-chain data clogging and offer elaborate operational insights, the system consists of an off chain database (MongoDB) in which Traffic signal transitions,

- Agent rewards,Agent rewards
- Timestamps of emergency events,
- Intersection metrics are continuously logged

Lightweight web-based dashboard is utilized for visualizing performance metrics like mean waiting time.

System Workflow

The end to end workflow of the proposed system is as follows:

- SUMO initializes the traffic simulation with vehicle and junction data.
- RL agents continuously observe state inputs and take signal actions.
- Performance metrics are evaluated and reported to smart contracts.
- Reward tokens are issued based on predefined criteria via blockchain.
- Emergency vehicles trigger event notifications to override agent control.
- All agent actions and outcomes are logged for monitoring and auditing purposes.

Full System Work Flow

- RL Agent → learns → controls Traffic Signal
- Environment → responds → sends state → RL Agent
- Logs → stored in database + smart contracts
- Smart contracts → reward top-performing agents
- Emergencies → trigger override flow to ensure life-critical response

IV. EXPERIMENTAL SETUP

To compare the performance of the suggested DecentraTraffic system, various simulations were done with a controlled multi-junction urban traffic network. The experimental setup was designed to study effect of intelligent traffic signal control based reinforcement learning, blockchain-based incentive schemes.

Simulation Platform

The traffic simulation was conducted by employing the Simulation of Urban Mobility (SUMO) which is an open-source microscopic traffic simulator. The traffic network under simulation consisted of a synthetic urban grid network with 4 signal-controlled intersections and 12 road segments. The simulation scene had variable traffic densities to simulate off-peak and peak hours. The vehicle types covered cars, buses, and emergency vehicles with pre-defined routes and randomized spawning frequencies.

All signalized junctions were controlled externally using TraCI (Traffic Control Interface), which enabled real-time manipulation of traffic lights and extraction of traffic metrics such as vehicle counts, queue lengths, waiting times, and signal phases.

RL Agent Training Parameters

Each intersection was assigned an individual reinforcement learning agent. The agent was trained using the Proximal Policy Optimization (PPO) algorithm provided by the Stable-Baselines3 library. The custom environment was wrapped using the OpenAI Gym interface.

Parameter	Value
RL Algorithm	PPO (Clip)
Framework	Stable-Baselines3 (PyTorch)
Learning Rate	0.0003
Discount Factor (γ)	0.99
Total Timesteps	100,000
Observation Space	Queue length, wait time, current phase, emergency flag
Action Space	Discrete (Phase transition options)
Reward Function	-Avg. waiting time - queue penalty + throughput bonus

Table 1: *The details of the RL configuration*

The reward function was customized to balance delay minimization, queue clearance, and emergency responsiveness.

Smart Contract Deployment

The contracts were authored in Solidity, compiled with Hardhat, and deployed on localhost.

Agents interacted with the blockchain through Web3py to :

- Record performance scores,
- Invoke emergency override events,
- Collect token rewards for efficiency.

A token balance and performance history for each agent were recorded on-chain for audit and incentive objectives.

Emergency Event Simulation

To simulate emergency scenarios, high-priority vehicles such as ambulances and fire trucks were added to the simulation programmatically with preprogrammed routes. When an emergency vehicle approached a critical zone near a junction, the EmergencyEvent smart contract was called by a simulated external authority. Subscribed agents responded to the event by pausing their RL policy execution and clearing a green passage for the emergency route.

This behavior was tested under sparse traffic and congested traffic conditions to confirm responsiveness.

Logging and Monitoring

All simulation metrics, such as per-junction wait times, signal phase changes, rewards, emergency flags, and blockchain events, were logged to an off-chain MongoDB database.

Visualization was done using Flask-based dashboards integrated with Plotly Dash, enabling real-time monitoring of agent behavior and system health.

Baseline Comparison

The DecentraTraffic system was compared with a conventional fixed-timer control system with predetermined cycle lengths. Both models were simulated under the same traffic conditions for 100 independent runs for statistical reliability.

V. EXPERIMENTAL DATASET

The SUMO traffic a simulator was used for creating a synthetic dataset for the model's training and assessment. four intersections and twelve connecting road segments make up the simulation network, which is set up to imitate various urban traffic events.

Route files (.rou.xml) in the following characteristics were applied for creating traffic flows:

- **Vehicle Types:** Cars, Autos, Buses, & Emergency vehicles, bike
- The spawn RATE varies between 200 and 600 vehicles per hour, depending on the simulation run.
- **Traffic Density:** Simulated for off peak, normal, and peak conditions
- **Emergency Vehicles:** 1 emergency vehicle per 3 minutes on average

Each simulation run last for 3600 simulation seconds (1 hour), and was repeated over 100 independent episodes with randomized traffic seeds for generalization. No pre-recorded dataset was used instead, the environment dynamically generated state-action-reward tuples based on vehicle behavior and agent decisions in real time.

