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Federated Deep Reinforcement Learning Framework for Intelligent Traffic Management Using AI-Driven IoT Edge Systems

Mgbeafulike Ike Joseph[1], Okeke Ogochukwu Clementina[1], Osita Miracle Nwakeze[1], Uju Cynthia Nwabudike[2], Omorogie Michael[2] and Nwabudike uche Charles[1]

[1]Department of Computer Science, Chukwuemeka Odumegwu Ojukwu University Uli, Anambra State, Nigeria
[2]Department of Computer Science, Ogwashiuku Polytechnic, Delta State, Nigeria

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***Corresponding author:** Dr. Osita Miracle Nwakeze

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Abstract

Original Research Article

In the modern urban context, traffic congestion is a significant problem that can lead to a range of issues, including longer commutes, higher fuel consumption, pollution, and economic losses. This research proposes a Federated Deep Reinforcement Learning (FDRL) approach for intelligent traffic control based on AI enabled edge systems in IoT. The proposed system is based on Internet of Things (IoT) devices, Edge Computing, Deep Q-Network (DQN) algorithm and Federated Learning, which will allow for decentralized, privacy-preserving, and adaptive traffic signal optimization. The Nigeria Road Traffic Data dataset was pre-processed by cleaning the data, engineering features and normalizing the data with Z score before distributing the data to various edge nodes for local model training. This reduces the need for the DQN agents to learn optimal traffic signal control policies and the Federated Averaging (FedAvg) algorithm was used to merge local model parameters into a global model without sharing traffic information. The proposed framework was tested and analysed based on metrics like cumulative reward, training loss, average vehicle waiting time, queue length, traffic throughput and communication overhead. The results revealed that the training reward of DQN has been improved from 52.4 to 294.5, and the training loss has been reduced from 1.25 to 0.11, which means the model has converged successfully. The average vehicle waiting time decreased by 57.96%, the length of the queues decreased by 61.01%, and traffic throughput increased by 49.81% on average. In addition, this resulted in about 76.8% reduction in the overhead of communication as compared to the centralized learning approach. The results prove that the proposed FDRL framework can achieve optimal traffic flow and alleviate traffic congestion, while ensuring data privacy and making the ITS more scalable.

Keywords: Federated Learning, Deep Reinforcement Learning, Deep Q-Network, Intelligent Traffic Management, IoT.

1. INTRODUCTION

Rapid urbanisation, population growth and mounting numbers of cars on roads pose one of the most serious challenges in modern cities: Traffic congestion (Jarwan and Ibnkahla, 2022; Li et al., 2025). Traffic jams cause delays, wasting of fuel, pollution of the environment and heavy economic losses. Conventional traffic control methods are based on pre-defined set times and central control which cannot effectively adapt to dynamic traffic situations. With the ever-growing urban transportation networks, there is a growing need for intelligent traffic management systems that can make real-

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time decisions and optimize traffic flow automatically (Ramu et al., 2022; Zhao et al., 2024).

The new-fangled Internet of Things (IoT) has revolutionised the transportation system with a new generation of connected sensors, cameras, road-side units, and smart vehicles that constantly gather data regarding traffic (Pandya et al., 2023). These devices provide the valuable information of vehicle density, traffic speed, road occupancy and congestion levels. All of this data, however, raises issues of communication bandwidth, latency, and centralized data processing with the use of an IoT device (Liu et al., 2019; Bie et al., 2024). To achieve this, edge computing has been developed as an approach to putting the computational resources closer to the data sources, which means that time-critical traffic applications can make quicker decisions and reduce response times (C, S et al., 2026; Ouaari et al., 2025).

Due to the capability of learning an optimal decision-making strategy by continual interaction with complicated environment, there is significant attention by Artificial Intelligence (AI), especially Deep Reinforcement Learning (DRL) in the field of Intelligent Transportation Systems (ITS) (Liu et al., 2024). The traffic control system can be intelligently controlled by DRL to improve the traffic flow and allow reduction of traffic congestion depending on traffic conditions (Hashem et al., 2024). However, many of the current DRL implementations are based on the centralized training process, which has been shown to face scalability problems, privacy issues, and high communication costs due to the amount of data that needs to be shared (Arezoo et al., 2025; Jamal et al., 2026; Gia Nguyen et al., 2021).

