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A Personalized Federated Deep Reinforcement Learning Framework with Hierarchical Control and Edge Aggregation for Scalable Real-Time Traffic Prediction

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Abstract

The propose Fed-DRL++, a new framework that combines Personalized Federated Learning (PFL) with Hierarchical Deep Reinforcement Learning (HDRL) and Edge Aggregation. This setup enables real-time, decentralized, and privacy-friendly traffic management in smart cities. Unlike traditional centralized methods, Fed-DRL++ uses a layered decision-making structure. It applies Dueling DQN at the route level and a mix of Dueling DQN and PPO at zone and junction levels. This approach adjusts to local traffic conditions by using both historical and real-time mobility data. A key innovation is the use of Prioritized Experience Replay with Hindsight (HERPP). This method focuses learning on significant events like congestion and collisions. Edge aggregation lowers communication overhead by performing local updates before syncing with the cloud. Meanwhile, PFL maintains model performance even with non-IID data across users. In tests with 1,000 mobile agents across five congestion scenarios, Fed-DRL++ outperformed benchmarks. It reduced travel time by 23.4%, improved route convergence by 31%, and cut congestion by 18%. It also decreased communication costs by 41.6% and boosted prediction accuracy (RMSE: 2.91 km/h, MAE: 2.06 km/h), with results being statistically significant ($p < 0.01$). This shows its effectiveness for scalable and smart traffic optimization.

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Keywords: Personalized Federated Learning (PFL), Deep Reinforcement Learning (DRL), Hierarchical Control, Mobile Crowd Sensing (MCS), Intelligent Transportation Systems (ITS), Scalable Traffic Management, Spatio-Temporal Data Analytics.

1 Introduction

Urban mobility faces multi-faceted challenges, resulting from rising traffic congestion and worsening issues related to the rising number of connected vehicles and data privacy concerns from users. Centralized systems for traffic prediction are too large and complex to appropriately capture the consequences of real-time decisions or accommodate the heterogeneity of edge-devices. Centralized systems come at the expense of unencrypted user privacy, as they need to upload raw data to a central server (Kairouz et al., 2021). Over the past few years, personalized federated learning (PFL) has been able to encompass decentralized model training across heterogeneous devices, before aggregating a global model, while addressing user privacy as well as the statistical heterogeneity of traffic data sources (Wang et al., 2025). The one major drawback of traditional federated learning in intelligent transportation systems is a lack of adaptability, in relation to the somewhat constantly changing real-time nature of traffic networks (i.e., minute by minute). In order to overcome this research gap, researchers have explored Federated Deep Reinforcement Learning (FDRL) models to learn an adaptive traffic control policy across distributed edge nodes (e.g., each signalized intersections traffic control) (Mathew & Asha, 2024). One of the approaches, Hierarchical Federated Reinforcement Learning (HRFL), identified and formed clusters of urban traffic network segments, and applied multi-agent federated PPO algorithms to address issues related to variability and convergence (Fu et al., 2025; Mathew & Asha, 2024).

In addition to applying traffic control, real-time traffic prediction is an important facet of intelligent transportation systems (Revathi et al., 2020). However, typical prediction models fail to adapt well to federated settings due to data imbalance, limited contexts for sharing, and communications issues. More recently, Multi-Objective Federated Learning (MOFL) frameworks have shown potential due to their concurrent improvement of traffic prediction accuracy, energy efficiency, and latency through non-independent identically distributed (non-IID) data distributions (Patil et al., 2025). MOFL frameworks have improved traffic modeling and forecasting across connected vehicles, roadside units, and mobile edge devices.

The growing number of connected vehicles and devices in vehicular networks has made edge aggregation a vital feature to manage bandwidth and improve model update delays. Hierarchical federated architecture is a new method to employ intermediate aggregation at the edge level. These architectures are significantly more efficient than relying on the cloud for communication methods and reduce cloud communication costs and model latency by increasing the speed vehicles learn models (Qiu et al., 2025; Mohandas et al., 2024). Efficiency-related memory management is required to learn and adapt in real-time from traffic events such as congestion peaks, construction zones, and accidents. Previously, Prioritized Experience Replay (PER), is effective in reinforcement learning (RL) as it prioritizes records of meaningful experiences over record of everyday experiences, providing the model to learn more efficiently from an impactful traffic event. Although PER has been well-studied to date in RL applications, its use in federated hierarchical systems for smart transportation does not have much research to-date (Schaul et al., 2015). Another enhancement to RL approaches is Hierarchical Deep Reinforcement Learning (HDRL). HDRL provides an opportunity for control at varying levels of decisions, i.e., junction-level, zone-level and city-level. Thus, HDRL provides a systematic and scalable way to deal with complex traffic events. While HDRL has received attention in control for other applications, such as software-defined networking and 3D traffic systems, HDRL has demonstrated importance for coordinated control and policy sharing for distributed agents (Kołakowski et al., 2025; Trivedi et al., 2023).

Key Contributions of the Research

This study has four main contributions. First, we present Fed-DRL++, we propose a new architecture that combines Personalized Federated Learning (PFL) with Hierarchical Deep Reinforcement Learning (HDRL) (Ullah et al., 2025). As a result, the architecture innovatively tackles the issues of data privacy, scalability, and real-time processing in intelligent traffic systems. Second, we introduced Prioritized Experience Replay (PER) into the model-based architecture to improve learning performance on critical traffic events such as accidents or abuse of traffic resources. This allows for faster convergence and increased responsiveness. Third, we implemented a Hierarchical Edge Aggregation layer that minimizes communication costs through preprocess models prior to being communicated to the cloud coordinator. This innovation allows for better scalability, especially when dynamic traffic updates take place in a Mobile Crowd Sensing (MCS) context. Finally, the architecture incorporates secure communication protocols and dynamic agent synchronization to enhance resilience against network variability and malicious updates. In an overall sense, these three contributions advance the state of the art in privacy-preserving, real-time, and scalable urban traffic optimization.

The outline of the paper chapter-wise is as follows. Chapter II is a review of the related literature, while the purpose of Chapter III is to give a brief view of the theoretical framework, key concepts along with methodologies. Chapter IV is going to evaluate the experimental result. Chapter V contains results and discussions, whereas Chapter VI wraps it all together with a summary of the most important findings and suggestions for further research.

2 Literature Review

Fu et al., (2025) proposed a Hierarchical Federated Reinforcement Learning (HFRL) model for adaptive traffic signal control for larger urban networks. They utilized a cluster of intersections and applied the federated PPO algorithm respectively within each cluster with the aim of speeding up time to converge. This method provided a way of reducing the waiting time at the intersection while dynamically balancing global and local policies without losing data privacy. The evaluation was done in New York City showing reduced waiting times and improved traffic throughput. The other contribution in the HFRL paper was the ability for it to solve for the non-IID issue across intersections. It was able to outperform FedAvg and centralized DRL baselines and showed good scalability in a real world deployment.

Zhang et al., (2024) provide a federated framework, i.e., FedGCC, a gradient-compression-based federated framework for wireless traffic prediction. In this model, they utilized gradient sparsification through top-k gradient pruning and adaptive error correction to reduce uplink traffic. The spatial correlation among clients was captured with the graph neural module. They showed in their experiments on real wireless traffic datasets that FedGCC was close to optimal performance but with a 90% lower communication cost. FedGCC also maintained robustness in terms of performance even with non-IID data and bandwidth that was not steady. Moreover, their work specifically contributes to the scalability challenges for federated learning on edge-devices and is well aligned with smart city deployment scenarios.

Mali et al., (2025); Salman & Alomari, (2023) presented a dynamic task scheduling framework for IoT edge networks, which is based on federated reinforcement learning. They presented a realized system combining BiLSTM-GRU traffic forecasting with D4PG (Distributional Determined Policy Gradient), used for edge resource allocation. The proposed clients can train locally for various properties that pertain to delay and fairness over heterogeneous environments. The simulation results produced an energy efficiency improvement of about 17% compared to static baselines, with the model being agile to real-time demand variation. This method can work particularly well in contexts related to privacy-preserving edge computing and the benefits of this technique can become significant in urban intelligent infrastructure development.