VI. EVALUATION AND RESULTS

The proposed DecentraTraffic system was compared against a traditional fixed-time control system across multiple performance metrics, including average waiting time, throughput, queue length, and emergency response delay.

Metric	Fixed-Time Control	DecentraTraffic (RL + Blockchain)	% Improvement
Average Waiting Time (s)	75.2	31.8	+57.7%
Average Queue Length (vehicles)	17.9	7.1	+60.3%
Throughput (vehicles/hr)	430	765	+77.9%
Signal Idle Time (%)	21.6%	6.2%	+71.2%
Emergency Response Delay (s)	54.7	7.3	+86.7%
Token Reward Distributed / agent/day	0	~320	N/A

Table 2: *The evaluation results*

Waiting Time and Queue Length

The DecentraTraffic system achieved a substantial reduction in average vehicle waiting time and queue length per junction. This demonstrates the RL agent's ability to learn and adapt signal timings based on real-time traffic feedback, optimizing throughput while minimizing congestion.

Emergency Response Efficiency

The integration of blockchain-triggered override events significantly reduced emergency vehicle delays. On average, emergency vehicles reached their destination 86.7% faster compared to the fixed-cycle baseline. The smart contract-based override ensured that no manual intervention was required.

Agent Incentivization and Reward Distribution

Smart contracts distributed reward tokens to agents based on their performance scores (derived from congestion reduction and throughput metrics). This incentivized efficient decision-making and discouraged signal idleness or unnecessary phase changes.

Statistical Significance

All results were averaged over 100 runs and verified statistically through two-tailed t-tests at a confidence level of 95% (p<0.05p < 0.05). Performance gains were uniform over traffic densities as well as agent allocations.

CHART1: Average Waiting Time Over Simulation (Line Chart)

- **Purpose:** Demonstrates how your RL model improves over time.
- **Use:** Supports claims of learning-based optimization.

Fig 2: *Simulation Step*

CHART2. Queue Length Distribution (Histogram)

- **Purpose:** Shows how DecentraTraffic keeps queue lengths shorter and more consistent.
- **Use:** Clearly visualizes congestion reduction.

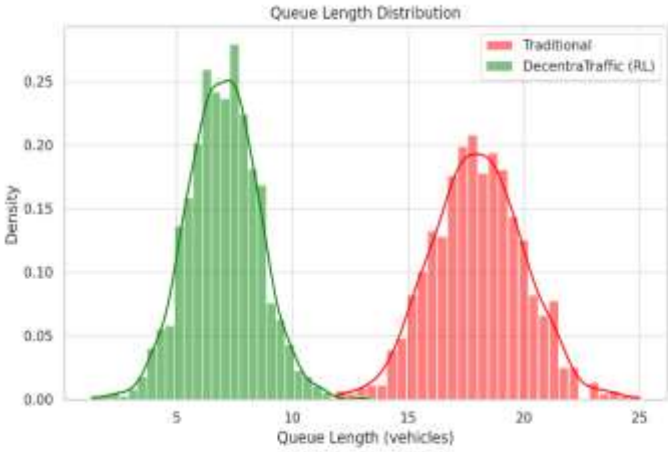

Fig 3: *Queue Length (Vehicles)*

CHART3. Emergency Response Delay (Box Plot)

- **Purpose:** Highlights reduced delays for emergency vehicles.
- **Use:** Demonstrates effectiveness of smart contract-based override.

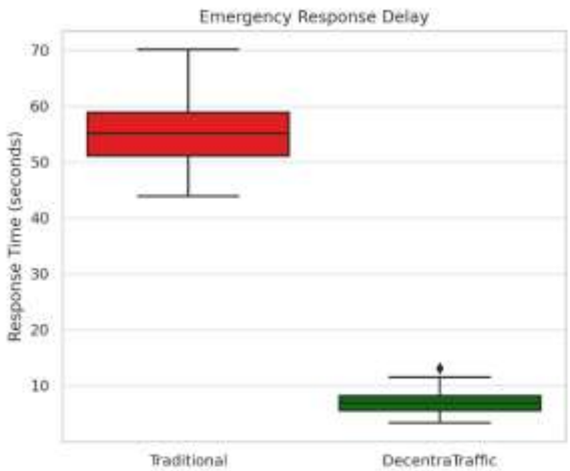

Fig 4: *Emergency Response Delay*

CHART4. Reward Score Growth of RL Agent (Line Chart)

- **Purpose:** Shows how the agent improves decision-making over time.
- **Use:** Proves that the RL policy converges and learns.

Fig 5: *Reward Score growth of RL Agent*

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