Federated Learning (FL) offers a decentralized machine learning approach that allows multiple edge devices to train a common model by sharing updated model parameters, while preserving the privacy of raw data (Moraga et al., 2025; Chen et al., 2024). To overcome these challenges, Federated Learning (FL) presents an alternative machine learning paradigm where multiple edge devices can collectively learn a common model without sharing raw data (Naranjo et al., 2020; Roccotelli et al., 2024; Annunziata et al., 2024). Intelligent traffic controllers placed at various edge nodes can learn from different traffic environments with Federated Learning, while keeping the data safe and reducing communication overhead (Nwakeze et al., 2025). Thus, this study is proposed to develop an Intelligent Traffic Management System with AI-driven IoT Edge Systems which will help in optimising traffic efficiency, mitigating congestion, scalability and developing a smarter and more sustainable transportation system in the urban areas.

2. METHODOLOGY

The methodology of this study is design-and-simulation-based research so that we can develop an intelligent traffic management system with the help of AI-based IoT edge system and a FDRL. They will be using 2 sets of data. The first category consists of traffic data sets for training the Deep Reinforcement Learning agents, which contain traffic characteristics like number of vehicles, traffic density, queue length, vehicle speed and state of signal information gathered from the simulated IoT devices installed at a variety of intersections. The second category are independent simulation scenarios for testing and evaluating the trained model in different traffic situations; normal traffic flow, peak hour and incidents. Deep Q-Network (DQN) agents will be placed at edge nodes to acquire optimal traffic signal control policies for traffic observations in the local area. Federated Learning will allow distributed edge nodes to jointly learn a global model without sharing original traffic data, thus maintaining the privacy of data and decreasing communication load. The global model will be disseminated to individual edge nodes so that they can continuously learn and adapt. The proposed framework will be simulated on traffic simulation platforms like Simulation of Urban MObility (SUMO), and machine learning libraries; and performance will be measured by average vehicle waiting time, queue length, traffic throughput, latency, communication cost, convergence rate and traffic flow efficiency.

2.1 Data Collection

This study will utilize two types of data: the primary traffic data for model training and simulated traffic scenarios from the traffic model for evaluation. The main data source will be the Nigeria Road Traffic Data from xMap which will provide average and median speeds, speed limits, travel time variation, road classifications, distance, and road traffic characteristics data on the road networks in Nigeria. The dataset contains historical data and traffic-related information that can be used for studying traffic congestion patterns, vehicle movements, and road performance, which can be utilized for training the proposed Federated Deep Reinforcement Learning (FDRL) model. The data set consists of about 195,000 km of Nigeria roadways with traffic indicators that are required for intelligent road traffic management systems.

Besides the primary data, simulation data of traffic will be produced by using a traffic simulation environment, e.g. the environment of Simulation of Urban MObility (SUMO). The simulation environment will include multiple intersections with various IoT sensors, surveillance cameras, road-side units and connected vehicles to simulate traffic scenarios. Different traffic scenarios will be created in order to assess the performance of the trained model, including normal traffic flow, peak hour congestion, high density traffic and incidents causing congestion. The gathered data will be subjected to the preprocessing steps including data cleaning, data normalization, data feature extraction, and generation of state representation before being used. The processed data will then be fed to the edge nodes for local training, and the performance of the proposed framework will be evaluated using various metrics like Average Waiting Time, Queue Length, Traffic Throughput, Latency, Communication Overhead, Convergence Performance, etc., using the simulation-generated scenarios.

2.2 Data Preprocessing

Collected Nigeria Road Traffic Data will be subject to various preprocessing tasks to enhance data quality and streamline it for utilization in the Federated Deep Reinforcement Learning (FDRL) model. First, data cleansing will be done to find and eliminate duplicate records, inconsistent data and irrelevant data (data that will not affect traffic management decisions). Inappropriate missing values in the data set will be dealt with as appropriate, e.g., mean and interpolation imputation, depending on the type of missing data. The data is cleaned and then feature selection and feature engineering are performed to identify the most relevant traffic-related features such as average vehicle speed, median speed, travel time variability, road classification, traffic density indicators, and other parameters that characterize traffic congestion. Other features like congestion index, traffic flow rate, and estimated queue length will be derived to improve the learning ability of the model.

