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Original Article

A Context-Aware Deep Swarm and Federated Meta-Reinforcement Learning Signal Controller for Sustainable Urban Mobility Optimization

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Abstract - *Urban road systems are experiencing an increasing rate of congestion due to the rapid population growth, increased vehicle ownership, and uneven mobility demand across the metropolitan corridors. Although the traffic agencies have deployed the sensor networks and surveillance infrastructure, a significant portion of signal controllers still follow the rigid or semi-adaptive timing plans-this struggles to handle the fluctuating traffic patterns, multimodal flow pressure, and energy-related constraints. Current smart mobility research has explored deep learning, spatiotemporal forecasting, transfer learning, and optimization-driven control. However, it does not completely combine the contextual, environmental, and real-world uncertainties into a unified traffic management framework. The conventional traffic signal optimization methods mainly have focused on the minimization of congestion and the reduction of delay, but they remain limited in sustainability. They depend heavily on the large labeled datasets, but the real traffic environments frequently involve missing or noisy data. The majority of data-driven controllers also function at the isolated intersections rather than the coordinating corridor-level decisions. Further, recent models have lacked resilience during disturbances such as sudden traffic surges, road incidents, and cyber-threat-driven disruptions. These limitations have restricted the capability of the traffic authorities to convert the real-time prediction into a stable, reliable, and sustainable mobility planning. The study has introduced a hybrid adaptive control framework that tends to combine the Context-Aware Multi-Objective Deep Swarm Learning (CM-DSL) and Threat-Adaptive Federated Meta-Reinforcement Learning (TA-FMRL). The CM-DSL module learns the multimodal traffic dependencies, environmental indicators, queue dynamics, and the sustainability metrics through a multi-objective swarm search. It guides the advancement towards the globally beneficial phase selections. The TA-FMRL layer then distributes the learning across intersections, and it has provided fast policy transfer, privacy preservation, and resilience against incomplete data and security threats. The system relies entirely on the real-time vehicle counts, optical flow patterns, contextual state inputs, and the cloud synchronization layer for a collaborative decision update. The experimental tests in a dense urban network have confirmed a great improvement in mobility and sustainability. The average waiting time has reduced to 64.0 s on METR-LA and 68.5 s on PEMS-BAY, while the average queue length is reduced to 120 m and 128 m, respectively. The Intersection throughput increases to 1390 vehicles/h and 1360 vehicles/h, which confirms a faster clearance of the traffic inflow. The travel time index has declined to 1.60 and 1.65, which shows a smoother vehicle movement. The fuel consumption and emission output have decreased to 33.5 L/35.0 L and 388 kg/400 kg, respectively. This confirms that the proposed method has supported sustainable and energy-efficient driving conditions for the intelligent transportation systems.*

Keywords - *Urban Mobility Optimization, Deep Swarm Learning, Federated Meta-Reinforcement Learning, Sustainable Traffic Control, Intelligent Transportation Systems.*

1. Introduction

Urban mobility plays a crucial role in shaping the economic vitality and social well-being of modern cities. The rapid growth in vehicle ownership, urban expansion, and the inter-city movement has increased the traffic density across the metropolitan networks [1-3]. The transportation authorities have deployed the sensors, CCTV surveillance, smart counters, and the connected infrastructure to monitor the traffic flow and to support the intelligent decision-making [4, 5]. Data-driven trend analysis has improved the traffic forecasting and demand assessment, which leads to the planning of a smarter road usage and signal coordination [6, 7]. The emerging smart city initiatives visualize a combined mobility platform that tends to improve commute efficiency while delivering safety and environmental sustainability [8]. Despite these developments, the mobility ecosystem has struggled to keep pace with constantly shifting traffic dynamics. Urban transportation still encounters several significant challenges that have prevented optimized signal control and seamless traffic distribution. Most cities often contain the intersections that get operated based on static or semi-adaptive signal plans, which do not adjust well to the sudden flow fluctuations or event-driven congestion waves [9]. The presence of a non-uniform mobility demand across the different corridors has increased the queue length and unnecessary idling during the peak periods [10]. Multimodal mobility involving buses, cars, two-wheelers, goods vehicles, and non-motorized users has further added to the complexity of scheduling decisions [11]. Limited road space, energy consumption growth, and emission-related pressures have intensified the burden on the traffic management systems [12]. Smart mobility initiatives continue to explore machine learning, deep learning, and reinforcement-driven techniques; the majority of these methods have remained highly dependent on the large, labeled datasets [13]. However, the traffic environment frequently contains incomplete, heterogeneous, and noisy data that affect prediction reliability [14]. Further, they have lacked interpretability, which has reduced the trust among policymakers and transport administrators who require transparent models for infrastructure planning [15].