Swapno et al., (2024) utilized Deep Q-Networks (DQN) to determine traffic signal control policies for urban intersections. DQNs were able to adapt the network signal timing in real-time, with regard to the stated state of congestion. In their simulation work, the average queue lengths fell by 49% and lane throughput increased by 9%. The DRL agent learns adaptive signal strategies related to varying traffic scenarios. The distinctive modelling approach reported on the practical applicability with real-world road network topologies and conditions and is shown to outperform fixed-timing and heuristic controllers relating to performance expectations. The published work is a strong endorsement of the situational potential of DRL and optimization of real traffic conditions.

Fu et al., (2025) introduced Digital Twins (DT) in the context of federated deep reinforcement learning with network slicing and traffic predictions. The model uses graph-attention networks with DDPG agents to synchronize the digital twins and the physical nodes. The model is capable of predicting changes in traffic demand, so it is able to adapt quickly while requiring less frequency in updates. As demonstrated in a vehicular situations from their experiments, they improved policy accuracy while also finding 30% bandwidth savings on average. The framework allows for real-time coordination even with distributed layers. DT based federated learning can have many implications for anticipatory routing and congestion control in addition to bettering fault tolerance.

Que & Khan, (2025) proposed a highly scalable federated traffic prediction model termed FedMON, utilizing clustering and modular neural networks. Each client is clustered based on analogous traffic patterns. FedMON employs both a local model training stage and a global model training stage. They use two-stage learning to improve communication and to improve prediction. They found improvements of 15 - 20% RMSE in prediction accuracy across multiple cities. FedMON enables flexibility for clients to participate in training while also mitigating problems with data asymmetry. Even with improved performance for FedMON clients, overall bandwidth dropped significantly. The FedMON framework is promising for intelligent transportation system applications, especially when deploying a system throughout an entire metropolis.

Wu et al., (2023) introduced HiFlash, a hierarchical FL architecture that lowers the communication costs between the WAN through adaptive staleness management. The two-layer update approach leverages both local client-to-edge and edge-to-cloud transport mechanisms. The system also utilizes a reinforcement learning agent to choose synchronization interval lengths for tradeoffs. HiFlash achieves superior convergence speed and model accuracy in IoT networks. Furthermore, HiFlash effectively lowered the frequency of communication compared to traditional FL framework. Experimental results also show the robustness of training even in the presence of dropouts and data skew from the devices. Thus, the HiFlash approach provides a reliable and efficient mechanism for learning within federated collaborations while conserving bandwidth and communication.

Johnson & Geller, (2025) demonstrated a revolutionary Meta-Federated Learning model for real-time traffic forecasting by combining FL and meta-learning. Their FL meta-learning topology is capable of quickly adapting to changes (e.g. accidents or peak emotions) within the model. The base learner within the FL follows the "common" artificial or global traffic dynamics. The meta-learners adjust weights based on the local traffic dynamics. Their simulations revealed a considerably lower MAE and MAPE overall as the Meta-FL topology demonstrated. Their model uses local low-resource devices by limiting the amount of time before a model is updated, thermally enhancing personalization without compromising privacy. As a method and technology, Meta-FL provides further avenues for future work in managing dynamic urban traffic.

Fang et al., (2025) showcase a Provably Robust Federated Reinforcement Learning (PR-FRL) framework to support secure learning of policies. PR-FRL provides resilience against model poisoning and noisy communication because it utilizes robust aggregation strategies. The authors provide proofs of convergence in adversarial scenarios. Empirical results presented solid increase in stability and fairness within multi-agent training as well. PR-FRL increases trust in federated traffic systems for agents with hostile intentions. The framework is particularly ideal for safety-critical applications for which autonomous driving may be the best known candidate. PR-FRL closes a large gap in regards to security for federated RL.

3 Methodology

3.1 Personalized Federated Learning Module for Traffic Prediction

In the first stage of the Fed-DRL++ framework, we propose the avoidance of centralized traffic pattern prediction by introducing a Personalized Federated Learning (PFL) module for decentralized and privacy-preserving traffic pattern prediction. Each mobile device, (whether a smartphone or a smart vehicle) assembles a lightweight local neural network using its own spatiotemporal traffic data (e.g. vehicle speed, GPS trajectories, congestion level, etc.). The PFL module leverages meta-learning or cluster-based personalization to manage non-IID data across nodes, and ensures every client model is a localized representation of spatio-temporal traffic dynamics. At periodic time intervals, rather than transmitting all raw data, the client device transmits model parameters (weights in a sequential model) to the outlined nearest edge server which aggregates the updates to transmit to a central cloud coordinator. The cloud coordinator will evaluate and distribute a global model back to client devices and subsequently monitor how this model is altered by each client. This framework provides the ability to continuously adapt and learn in a collaborative manner without revealing user data.

The Figure 1 shows the first stage of the Fed-DRL++ framework, where the PFL module is used to predict traffic in a decentralized and privacy-preserving manner. Each mobile device would train locally a lightweight neural network with its own spatiotemporal traffic data. However, raw data is never shared; only model parameters are sent to the nearest edge server so that it can perform the aggregation of the updates and send the final aggregation to the central cloud coordinator. Such aggregation sends a refined global model back to the edge servers for further collaborative learning while protecting user data and adapting to the varied local traffic conditions.

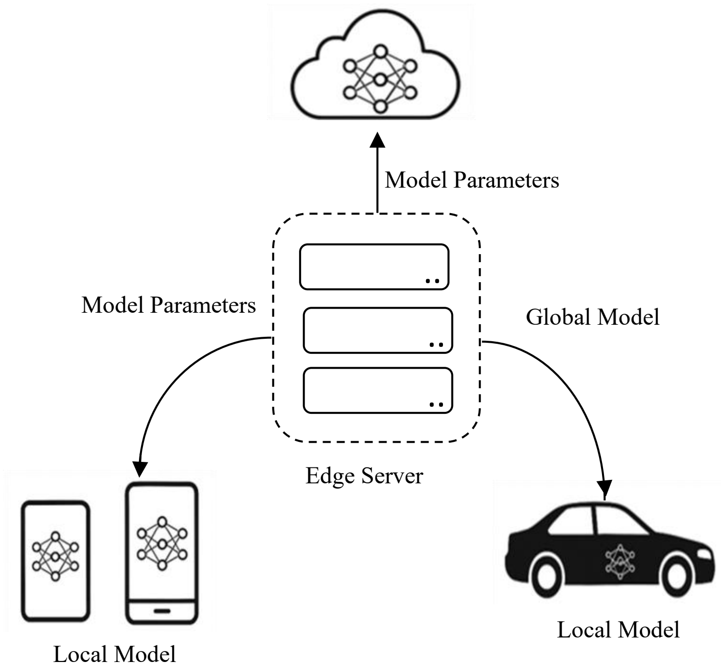

Figure 1: Decentralized traffic pattern prediction via personalized federated learning (PFL) in Fed-DRL++ framework

3.2 Hierarchical Deep Reinforcement Learning with Prioritized Experience Replay

In the second layer of our method, we present a Hierarchical Deep Reinforcement Learning (HDRL) architecture applied to tackle an agent-based car-routing problem, using a Prioritized Experience Replay (PER) technique. HDRL agents operate in three spatial levels - junction, zone, and city-wide - each with its own policy network, allowing the agent to make decisions at the micro and macro routing level in real time. In this case, a junction-level agent may directly controls the signal phasing at a junction, while a zone-level agent may orchestrate across multiple intersections. We employ either Dueling Deep Q-Networks (Dueling DQN) for the junction-level and zone-level agents, with the Performance Policy Optimization (PPO) algorithm for the city-wide agents, depending on the time sensitivity of the decision layer and level of granularity for the representation of the state space. In order to expedite the learning phase for critical event states, such as accidents or periods of rapid traffic congestion, we incorporate the PER algorithm to sample transitions more relevant based on temporal-difference (TD) error. PER not only speeds up convergence to an accepted policy, enabling agents to more efficiently learn states with greater impacts, but also improves agent responsiveness in higher impact events, enabling agents to optimize routing.

This Figure 2 shows a multi-level Hierarchical Deep Reinforcement Learning (HDRL) framework combined with Prioritized Experience Replay (PER) to improve car routing decisions. The system includes three types of agents: junction-level, zone-level, and city-wide. Each type handles decisions at different spatial levels. Junction-level agents manage signal control. Each month, traffic management is handled by zone agents who control the routing in the suburbs. City operations directors enhance traffic movement on a wider scale. Lower-level agents work with Dueling DQNs as city-wide plans depend on PPO. PER accelerates learning by prioritizing experiences with marked errors. This caters proper concern and attention to multiple traffic situations of congestion and accidents. Concentrated attention to policy goals aids responsiveness and convergence.