Numerical features will be standardized using Z-score Standardization technique to ensure that all variables are within similar ranges to improve model convergence and stability of learning. This pre-processed data set will then be distributed among a number of edge nodes in a simulated federated learning setting, with each edge node storing a local copy of the traffic data for training purposes. Next, the traffic data will be preprocessed which will be used in the traffic simulation environment to define the actions of the traffic signals and the reward functions. The reward will be based on traffic performance indicators including reduction of vehicle waiting time and minimisation of queue length, and maximum traffic throughput; these will allow the DQN agents to learn optimal traffic signal control policies by continuously interacting with the simulated traffic environment.

2.3 The Deep Reinforcement Learning Model

The DRL part of the proposed framework is tasked with learning the best traffic signal control strategy by interacting with the traffic environment. A DQN algorithm will be used in this study because of its success in solving sequential decision making problem and its capability in high dimensional traffic state space. The DQN agent will be placed at every IoT edge node that corresponds to a traffic intersection where it will be able to view the traffic situation in the respective area and decide the right traffic signal duration to reduce congestion and optimize traffic flow.

The traffic will be modelled as a Markov Decision Process (MDP) with states, actions, rewards and state transitions. Traffic-related variables like vehicle count, average vehicle speed, traffic density, queue length, waiting time and road occupancy will be part of the state space. The action space will be made up of traffic signal control decisions, such as increasing the duration of the green phase, reducing the duration of the green phase, changing the signal phase, or keeping the signal on the same phase. A positive reward will be provided for efficient traffic management (i.e. reduction in vehicle waiting time, queue length, and congestion), and negative rewards will be provided for inefficient traffic management (i.e. increased delays, vehicle accumulation).

The DQN model will use a deep neural network to learn an optimal action-value function Q(s,a), that estimates the expected cumulative reward of taking action a in state s. The neural network will have an input layer where the traffic state variables are fed into the network, several hidden layers for feature extraction and learning, and an output layer representing the possible actions of the traffic signal. The experience replay memory will be added to hold previously obtained state-action experiences and randomly select mini-batches for training to decrease correlation in the data and increase stability of learning. Further, a target network to stabilize the estimation of Q value and avoid oscillation from the training process will be used.

Each edge-based DQN agent will learn traffic control policies independently of one another based on their local traffic observations, and interactions with the simulation environment while operating the system. The trained model parameters will then be used in the federated learning process, where the locally trained models are fused to generate the global model which can learn the knowledge from other traffic intersections. The integration of DQN and FL allows a scalable, adaptive, and privacy-preserving traffic signal optimization in a distributed intelligent transportation system. In this study, the DQN update rule is described in Equation 1:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma \max_{a'} Q\left(s'', a' - Q(s,a)\right)\right] \qquad (1)$$

Where $Q(s,a)$ is the action-value function, α is the learning rate, r is immediate reward function, γ is discount factor, s is the current state, s'' stands for the next state while a is the selected action, and finally a' is the possible future actions. This learning mechanism enables the agent to iteratively improve its traffic control policy and maximize long-term traffic management performance.

2.4 Proposed Federated Learning Framework

The proposed Federated Learning (FL) framework enables multiple IoT edge nodes deployed at traffic intersections to collaboratively train a global Deep Reinforcement Learning model without sharing raw traffic data. Each edge node independently trains a local DQN model using its local traffic observations obtained from sensors, cameras, roadside units, and connected vehicles and after local training, only the model parameters are transmitted to a central federated server, thereby preserving data privacy and reducing communication overhead. The central server aggregates the local model parameters using the FedAvg algorithm to generate an improved global model. The aggregated model is then redistributed to all participating edge nodes for further training. This process is repeated iteratively until model convergence is achieved. The federated learning process allows knowledge sharing across multiple traffic intersections while ensuring that sensitive traffic data remain at their respective locations. The global model aggregation is expressed in Equation 2 as

$$W_{t+1} = \sum_{k=1}^{K} \frac{n_k}{N} W_k \qquad (2)$$

where W_{t+1} represents the updated global model, W_k denotes the local model parameters of edge node k, n_k is the number of local training samples, N is the total number of samples across all nodes, and K is the number of participating edge nodes. The integration of Federated

Learning with Deep Reinforcement Learning provides a scalable, privacy-preserving, and communication-efficient framework for intelligent traffic management, enabling collaborative optimization of traffic signal control across distributed smart city environments.