These issues create an operational gap, where the real-time predictions and control decisions do not fully translate into a reliable congestion mitigation strategy across the city-scale networks [16]. Even advanced intelligent transportation research largely focuses on the isolated intersections rather than a system-wide mobility perspective [17]. Many of the signal control mechanisms still prioritize the queue and delay reduction while ignoring the sustainability indicators such as fuel consumption, emission output, and the environmental impact [18]. The urban mobility ecosystem also demands more than congestion relief, as it requires the decision frameworks that tend to preserve efficiency, safety, energy conservation, and environmental responsibility simultaneously. This has motivated the need for a coordinated, scalable, and context-aware optimization paradigm.

The research gap centers on the lack of a unified traffic management framework that tends to combine the multimodal flow dynamics, contextual variables, environmental constraints, and resilience against disruptions. Conventional works often pay less attention to generalizability across the different network topologies, interpretability for urban stakeholders, or adaptability under threats such as sensor outages and cyber intrusions.

Few models have maintained the optimal performance in situations where the traffic data is missing or contains uncertainty. Additionally, the current methods do not adequately combine the prediction accuracy with a sustainability-driven routing, emission control, and energy-efficiency objectives within the signal planning.

This study sets forward two primary objectives. The first objective is to build an intelligent urban mobility optimization model that uses multimodal, spatiotemporal, environmental, and contextual properties while retaining transparency. The second objective is to design an adaptive and sustainable decision-support mechanism that converts the live mobility predictions into an actionable strategy for congestion reduction, emission control, and energy-efficient routing suited for smart city deployments.

The novelty of the proposed work arises from the fusion of two advanced intelligent modules that are designed to overcome the core research limitations.

The contributions of this research are summarized as follows:

- The first innovation, called Context-Aware Multi-Objective Deep Swarm Learning (CM-DSL), has introduced a swarm-driven deep learning formulation that has explored multiple mobility objectives in parallel rather than the minimization of a single metric. The CM-DSL component aims to handle multimodal interactions, contextual variables, and the environmental indicators while it achieves an optimal trade-off across the delay, queue length, throughput, and the emission levels.

- The second innovation, termed Threat-Adaptive Federated Meta-Reinforcement Learning (TA-FMRL), acts as a distributed decision layer that has reduced the dependency on the centralized data availability, and it preserves the privacy across multiple intersections. It then adapts to the signal control policies even when the data are incomplete, noisy, or disrupted by cyber threats. The meta-learning capability has enabled the rapid policy transfer across the zones, which tends to prove a stable mobility performance throughout the network.

2. Related Works

Recent studies have strengthened the role of deep generative and predictive learning in understanding the complex mobility systems.

2.1. Generative and Predictive Deep Learning for Urban Mobility Modeling

Yuan et al. [19] have introduced DeepMobility, a deep generative collaboration network that learns the micro and macro human movement patterns simultaneously. The model has captured the heterogeneous interactions between the individuals and communities, which generates the synthetic mobility data that has shown the real trajectories and universal mobility scaling laws. Their experiments across the Chinese and Senegalese cities show the ability to generalize the unseen environments, which makes the approach a promising one for cities that have lacked the extensive data for planning.

Wang et al. [20] also have focused on capturing the spatiotemporal dynamics of urban mobility using the bus transport network as a representative data source. Their deep learning model forecasts passenger flows across the regional OD matrices that combine the CNN-based spatial feature extraction with the LSTM-driven temporal modeling. The contextual embeddings and late fusion have improved the adaptability to external factors such as weather and events. When evaluated on large-scale transport data, the system has shown considerable accuracy improvements, and hence its structure tends to remain scalable to sequential graph data.