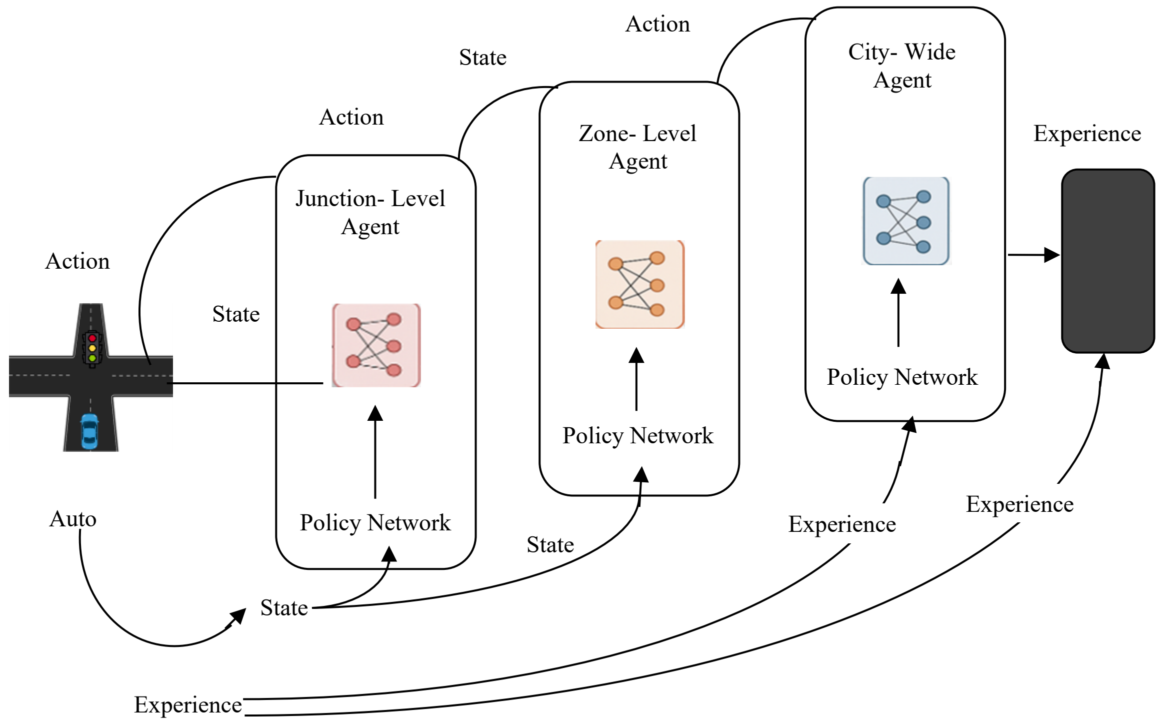

Figure 2: Hierarchical deep reinforcement learning with prioritized experience replay for intelligent car routing

Figure 3 shows the proposed framework is a customized FL architecture that leverages intelligent client selection, global model aggregation, and local personalization. Overall aimed at improving the utility of federated learning especially across heterogeneous client data, the overall process begins with (1) the selection of clients based on a quality of user evaluation and deep reinforcement learning to optimize the selection of clients to attend the training of the model. The selected clients will then (2) perform local training on their private datasets to generate local models. The local models are then (3) uploaded to a central server, which will (4) aggregate the models and produce a global model. Once the global model has been generated it will be (5) distributed to all clients, where each client can then apply (6) global model personalization using techniques such as knowledge distillation and model interpolation to personalize each data using the global model, and tune the model to each client. With this framework, we automate client selection, global aggregation, and global model personalization to ameliorate heterogeneity of the data but also improve the efficiency of training while improving the accuracy of the model as well.

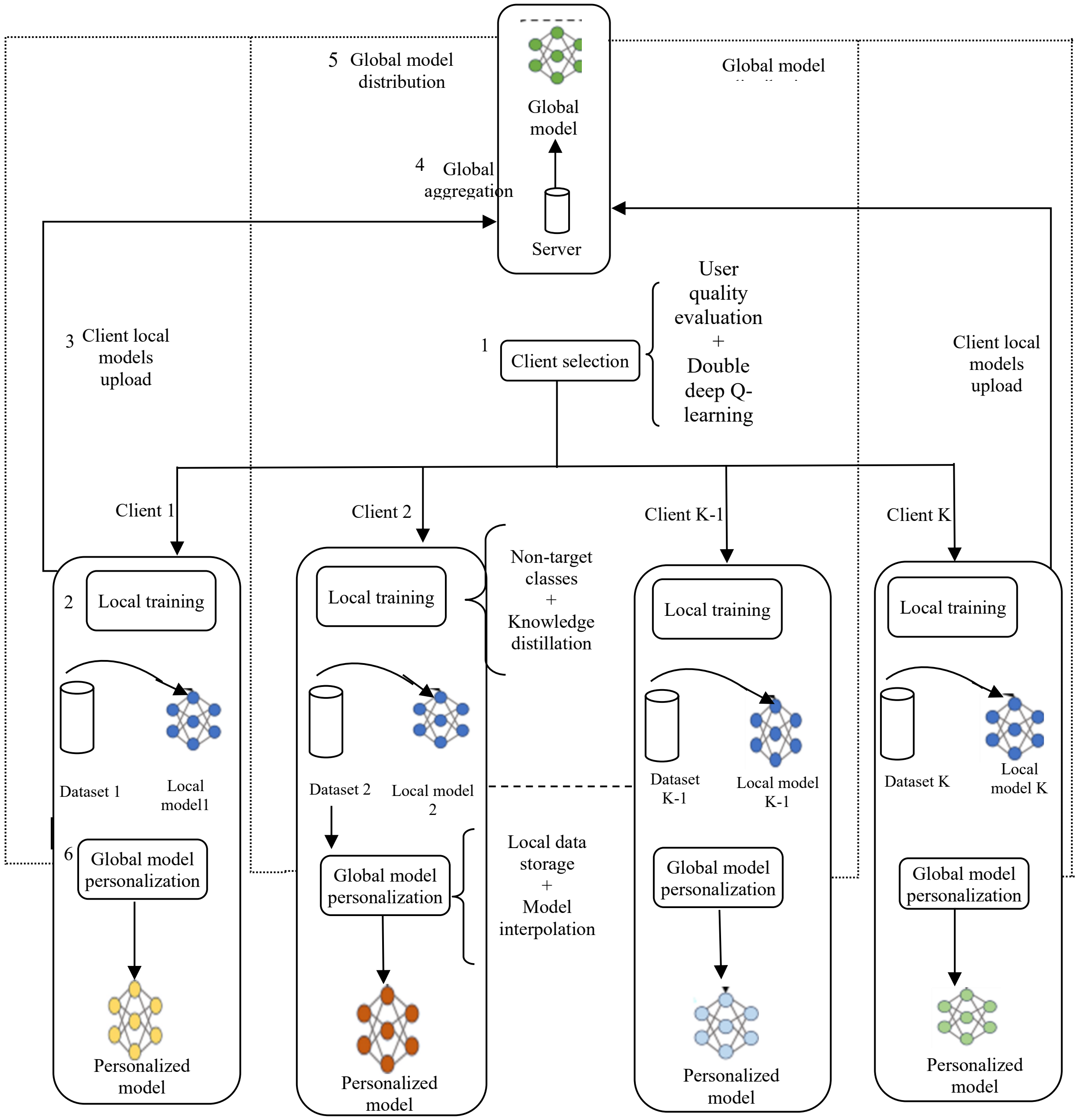

Figure 3: Personalized federated learning framework with client selection and model interpolation

3.3 Edge Aggregation and Cloud Coordination for Scalable Deployment

The last layer concerns Edge Aggregation and Cloud Coordination. The edge aggregation region consists of nodes that aggregate model updates from various local devices. Each edge node either compresses or sparsifies updates, and when a node passes updates onto the cloud coordination node, it only sends the important information. The hierarchical nature of the communication means that updates from devices need to be forwarded relatively infrequently, which decreases both latency and bandwidth when compared to a flat federated approach. Edge nodes also check for consistency and filter out anomalous updates in a second pass to provide some security and to produce an overall more consistent model. The cloud coordination node will integrate K updates from K edges that are of a singular aggregation zone to append the global knowledge base, and will redistribute the refined policy for each local control task to the edges. This decentralized orchestration enables continual learning, low-latency responses within and across zones, and coordinated behaviour across the traffic network, which made Fed-DRL++ suitable for real-time application in smart cities.