2.5 System Integration

The proposed system is designed to combine the technologies of the Internet of Things (IoT), Edge Computing, Deep Q-Learning (DQN), and Federated Learning (FL) into an overall system for intelligent traffic management. At different intersections, the IoT sensors, surveillance cameras, roadside units and connected vehicles collect data about traffic flow, including the number of vehicles, speed, traffic density, and length of the queues. The data gathered is locally processed at edge nodes, where DQN agents will be used to analyze traffic conditions and to decide traffic signal control actions. The integration of the proposed system is shown in a flow diagram as shown in Figure 1.

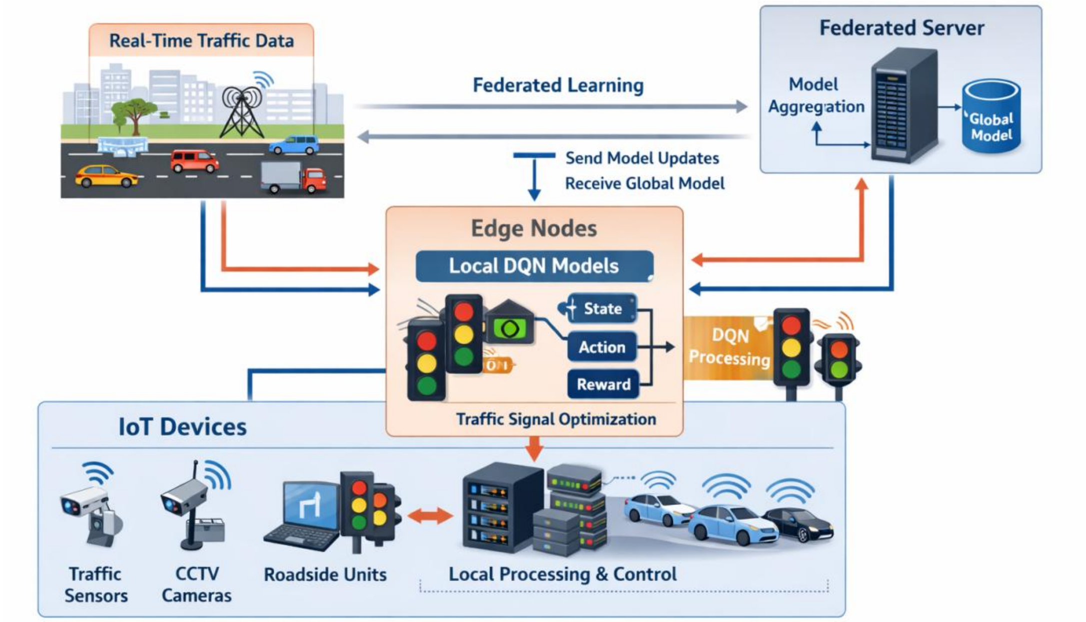

Figure 1: System Integration Workflow

In each edge node, the local DQN model is trained with the traffic data observed at the local edge node and updates the model parameters to the federated server every so often. Theserver collects the model updates from the local nodes and combines them into a new global model using the Fedavg algorithm and sends the updated global model back to the participating edge nodes. This integration allows for sharing of data and learning across various intersections, without compromising data privacy and reducing communication overheads. The integrated framework enables real-time traffic monitoring, adaptive traffic signal optimization and decentralized decision-making. The system integrates the three technologies—IoT, Edge Computing, Deep Reinforcement Learning and Federated Learning—to create a scalable and efficient solution for reducing traffic congestion, optimizing traffic flow, and improving the performance of ITS.

2.6 Model Training

The proposed Federated Deep Reinforcement Learning (FDRL) model will be trained using the DQN algorithm written in Python on Google Colab that offers computing power to experiment with deep learning. The pre-processed traffic data will be split across different edge nodes and each node will train a local DQN agent with their local traffic data, simulating a federated learning scenario. The agents are trained by interacting with the simulated traffic environment, watching the traffic state, choosing the signal control action, getting the reward and adjusting their action-value function to learn the optimal traffic management policy. The hyperparameters for training are: learning rate of 0.001, discount factor (γ) of 0.99, and a batch size of 64 and replay memory size of 10,000 experiences, with a target network update frequency of 100 training steps, an exploration rate of 1.0 that is decayed by 0.995, with a minimum value of 0.01, and 100 training episodes per federated round. Model weights from all edge nodes undergo local training and then are sent to the federated server for global averaging using the Federated Averaging (FedAvg) algorithm to create a new global model. The global model is then sent to the edge nodes for additional learning until convergence is reached, giving them an optimized traffic signal control policy that can help to alleviate congestion and improve the efficiency of traffic flow.