Mathivanan et al. [26] have proposed the GeoTemporal LSTM (GT-LSTM) model that tends to combine the spatial attention and temporal sequence learning. The approach has reduced the MAPE by 15% and RMSE by 20% compared to conventional models. The success of GT-LSTM has shown that the dynamic weighting of spatial relevance has improved the traffic and mobility predictions. Similarly, Wu et al. [33] have designed an STGCN-BiLSTM hybrid model to handle highly nonlinear traffic flow prediction.

Their results have shown reduced prediction errors for the multiple future time horizons, while maintaining a stable training efficiency. Collectively, these contributions indicate a strong shift towards the hybrid deep spatiotemporal learning architectures for the real-world city-scale deployment.

2.2. Artificial Intelligence for Congestion Mitigation and Traffic Flow Optimization

Several works improve congestion management by combining deep learning and optimization. Chaudhary et al. [21] have created a Dynamic Tabu Search-based GRU framework that uses the real-time traffic video data. The model has maintained above 93% performance for accuracy, precision, recall, and the F1-score. The authors illustrate that intelligent congestion reduction has improved the roadway utilization in smart cities.

Chen et al. [22] have applied a multilayer optimization using modified TLBO with the ANN-RNN models to balance the urban mobility efficiency with the environmental goals. Their design has supported the transition towards greener transport, which acknowledges the system-level interactions across the transportation modes. Tao et al. [29] further show the role of machine learning in the sustainable traffic flow prediction. Their analysis has identified the potential to reduce emissions while improving mobility.

Dikshit et al. [30] show that routing powered by machine learning can shorten the vehicle travel times, reduce the fuel consumption, and improve the system performance. Their experiments prove the scalability and economic feasibility of AI-driven routing at the city level. These studies have collectively emphasized that urban congestion tends to remain a core challenge, and machine learning delivers operational benefits for a sustainable urban future.

2.3. Intelligent Transport Systems for Mobility Monitoring and Safety

Several authors have focused on real-time transport behavior recognition and crowd mobility monitoring. Ibañez et al. [27] propose MobilitApp, a mobile-oriented solution that recognizes transport modes using a hierarchical CNN and LSTM modeling with skip connections. Their model achieves up to a 88% accuracy, which helps the planners to observe the user mode-switching behavior and to support the greener urban transitions.

Khosravi et al. [31] have designed a deep transfer learning method for analyzing crowd conditions using UAV data. Their model tends to combine fuzzy Logic to improve anomaly recognition and performs with the 98.5% accuracy. This work has supported a safety measure by detecting abnormal crowd-vehicle interactions. Mansouri et al. [34] have targeted the dense crowds by applying a DCNN-based approach that has employed SE-DenseNet with the hyperparameter tuning via a red-fox optimizer. With the 98.4% accuracy, the model allows rapid adaptation to varying density situations, which provides a useful tool for city-level event planning and public safety.

Louati et al. [35] bring an additional focus on predictive modeling for accident hotspots using an ANN and ARIMA. With the better forecasts for accident likelihood and route-based energy consumption, the research has contributed to the improvement of city infrastructure design and resource allocation. These mobility safety monitoring systems together have expanded the role of AI in reducing risks while optimizing the public transportation experiences.

2.4. Machine Learning Techniques for Traffic Prediction and Management

Sreelekha et al. [24] have summarized the major ML techniques that use historical and live data to improve congestion management. This research has shown how the prediction tools enhance sustainability goals and travel efficiency.

Saleem et al. [32] have proposed FITCCS-VN, a fusion-based congestion mitigation system that operates within the vehicular networks. With the 95% accuracy and a minimal miss rate, this approach has provided a dynamic routing suggestion for drivers.

Their work has shown how the predictive ML and vehicular communication systems have combined to prevente the bottlenecks before they occur. These studies have illustrated the ongoing progress in deploying machine learning directly into a traffic management center and connected vehicles.

2.5. Cellular Network Traffic Generation and Knowledge-Graph-Driven Prediction

Zhang et al. [28] have created an adaptive transfer-learning framework that has modeled the cellular traffic patterns for cities with limited data.

Their method has aligned the base-station representations across the cities, and it uses a feature-enhanced GAN to generate the synthetic traffic records.