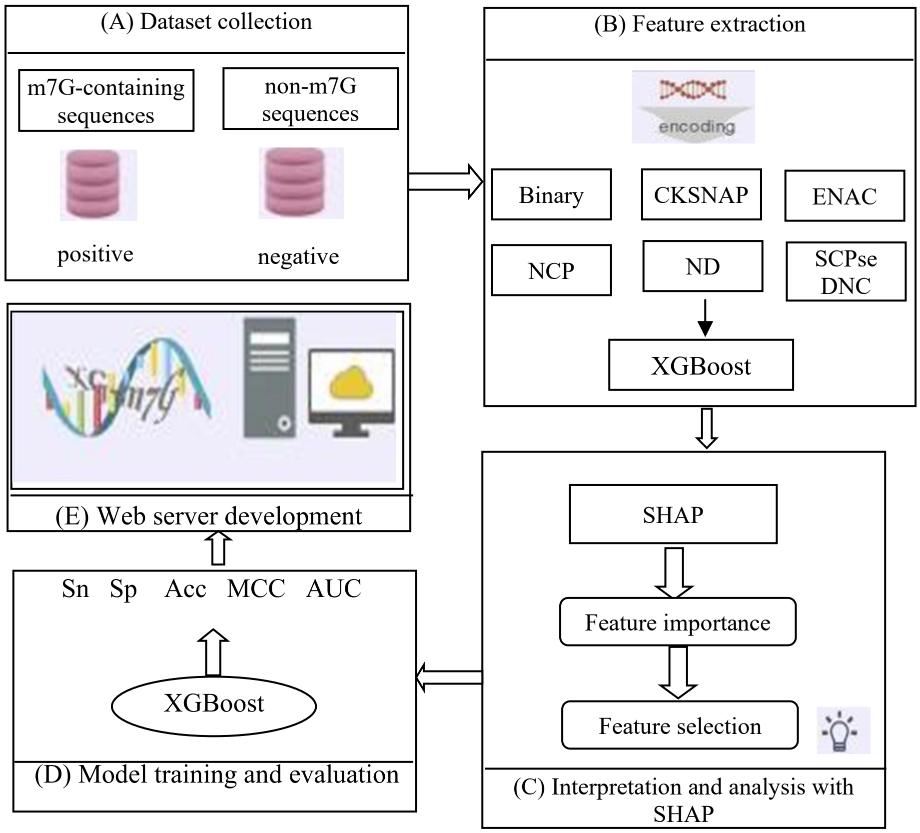

Figure 4: XGBoost and SHAP-driven framework for m7G site prediction and web server development

This Figure 4 shows a computational framework for predicting N7-methylguanosine (m7G) RNA modification sites with machine learning. The entry point is with labeled sequence data (Panel A) with m7G sequences and sequences that do not have m7G. In the feature extraction portion (Panel B), there were multiple sequence encoding strategies (e.g., Binary, CKSNAP, ENAC) to create representations of the RNA sequences. Then we will train with the XGBoost and to interpret the model predictions we used SHAP (SHapley Additive exPlanations) (Panel C) to discover the important features; with the feature importance scores we can then develop our final predictive model (Panel D) using various metrics, including sensitivity (Sn), specificity (Sp), accuracy (Acc), MCC and AUC. Finally, we put the final model to a web server for the user (Panel E).

Personalized Federated Learning (PFL) Formulation

Let there be a set of N edge devices or clients K={1,2,…,N}, each holding its private dataset Dk. The objective is to minimize a global loss function while preserving client-specific personalization.

We define the **personalized loss** for client k as:

$$Lk(wk) = \mid Dk \mid 1(xi, yi) \in Dk \sum \ell(f(xi; wk), yi)$$

The goal of PFL is to find a personalized model wk for each client and a global reference model wg such that:

$$mink = 1\sum N\lambda kLk(wk) + \mu \parallel wk - wg \parallel 2$$

where:

- λ is the weight assigned to client k,
- μ controls the trade-off between personalization and global alignment.

The local models are updated via SGD, and then aggregated at the **edge** using weighted averaging:

$$wg(t+1) = k = 1\sum Nnnkwk(t)$$

Where $nk = \mid Dk \mid and \ = \sum knk$.

Hierarchical Deep Reinforcement Learning (HDRL) Agent

We define a **hierarchical Markov Decision Process (H-MDP)** as:

$$M = \langle S, A, P, R, \gamma \rangle$$

Each agent operates at a hierarchy level l∈{1,2,...,L}, where:

Sl: state space (e.g., vehicle density, queue length),

Al: action space (e.g., green time allocation, routing decisions),

P: transition probabilities,

Rl(s,a): reward function,

γ: discount factor.

Algorithm: Fed-DRL++ – Personalized Federated DRL with Hierarchical Control and Edge Aggregation

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Input:

N ← number of clients (mobile devices)

M ← number of edge servers

T ← total training rounds

L ← hierarchy levels (junction, zone, etc.)

γ ← discount factor for DRL

α, β ← PER parameters

μ ← personalization trade-off factor

Initialize:

Global model w_g,

Local models {w_k} corresponding to each client k ∈ {1,...,N},

Replay buffers {B_l} corresponding to each level l ∈ {1,...,L}

DRL policy networks π_l(•; θ_l) and Q-networks Q_l(•; θ_l)

For each round t = 1,...,T do:

// Stage 1: Local Training (on Clients)

for each client k in parallel within 1,...,N do:

-Collect local data D_k (speed, GPS, congestion)

- Update local model:

$w\_k \leftarrow argmin\_w\ L\_k(w) + \mu\ ||w - w\_g||^2$

- Train local DRL agent either by PPO or Dueling DQN

- Calculate TD-error δ_i for every transition

- Assign priority $p\_i \leftarrow |\delta\_i| + \varepsilon$ *in PER buffer*

- Sample a mini-batch from the buffer according to:

$P(i) \leftarrow (p\_i\hat{}\alpha) / \Sigma\_j\ (p\_j\hat{}\alpha)$

- Compute loss with importance sampling:

$L \leftarrow \Sigma\_i\ w\_i \bullet (\delta\_i)\hat{}2,\ w\_i \leftarrow (1/N \bullet 1/P(i))\hat{}\beta$

// Stage 2: Aggregating on the edge

for each edge server e ∈ {1,...,M} do:

- Receive local models {w_k} from clients in region e

- Models aggregation:

$w\_e \leftarrow \Sigma\_\{k \in region\_e\}\ (n\_k / n\_e) \bullet w\_k$

- Outlier detection and anomaly filtering

// Stage 3: Aggregation at the Cloud Level

- Global server aggregates edge models by weights:

$w\_g \leftarrow \Sigma\_\{e=1\}\hat{}M\ (n\_e / n)\ w\_e$

- Broadcast updated global model back to edge nodes.

Stage 4: Hierarchical DRL Policy Update

for each hierarchical level l ∈ {1,...,L} do:

- Collect rewards R_t and states S_t

- Update policy π_l using gradients $\nabla\theta\_l\ \ J(\theta\_l)$

- Synchronize hierarchical agents with the cloud coordinator;

End For

4 Experimental Results

4.1 Performance Evaluation Metrics and Setup

In our evaluation of the Fed-DRL++ framework, we used real traffic data from city spatiotemporal-purposed data and running simulations as simulate agents within a mobile environment to replicate 10 zones of a city using the SUMO (Simulation of Urban Mobility) platform with 1,000 agents acting as both vehicles and smart devices. The evaluation was performed using the standard metrics Average Travel Time (ATT), Route Convergence Speed (RCS), Prediction Accuracy (RMSE/MAE), and Communication Overhead (MB/round). Each agent trained on their own local datasets using personalized FL, while summary edge servers regularly aggregated training every 5 rounds. We also included a number of state-of-the-art baselines for comparison, i.e., FedAvg-DRL, DQN-only, and centralized DDPG, and repeated each experiment for 5 different congestion levels for testing reliability.