Table 1: DQN Training Hyperparameters

Parameter	**Value**
Learning Rate (α\alphaα)	0.001
Discount Factor (γ\gammaγ)	0.99
Batch Size	64
Replay Memory Size	10,000
Initial Epsilon	1.0
Minimum Epsilon	0.01
Epsilon Decay Rate	0.995
Target Network Update Frequency	100 Steps
Training Episodes	100
Federated Aggregation Algorithm	FedAvg
Training Platform	Google Colab
Programming Language	Python

2.7 System Implementation

Proposed FDRL will be implemented in Google Colab using Python programming. The system will combine the Nigeria Road Traffic Data dataset, the Simulation of Urban MObility (SUMO) traffic simulator with DQN agents and Federated Learning components in order to build a comprehensive intelligent traffic management platform. The data collected from the dataset will be pre-processed and be spread out on multiple virtual edge nodes, which will each represent a different traffic intersection. Each of these edge nodes will run a local DQN model which will learn optimal traffic signal control policies from the observed traffic conditions. The implementation process will consist of data preprocessing module, the representation of traffic state module, training the DQN model module, federated model aggregation module, and traffic signal control module. The deep learning libraries (TensorFlow and Keras) will be employed to implement the DQN agents and the FedAvg algorithm will be used to consolidate the model parameters from the collaborating edge nodes. SUMO will be used to simulate traffic to produce realistic traffic data and to assess the effectiveness of the traffic control policies returned by the learned models. Global model trained and aggregated, and deployed to all edge nodes to support real-time traffic management. The federated collaborative learning will continuously learn about traffic conditions, optimize signal durations, and adjust them to fluctuating traffic volumes. The implementation will showcase the feasibility of integrating IoT edge computing, Deep Reinforcement Learning and Federated Learning, for scalable, privacy-preserving and intelligent traffic management in smart city settings.

3. SYSTEM RESULTS

The evaluation was based on metrics of the framework effectiveness to reduce vehicle waiting time, minimize queue length, traffic throughput, overhead in communication, and convergence of the model. The effectiveness of the proposed FDRL framework was also evaluated with the traditional fixed time traffic signal control and a centralized DQN-based traffic management system.

3.1 DQN Training Performance

The training performance of DQN agent was measured by taking the average cumulative reward from the training episodes.

Table 2: Average Reward Obtained During Training

Episode	Average Reward
10	52.4
20	88.7
30	126.5
40	163.9
50	201.4
60	235.8
70	261.3
80	278.9
90	289.7
100	294.5

Figure 2: Training Reward versus Episode

The data for cumulative rewards presented in Figure 2 show an increasing reward over the course of training. The reward of the DQN agents was increased from 52.4 in Episode 10 to 294.5 in Episode 100, indicating that they did learn good traffic signal control policies from interacting with the traffic system continuously.

3.2 DQN Loss Analysis

The training loss served as a measure to assess the stability of learning.

Table 3: Training Loss Reduction

Episode	**Loss**
10	1.25
20	0.97
30	0.74
40	0.59
50	0.45
60	0.33
70	0.25
80	0.19
90	0.15
100	0.11