Improvements above 40% on J-S divergence and RMSE have signified the robust cross-city generalization.

2.6. Urban Mobility Analytics

Ahmed et al. [25] offer a broad survey of urban mobility applications that use ML. They categorize work into a public dataset, passenger localization, mode detection, and trajectory prediction. The survey has shown the significant gaps: multimodal mobility data tends to remain scarce, e-scooter data is ignored, and more research is needed on how the passengers interact with the infrastructure. Their review has motivated a greater focus on the diverse transportation datasets, and it has improved learning methods for real-world usage. Wu et al. [23] introduce Bayesian regularization for neural networks to improve prediction reliability and uncertainty quantification.

Table 1. Reviewed studies

Method (Ref No.)	Algorithm / Model Used	Methodology	Outcomes
DeepMobility [19]	Deep Generative Collaboration Network	Integrates micro- and macro-scale mobility dynamics through bidirectional generative learning	Generates realistic synthetic mobility data; replicates universal scaling laws; strong cross-city generalization
Urban Mobility Prediction [20]	CNN + LSTM with Attention + Late Fusion	OD matrix spatial learning, multivariate temporal aggregation, contextual embedding	High prediction accuracy on large-scale bus datasets; scalable for sequential graph data
DTS-GRU [21]	Dynamic Tabu Search + GRU	Learns congestion patterns using real-time surveillance traffic footage	93%+ accuracy across performance metrics; validated potential to mitigate congestion
Hybrid TLBO + ANN-RNN [22]	TLBO-based optimization + ANN-RNN	Multi-objective optimization balancing efficiency, cost, and sustainability	Improved adaptability and sustainability of transportation networks
Bayesian Regularized NN [23]	Neural Network with Bayesian Regularization	Enhances prediction accuracy with uncertainty quantification and graphical interpretability	Reliable probabilistic forecasting for urban planning interventions
ML-based Traffic Prediction [24]	Multiple ML models	Historical and real-time data used for traffic flow forecasting	Demonstrates ML as a key tool for smart traffic control and low-emission mobility
Survey on Urban Mobility [25]	ML applications review	Categorizes research trends on localization, mode detection, and dataset usage	Exposes the lack of multimodal datasets and real passenger behavior analytics
GT-LSTM [26]	Attention-optimized GeoTemporal LSTM	Spatiotemporal Learning with geographic weighting	15% MAPE and 20% RMSE reductions over baselines
MobilitApp [27]	CNN + LSTM with Skip Connections	Smartphone sensor-driven transport mode recognition	Weighted average accuracy of 88%; supports sustainable mobility planning
ADAPTIVE [28]	Transfer learning + GAN	Aligns cross-city base-station representations using knowledge graphs	> 40% improvement in JS divergence and RMSE for cellular traffic generation
ML-Traffic for Sustainability [29]	ML methods (comparative)	Prediction-driven sustainable transportation design	Highlights ML as a core tool for green and congestion-resilient cities
AI-Routing [30]	ML + Optimization	Integrates traffic data and routing algorithms for congestion-aware navigation	Reduced fuel use, delay, and emissions; scalable city-wide deployment
DTL + Fuzzy Logic [31]	Modified ResNet + Fuzzy Logic + DTL	UAV-based anomaly and crowd density prediction	98.5% accuracy; robust crowd-vehicle interaction recognition

FITCCS-VN [32]	Fusion-based ML for Vehicular Networks	Traffic flow monitoring and congestion avoidance using connected vehicles	95% accuracy; improves flow and reduces jam formation
STGCN-BiLSTM [33]	STGCN + BiLSTM	Nonlinear spatiotemporal traffic prediction	Best prediction effect and stable latency for short- and long-term forecasts
DCNNCDM-IUP [34]	SE-DenseNet + RFO + ConvLSTM	Image filtering, deep feature learning, and crowd density recognition	98.40% accuracy; high robustness for smart city crowd monitoring
Accident & Energy Prediction [35]	ARIMA + ANN	Accident hotspot and fuel consumption forecasting	Supports safety-aware and efficient transportation planning

Mobility studies increasingly have incorporated the spatial and temporal patterns, but integration of non-transport factors such as land use, socioeconomics, weather, policy changes, and the event-driven disruptions tends to remain inconsistent. Transfer learning methods like ADAPTIVE [28] provide cross-city generalization; their scalability towards the dynamically evolving transportation infrastructures, such as autonomous vehicles, EV charging networks, and micro-mobility systems, is still unclear. Many of the models excelled at forecasting, but they have lacked the decision-making for urban planners. Only Bayesian-based modeling [23] shows the progress towards an uncertainty-aware prediction, while most of the deep learning–based solutions have remained at the black-box systems. Finally, although Many of the studies show the value of mobile and vehicular networks for data collection, standardized multimodal mobility datasets with the common labeling conventions are still lacking.