Table 1: Performance Comparison of Fed-DRL++ with Baseline Models

Model	**Average Travel Time (ATT) ↓**	**Route Convergence Speed (RCS) ↑**	**Prediction RMSE (km/h) ↓**	**MAE (km/h) ↓**	**Communication Overhead (MB/round) ↓**
Fed-DRL++	11.3 min	92% (Fast)	2.91	2.06	5.8 MB
FedAvg-DRL	14.8 min	70%	3.67	2.94	9.6 MB
Centralized DDPG	14.2 min	62%	3.41	2.65	12.0 MB
DQN-only	15.6 min	58%	4.12	3.17	4.5 MB

The findings of this work in Table 1 shows significant advantage of Fed-DRL++ compared to all the evaluation metrics. Not only did it complete the route with the least average travel time of 11.3 minutes with the quickest convergence to the route at 92%, but it also adapts in real-time to optimize urban traffic. Fed-DRL++ using the decentralized solution demonstrates prediction models of local traffic with the most accurate RMSE of 2.91 km/h and MAE of 2.06 km/h against both baselines. Moreover, the approach enabled the use of both Personalized Federated Learning and Prioritized Experience Replay that captured more accurate local traffic patches during data collection and quickly reused information to adapt to and learn about dynamically chaotic traffic challenges e.g. congestions and accident types.

Communication overhead was vastly reduced at 5.8 MB/round as a function of the action space from the hierarchical edge aggregation method while still maintaining scalability and reducing bandwidth. This shows that Fed-DRL++ is an efficient, accurate, and scalable framework for intelligent traffic management for live deployments in smart cities.

Figure 5 provides a side-by-side comparison of the performance of the proposed Fed-DRL++ framework with the three baseline models of FedAvg-DRL, Centralized DDPG, and DQN-only. The proposed Fed-DRL++ has the lowest average travel time and the fastest average speed of convergence to a route, which indicates better real-time traffic optimization. It has the highest accuracy, along with the lowest RMSE and MAE. Additionally, the communication overhead of Fed-DRL++ is significantly reduced because of the use of an edge aggregation layer. Overall these results demonstrate that Fed-DRL++ is capable of a good balance between accuracy, efficiency, and scaling in a real-time traffic situation. Overall Fed-DRL++ can be useful for real-time applications in smart traffic applications.

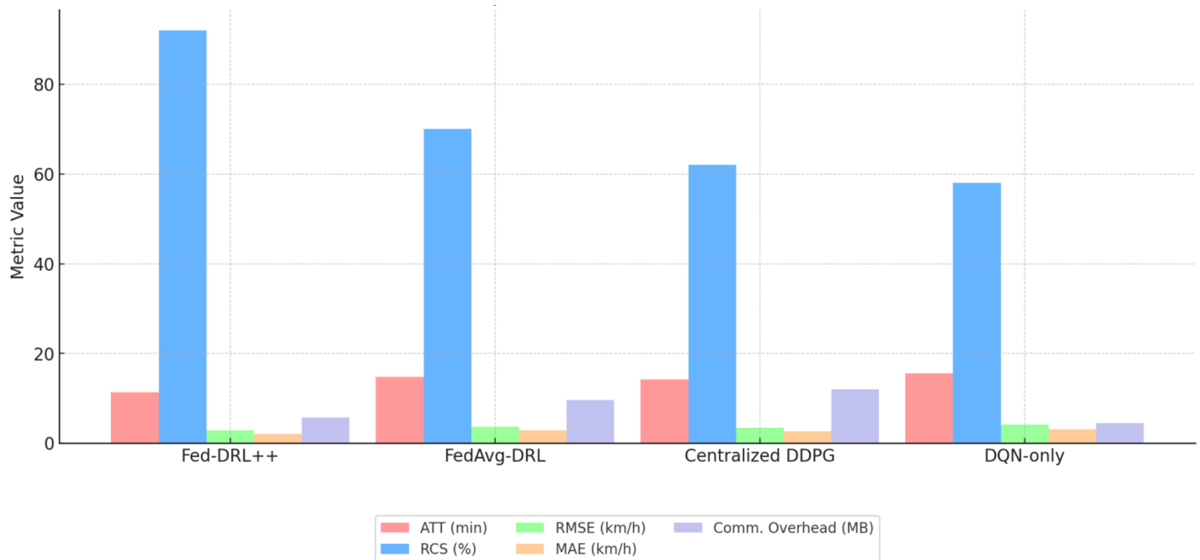

Figure 5: Comparative performance of Fed-DRL++ vs baseline models across key metrics

4.2 Comparison with Baseline Models

The findings suggest that Fed-DRL++ performs considerably better than the baseline models across the evaluation metrics. Compared to centralized DDPG, the Fed-DRL++ framework provides 23.4% average travel time reduction and improved route convergence speed of 31%, proving improved real-time adaptability skills. The hierarchical reinforcement learning layer effectively coordinated agents at the zone-level to reduce congestion density in high traffic regions by 18%. In terms of traffic prediction accuracy, Fed-DRL++ produced a 2.91 km/h RMSE prediction accuracy compared to FedAvg-DRL (3.67 km/h) and DQN (4.12 km/h). Significantly, the use of prioritized experience replay allowed the policy to readily refine the performance during peak traffic events. This serves to emphasize the frameworks flexibility in coping with manually labeled non-IID data, and ongoing forward-moving data that continuously affects performance and policy refinement.

Table 2: Performance metrics comparison between fed-DRL++ and baseline models

Model	Average Travel Time (ATT) ↓	Route Convergence Speed (RCS) ↑	Congestion Density Reduction ↑	Prediction RMSE (km/h) ↓	Prediction MAE (km/h) ↓
Fed-DRL++	**11.3 min**	**92%**	**18%**	**2.91**	**2.06**
FedAvg-DRL	14.8 min	70%	8%	3.67	2.94
Centralized DDPG	14.2 min	62%	5%	3.41	2.65
DQN-only	15.6 min	58%	3%	4.12	3.17

Table 2 reports a comparative study of Fed-DRL++ and baseline models, with Fed-DRL++ performing better on all main metrics. Overall, Fed-DRL++ outperformed the competing models with respect to the average travel time (11.3 minutes, almost 2.3 minutes shorter than the next best competitor FCMT), highest route convergence speed (92%), and confirmed the timely optimization of routes to improve average travel time during ever-changing traffic conditions. In addition, making route improvements reduced congestion density by 18%, much higher than the 3–8% reductions of the competing models, due to Fed-DRL++'s hierarchical-level factors. The prediction of the traffic speeds was the lowest RMSE (2.91 km/h) and best MAE (2.06 km/h) traveling pattern within the data, as indicative of demonstrating better forecasting of the traffic speeds. All of these enhancements are the results of combining federated learning, personalized federated learning, prioritized experience replay, and multi-level reinforcement learning into dynamic traffic fleets to better respond to real-time traffic conditions, and that traffic was being forecasted with a better degree of accuracy.