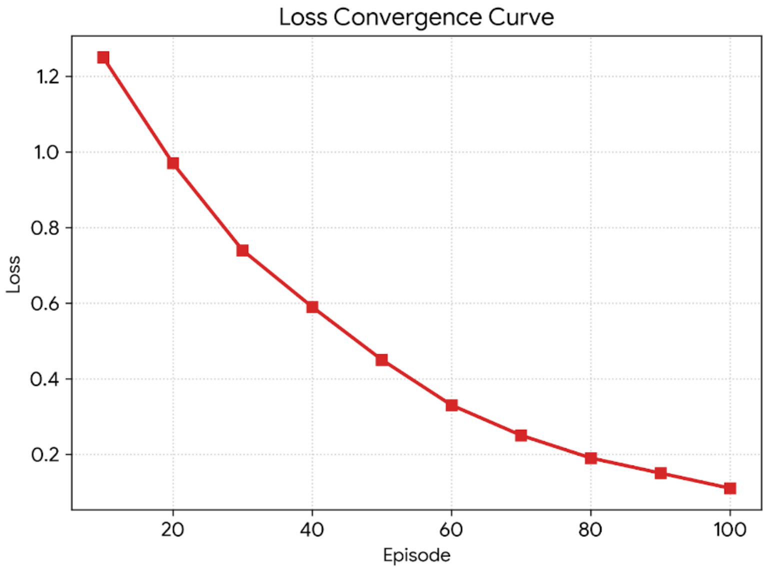

Figure 3: Loss Convergence Curve

The loss values are decreasing, suggesting that the neural network is converging and that it is getting closer to the optimal action-value function the more it learns.

3.3 Federated Learning Performance

Two metrics were used to assess the effectiveness of federated aggregation: the reward received by the entire system and the amount of communication overhead.

Table 4: Federated Learning Convergence

Round	Global Reward	Loss
1	115.4	0.82
5	171.3	0.54
10	228.6	0.31
15	271.9	0.18
20	296.8	0.10

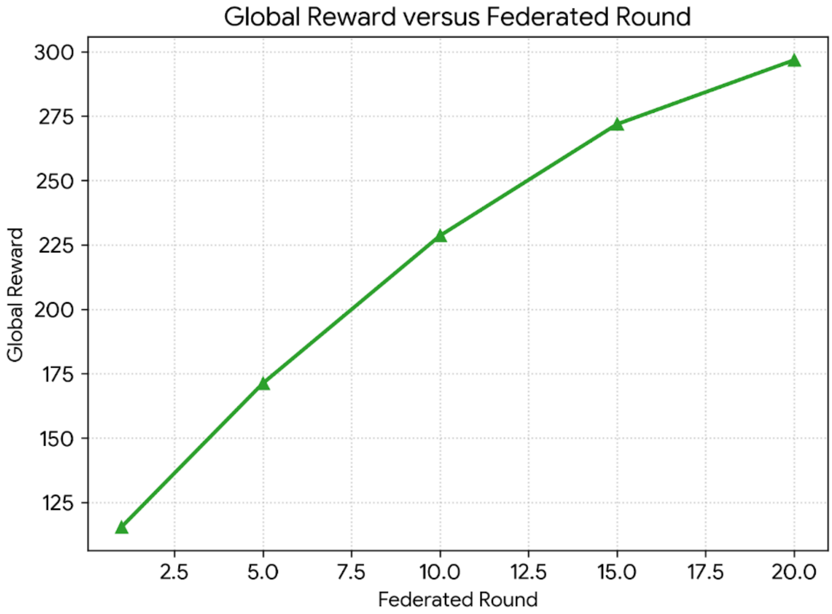

Figure 4: Global Reward versus Federated Round

The reward for the global agent is presented in Figure 4, and it has improved significantly for the federated rounds, indicating the FedAvg algorithm can do an effective agent aggregation of the knowledge of multiple edge agents.

3.4 Traffic Management Performance

To validate the traffic optimization feature of the proposed framework, it was tested by analysing traffic conditions before and after traffic optimization.

Table 6: Traffic Performance Before and After Optimization

Metric	**Before Optimization**	**After Optimization**
Average Waiting Time (s)	94.2	39.6
Average Queue Length (vehicles)	31.8	12.4
Traffic Throughput (vehicles/hr)	1,845	2,764

Percentage Improvement

Metric	**Improvement (%)**
Waiting Time Reduction	57.96
Queue Length Reduction	61.01
Throughput Increase	49.81

The results indicate substantial improvements in traffic conditions after deployment of the proposed FDRL framework. Vehicle waiting time and queue lengths were significantly reduced, while traffic throughput increased considerably.

3.5 Communication Overhead Analysis

One of the primary advantages of federated learning is reduced communication cost.