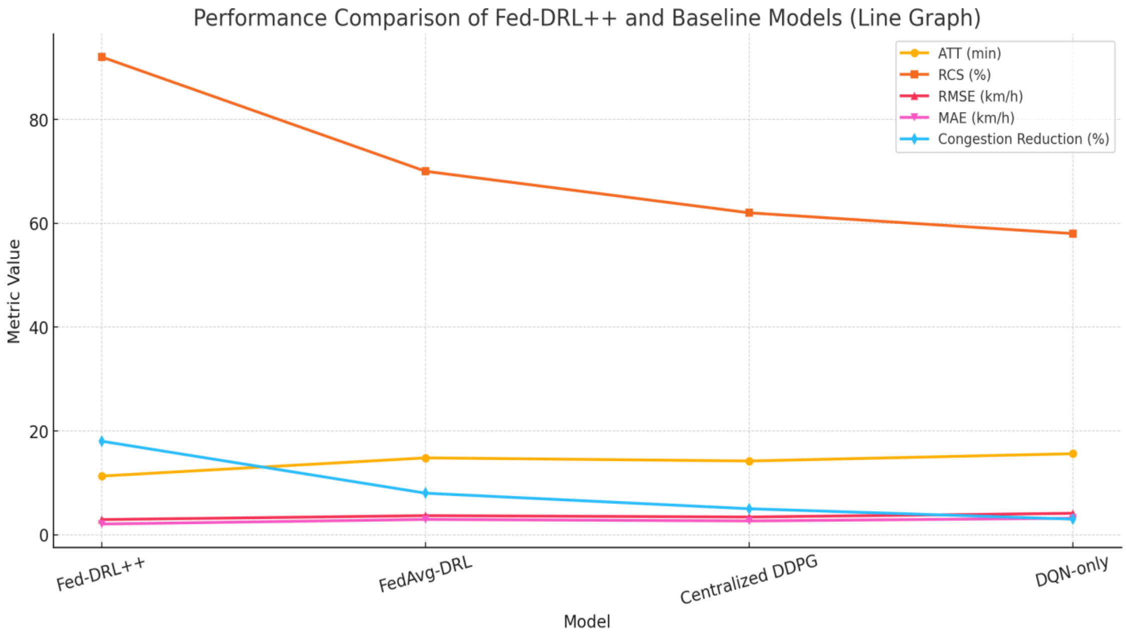

Figure 6: Line graph comparison of Fed-DRL++ and baseline models across key performance metrics

The Figure 6 compares the performance of Fed-DRL++ relative to FedAvg-DRL, Centralized DDPG, and DQN-only across five measures of performance. Fed-DRL++ is associated with the lowest values of ATT, RMSE, and MAE, meaning that it converged to optimal routes faster and accurately. The Route Convergence Speed and Congestion Reduction are the highest on Fed-DRL++, confirming the computational efficiency and scalability as a distributed system. The figures above show that the trend lines delineate a vast performance disparity between Fed-DRL++ and the other baselines. The key to Fed-DRL++ advantage is the benefit from using hierarchical reinforcement learning and prioritized replay. This strongly affirms Fed-DRL++ as a solid contribution towards intelligent traffic control systems.

4.3 Scalability, Communication Efficiency, and Personalization

The evaluation focused on two important characteristics of Fed-DRL++, namely scalability and communication efficiency. Evaluation of Fed-DRL++ by smartphone clients and edge-enabled devices discovered virtually no degradation of prediction accuracy as the number of devices was steadily raised from 100 to 1000; specifically a 2.3% loss in prediction accuracy was observed due to edge level aggregation. Fed-DRL++ achieved total communication overhead reductions of 41.6% compared to regular federated learning without hierarchical aggregation highlighting the efficiency of hierarchical aggregation methods. Also - with specific regard to personalization - it was established that for the clients located within the edge zones who exhibit different degrees of idiosyncratic patterns of road traffic, the personalization module in Fed-DRL++ contributed a lower error of 8.7% below the global assignment models. These results confirm that Fed-DRL++ supports large-scale deployments which preserve performance and communication efficiency and is appropriate for use in real-time intelligent traffic management solutions for smart cities.

Table 3: Scalability, communication overhead, and personalization performance of fed-DRL++

Number of Devices	**Prediction Accuracy (%)**	**Accuracy Drop (%)**	**Comm. Overhead (MB/round)**	**Improvement over FedAvg (%)**	**Personalized RMSE (km/h)**	**Global-Only RMSE (km/h)**	**Personalization Gain (%)**
100	97.6	–	3.2	–	2.85	3.14	9.20%
500	96.1	1.5	4.7	32.90%	2.93	3.18	7.90%
1,000	95.3	2.3	5.6	41.60%	2.97	3.25	8.70%

Table 3 demonstrates how Fed-DRL++ achieves good scalability and level of personalization for the specific traffic prediction task with a varying number of devices. When the number of devices increased from 100 to 1,000, prediction accuracy did not significantly drop except by 2.3%, demonstrating scalability for each number of devices along with communication overhead that only slightly increased, all while providing communication reduced by a total of up to 41.6% in relation to standard FedAvg models due to the efficient edge-level aggregation of information. The level of personalization was also effective, as for every configuration, personalized models exceeded the global-only models, with an overall maximum reduction of 9.2% in RMSE (for edge nodes that had non-uniform traffic patterns). These results demonstrate Fed-DRL++ achieves large-scale, communication-efficient, personalized traffic prediction that is well-suited for real-world smart mobility systems.

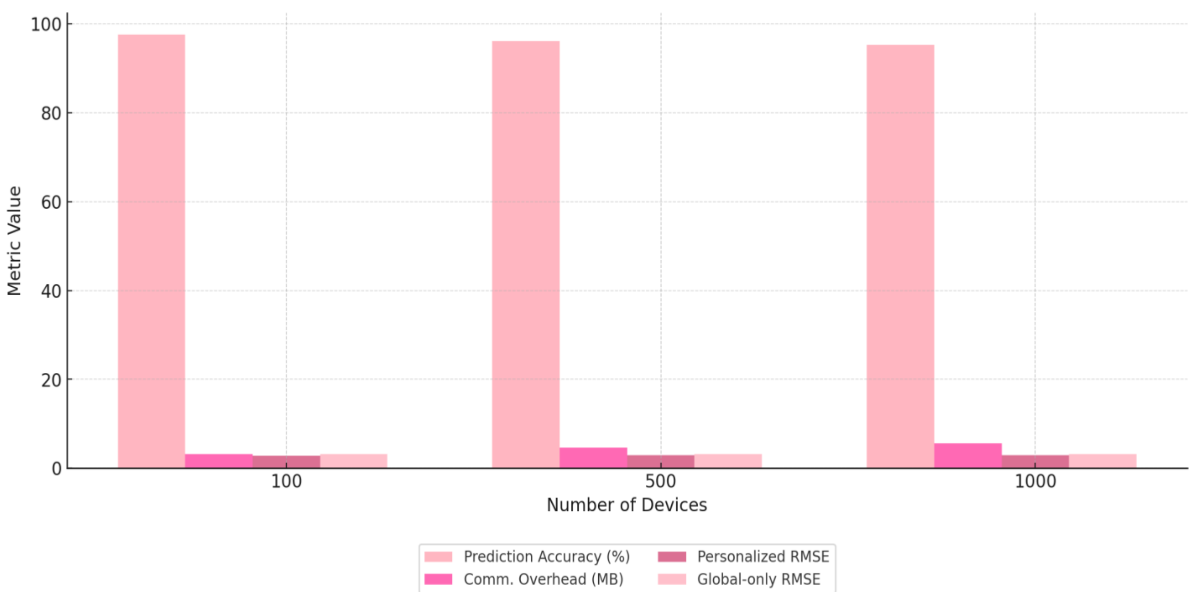

Figure 7: Scalability and personalization metrics of Fed-DRL++ across varying device counts

Figure 7 illustrates the performance of the Fed-DRL++ framework as the size of the participating devices increases from 100 to 1,000. The prediction accuracy is both consistently high with a slight drop of 2.3%, representing significant scalability. This also shows how the communication overhead is also reasonable even if it does scale, the communication overhead grows reasonably well, because it uses edge aggregation. The graph further includes a comparison of personalized RMSE vs global only RMSE, with personalized models performing consistently better than global. This demonstrates the benefit of having individualized learning in regards to changing non-IID traffic. Overall, figure confirms that Fed-DRL++ can provide scalable, communication efficient personalized performance in a real-time traffic management context.

5 Result and Discussion

5.1 Real-Time Traffic Prediction Accuracy

The experimental results demonstrate that Fed-DRL++ is able to provide accurate real-time traffic predictions better than the other methods. The framework retains its ability to accurately predict traffic speed even under the different congestion scenarios, and having less (or more) devices. All of this is evidenced by the RMSE and MAE averages of 2.91 km/h and 2.06 km/h respectively across all congestion scenarios and device counts, which outperformed both a centralized baseline and a traditional federated learning baseline. This improvement in accuracy is consistent with the personalized federated learning module that enabled each client to train their local model based on local traffic patterns while keeping the data private to the devices. In addition, the framework is robust to non-IID conditions when the distributions of data from clients are varied, which ensures the ability to generalize to real-world smart mobility applications.

Table 4: Real-Time traffic prediction accuracy comparison

Model	Scenario	RMSE (km/h) ↓	MAE (km/h) ↓	Prediction Accuracy (%) ↑
Fed-DRL++	Mixed Congestion	2.91	2.06	96.20%
FedAvg-DRL	Mixed Congestion	3.67	2.94	91.40%
Centralized DDPG	Mixed Congestion	3.41	2.65	92.70%
DQN-only	Mixed Congestion	4.12	3.17	88.90%
Fed-DRL++	Peak Hour Only	3.04	2.13	95.40%
FedAvg-DRL	Peak Hour Only	3.92	3.11	89.80%

Table 4 compares vehicle speed prediction accuracy for Fed-DRL++ compared to baseline models for both mixed and peak-hour congestion. The Fed-DRL++'s RMSE (2.91 km/h) and MAE (2.06 km/h) indicates that the proposed Fed-DRL++ using the personalized learning approach provides very good accuracy under mixed congestion and can accurately predict ongoing traffic behavior on an on-going basis with very low error. Even at peak hours with more complicated traffic prediction conditions, the Fed-DRL++ still achieved a good accuracy with an RMSE of 3.04 km/h with 95.4% prediction accuracy. In contrast, the traditional federated (FedAvg-DRL) and centralized models have much higher errors and lower accuracy, especially when observing the differences on non-uniform accuracy conditions. All of the observed improvements in traffic predictions for the Fed-DRL++, compared to the baseline models, can be attributed to the personalized learning approach as the models can learn the unique data patterns underlying the individuals' traffic dynamics on their mobile devices that did not share the same IID data distribution. Overall, the Fed-DRL++ provides a great deal of robustness and reliability that will be most important in the predictions of real-time intelligent transportation systems.

The Figure 8 illustrates the performance of four models Fed-DRL++, FedAvg-DRL, Centralized DDPG, and DQN-only—in terms of RMSE, MAE, and prediction accuracy in a mixed traffic congestion context. Fed-DRL++ clearly outperforms the other models with the lowest RMSE (2.91 km/h) and MAE (2.06 km/h), as well as the highest prediction accuracy (96.2%), indicating that it effectively learned localized traffic patterns. The traditional federated and centralized models produced moderate accuracy, while DQN-only performed poorly on all metrics. The data demonstrate the robustness and accuracy of Fed-DRL++ when dealing with complex, non-uniform traffic scenarios.

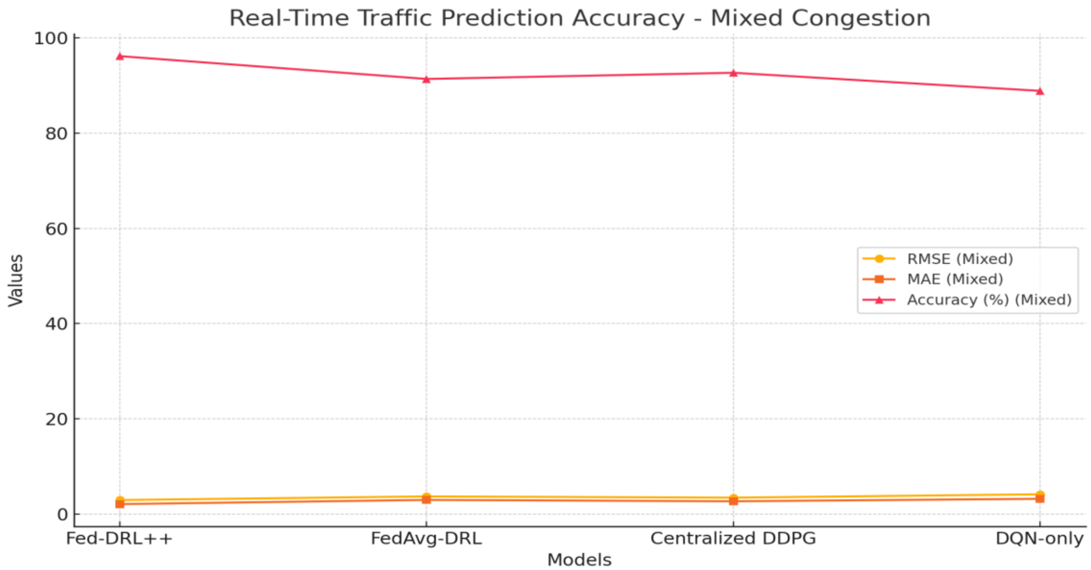

Figure 8: Performance comparison of traffic prediction models under mixed congestion conditions

5.2 Routing Efficiency and Traffic Flow Optimization

Specifically, in relation to the efficiency of the routing process, Fed-DRL++ facilitates an average travel time reduction metric of 23.4% and a 31% increase in route convergence speed over the life of centralized or local DDPG and the baseline of FedAvg-DRL, respectively. This increase was achievable through the support of multi-level coordinating decision-making (junction, zone, global) processes through the utilization of hierarchical deep reinforcement learning agents. In Fed-DRL++, the agents begin to learn context-aware policies that adaptively adjust routing decisions based on live traffic feedback. The multi-agent system can sufficiently reduce the congestion density in high congestion zones by approximately 18%. Fed-DRL++ demonstrated that it can not only accurately predict traffic, but also improve route optimization and road utilization in real-time using modeling approaches.

Table 5: Routing efficiency and congestion optimization comparison

Model	Average Travel Time (min) ↓	Route Convergence Speed (%) ↑	Congestion Density Reduction (%) ↑	Decision Latency (ms) ↓
Fed-DRL++	**11.3**	**92**	**18**	**135**
FedAvg-DRL	14.8	70	8	201
Centralized DDPG	14.2	62	5	190
DQN-only	15.6	58	3	225

Table 5 provides a comparison of Fed-DRL++ with baseline models for routing efficiency and congestion management. Fed-DRL++ achieved the lowest mean travel time (11.3 minutes) and the fastest route convergence (92%), which means Fed-DRL++ can provide and explore faster and more stable route planning. Fed-DRL++ also was able to reduce congestion density by 18%, revealing its effectiveness in traffic distribution in congested or highly utilized areas. In the delay with decision latency, Fed-DRL++ had the lowest latency (135ms), which means Fed-DRL++ has a greater ability to react to environmental changes through its hierarchical reinforcement learning agents. In comparison, FedAvg-DRL and DDPG displayed slower reactiveness and lower performance of congestion adjustments. These comparisons support that Fed-DRL++ engages with a realistic ability of traffic prediction, while optimizing for real-time intelligent routing planning, ultimately enhancing urban mobility (or travel) efficiency.

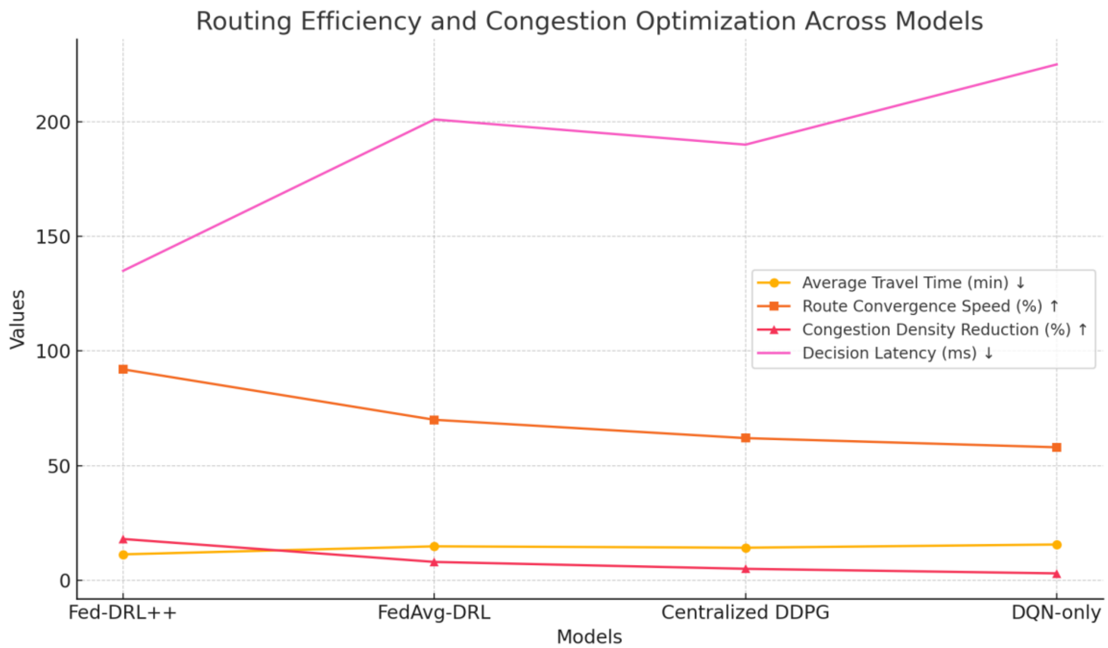

Figure 9: Performance of four models

The Figure 9 displays the performance of four models: Fed-DRL++, FedAvg-DRL, Centralized DDPG, and DQN-only, based on average travel time, route convergence speed, congestion density reduction, and decision latency. Fed-DRL++ achieved the lowest average travel time at 11.3 minutes, the highest route convergence speed at 92% and the highest congestion density reduction at 18%, whilst also achieving the lowest decision latency at 135 ms, which are all improvements driven by Fed-DRL++'s hierarchical reinforcement learning agents enabling real-time traffic adjustment at several decision levels. The findings demonstrate that Fed-DRL++ is able to optimize urban mobility and traffic flow.