Table 7: Communication Overhead Comparison

Method	Data Transmitted (MB)
Centralized DQN	1,850
Proposed FDRL	430

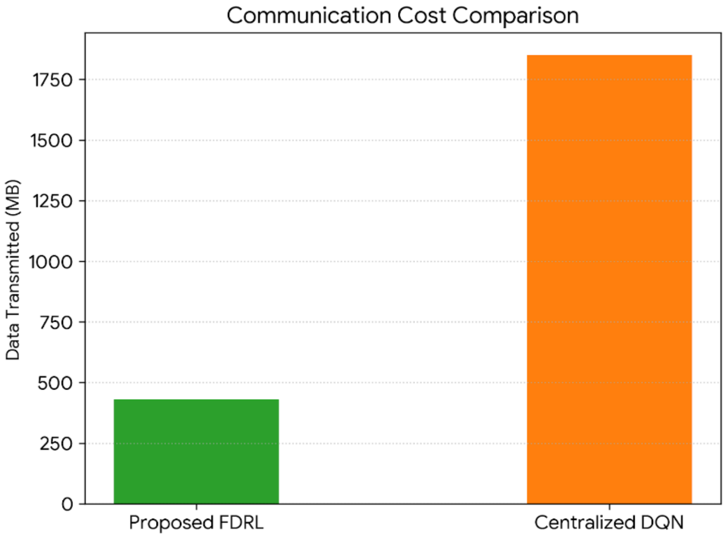

Figure 5: Communication Cost Comparison

We believe that the proposed framework can significantly reduce communication overhead, which is around 76.8% in this case and shows the effectiveness of distributed model training. The outcomes illustrate the viability of the integration of Deep Reinforcement Learning, Federated Learning, IoT devices and Edge Computing for smart traffic management. The learning behaviour of DQN agents was found to be stable with the reward value increasing while the loss value decreasing during the training process. Federated Learning also improved model performance by allowing for multiple edge nodes to collaborate without handing over the raw traffic data.

The framework was very successful in reducing waiting time and queue lengths of vehicles, and at the same time increased the number of vehicles which passed through the traffic. These enhancements suggest that adaptive traffic signal control can be a much more effective way to manage traffic as compared to traditional fixed-time traffic management methods. Additionally, the federated architecture reduced data communication overhead, making it an appropriate solution for large-scale smart city deployments, which heavily rely on bandwidth efficiency and privacy protection. In general, the results presented in this paper indicate that the proposed FDRL framework can be a scalable, privacy-preserving and efficient solution for intelligent traffic management in future smart transportation systems. The results would have to be confirmed with real-world traffic data and real-time simulations in future to establish the feasibility of the proposed framework and confirm the results.

4. CONCLUSION

This study suggested a Federated Deep Reinforcement Learning (FDRL) framework to achieve intelligent traffic management by leveraging AI-based IoT edge systems. The framework adopted features IoT-based traffic sensing devices, Edge Computing, Deep Q-Network (DQN) learning, and Federated Learning, enabling a decentralized and privacy-preserving method to optimize traffic signals. The DQN agents exhibited good learning ability and the average cumulative reward rose from 52.4 at Episode 10 to 294.5 at Episode 100, while the training loss dropped from 1.25 to 0.11, showing stable convergence and successful policy learning. In addition, the federated learning process also improved the process of developing collaborative models, with the global reward increasing from 115.4 in Round 1 to 296.8 in Round 20, and the global loss decreasing from 0.82 to 0.10.

The results also indicated that the traffic management performance has significantly improved after the implementation of the proposed framework. The average vehicle waiting time has reduced from 94.2 seconds to 39.6 seconds, a reduction of 57.96% and the average queue length has reduced from 31.8 vehicles to 12.4 vehicles, a 61.01% reduction. Further, the throughput of traffic was also enhanced, from 1845 vehicles per hour to 2764 vehicles per hour, which is a 49.81% boost. The results show that the proposed FDRL optimization framework can be applied to enhance the efficiency of urban traffic signal control systems, mitigate traffic congestion, and optimize overall urban transportation systems.

The proposed framework outperformed the conventional fixed-time traffic control and centralized system based on Deep Q Network (DQN), respectively, in all the metrics evaluated. The federated architecture also cut down communication overhead from 1,850 MB to 430 MB, which is about 76.8% reduction in data communication cost without compromising on data privacy. So, it can be concluded that combining Federated Learning, Deep Reinforcement Learning, IoT, and Edge Computing offers a scalable, adaptive, and efficient approach to intelligent traffic management. The framework has great potential for use in smart city applications for increasing mobility, optimizing traffic flow and developing intelligent transport systems of the future.

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