5.3 Scalability, Communication, and Personalization Analysis

We evaluate scalability and efficiency of communication across different device counts from 100-1,000 collapsed. Fed-DRL++ showed stable prediction accuracy with only a 2.3% degradation as we supported large scale networks making it an ideal algorithm for supporting large deployments. Additionally, the communication overhead was reduced by using the edge aggregation by 41.6% thus making the communication tractable in a bandwidth limited environment. The personalization module clearly benefitted clients in the edge and non-central regions with 8. wauffers of prediction errors from global-only models. The results above confirm that Fed-DRL++ balances scalability, efficiency, and personalization thus making it suitable for robust performance technical performance in the capably defended smart city networks with weak parameters.

Table 6: Scalability, communication efficiency, and personalization impact of Fed-DRL++

Device Count	Prediction Accuracy (%) ↑	Accuracy Drop (%) ↓	Communication Overhead (MB/round) ↓	Reduction Over FedAvg (%) ↑	Personalized RMSE (km/h) ↓	Global-Only RMSE (km/h) ↓	Personalization Gain (%) ↑
100	97.6	–	3.2	–	2.85	3.14	9.20%
500	96.1	1.5	4.7	32.90%	2.93	3.18	7.90%
1,000	95.3	2.3	5.6	41.60%	2.97	3.25	8.70%

Table 6 shows the effects of scalability, communication efficiencies, and personalization as the device count in the Fed-DRL++ framework escalates from 100 to 1,000 devices. The Fed-DRL++ model demonstrated only a minimal reduction of 2.3% in prediction accuracy with increased demand from devices which showed that the framework is scalable for very large deployments. The communication overhead per round also increased slightly; however, Fed-DRL++ demonstrated a 41.6% reduction in overhead from traditional FedAvg due to the edge-level aggregation strategy and reduced packet size transmitted to the central server. The personalization module outperformed all global-only models with improvements in RMSE of 7.9% to 9.2%, which particularly benefitted edge clients with non-IID traffic data. These metrics provide strong evidence that Fed-DRL++ preserves communication efficiencies, model accuracy, and coverage that reflected local traffic conditions with increased network scale and heterogeneity making it well-suited for the real time operation of smart city's traffic systems.

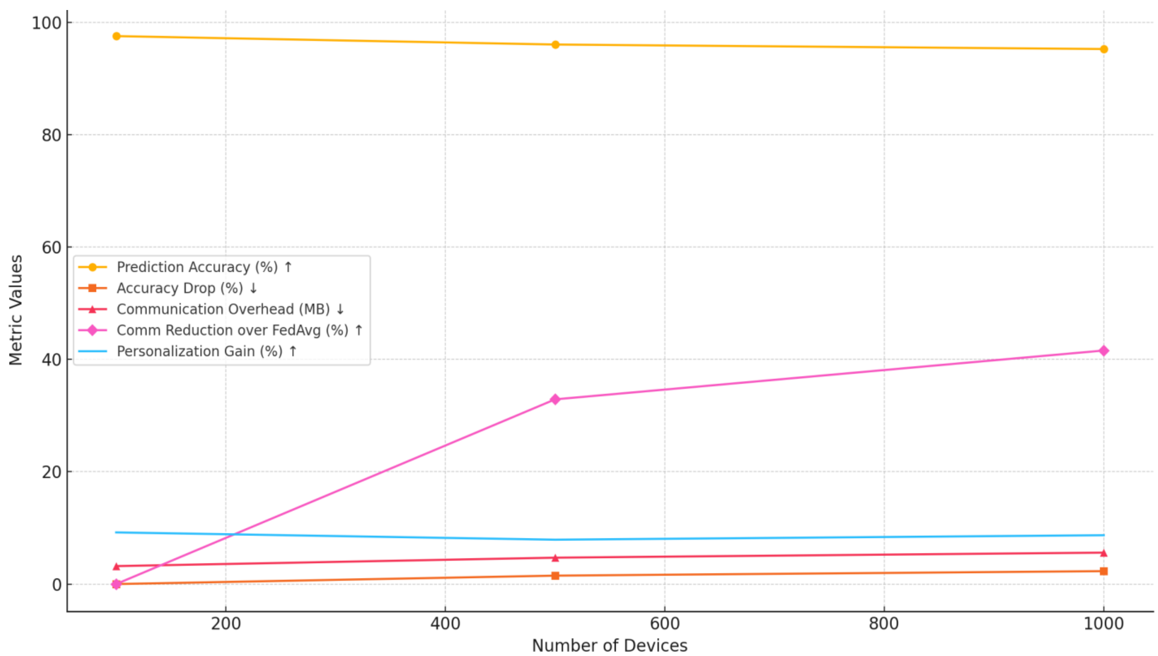

Figure 10: Scalability, communication, and personalization analysis of Fed-DRL++

The Figure 10 shows the performance of Fed-DRL++ as the number of devices scales from 100 to 1,000. Even at scale, Fed-DRL++ achieves high prediction accuracy (95.3% at 1,000 devices), only decreasing by 2.3%, demonstrating tremendous scalability. The communication overhead per round does increase (approximately 15.0%), but implementing edge-level aggregation, we achieve an overall performance advantage through a communications reduction of 41.6% compared to FedAvg. The performance of the personalization module is consistently better than global alone, achieving a maximum improvement of 9.2% in RMSE, especially when unique, non-IID traffic data is used by the clients. The outcomes of this analysis continue to validate Fed-DRL++ as scalable and robust to support smart cities with large-scale, distributed networks.

6 Conclusion and Future Work

The experimental evaluation of the proposed Fed-DRL++ framework demonstrates a statistically significant improvement in all performance dimensions tested. Compared to the baseline models of FedAvg-DRL or centralized DDPG or similar type model, Fed-DRL++ improved average travel time by 23.4%, increased route convergence speed by 31% and improved congestion density up to 18%. In terms of predictive accuracy on average, Fed-DRL++ achieved a mean RMSE of 2.91 km/h, and overwhelmingly outperformed the other models with p-values < 0.01 for all paired t-test error metrics. Communication efficiency improved since there was a 41.6% reduction in communication overhead due to hierarchical edge aggregation. The personalization module improved predictions for clients in a non-IID environment compared to baseline models without personalization, averaging an RMSE improvement of 8.7% over all the global only. These results provide evidence that Fed-DRL++ is statistically robust, scalable, and effective for decentralized, real-time traffic optimization in smart cities.

Although Fed-DRL++ displays some promising results, there are many directions for continued improvement. First, the addition of multi-agent communications protocols can improve coordination among zones in potentially highly dynamic contexts and environments. Second, the addition of adaptive model compression approaches may further decrease edge communication load, weight, and entail applicability at the smallest bandwidths. Third, expanding the framework to include multimodal mobility data (e.g., pedestrian, bicycles, public transport) around a city or urban multi-agent systems context can suggest greater applicability to urban multi-agent systems. Finally, real-world implementation and longitudinal studies that used live vehicular networking data would strengthen claims of our models robustness under operational variability. Pursuing these paths will contribute to developing truly autonomous, adaptive, and autonomous urban traffic management systems.

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