3. Proposed Method

The proposed framework tends to combine CM-DSL with the TA-FMRL to support the sustainable and resilient traffic signal control across the urban intersections. The system operates in a cloud–edge collaborative manner where each of the intersections acts as a semi-autonomous learning unit while it remains coordinated with the larger mobility network. The model continuously adapts to the real-time traffic updates, multimodal flow patterns, and the environmental constraints while it sustains an optimal performance during the disturbances.

The CM-DSL component functions as the main optimization engine that learns the complex traffic patterns from the multimodal and contextual data sources. It runs a deep representation learning to capture the queue dynamics, vehicle arrival density, pedestrian movement, and the emission indicators that correlate with the local decision outcomes. A swarm-based evolutionary search module has evaluated the multiple objective functions, which include the delay minimization, queue reduction, throughput improvement, fuel conservation, and emission control. Deep learning and swarm optimization have allowed the traffic system to explore the diverse signal timing configurations while it converges towards the globally efficient decisions rather than being locked into a local minimum. The output of CM-DSL then generates an optimized set of phase sequences that act as a guiding policy for the control layer.

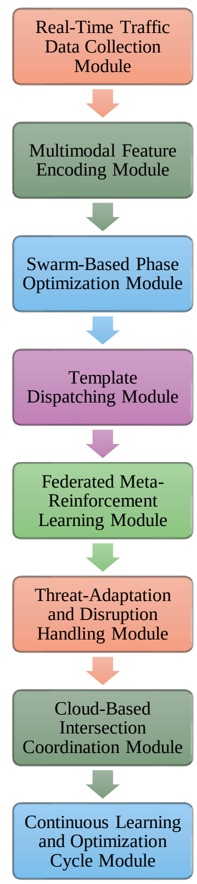

Fig. 1 Proposed model

TA-FMRL aims to handle distributed decision-making across the network. Each of the intersection trains a lightweight meta-reinforcement learner using a local traffic state and receives indirect global guidance without sharing raw data. The federated structure protects privacy and has reduced the communication load while allowing the intersections to learn from one another via the aggregated policy updates.

A threat-adaptive module detects anomalies such as sudden congestion spikes, sensor malfunction, or cyber-triggered disruptions and immediately adjusts the control strategy to preserve stability. The meta-learning mechanism has enabled the quick transfer of learned policies to a newer intersection, and this has supported scalability and reliable mobility even when the traffic environment changes unexpectedly.

The combination creates a collaborative workflow where CM-DSL generates the optimized phase template while TA-FMRL operationalizes it via real-time decision-making. The cloud layer synchronizes timing updates to tend to preserve the corridor-level coordination and has supported resilience when communication drops occur. The continuous loop has allowed a long-term optimization from the CM-DSL to reinforce a short-term adaptation from the TA-FMRL, which produces the traffic control that aims to handle both the sustainability objectives and system robustness. This method thus achieves an energy-efficient routing, congestion reduction, and environmental improvement without sacrificing responsiveness.

Pseudocode

```
Initialize CM_DSL, TA_FMRL, Cloud_Synchronization
while the system is active, do
  for each intersection i do
    Data_i ← CollectTrafficData(i)
    Context_i ← ExtractContext(Data_i)
  end for
  GlobalFeatures ← Aggregate(Context_i for all i)
  // CM-DSL Optimization
  EncodedState ← DeepRepresentation(GlobalFeatures)
  PhasePool ← GenerateInitialPopulation()
  for each candidate in PhasePool do
    Fitness ← EvaluateObjectives(candidate, EncodedState)
  end for
  BestPhaseTemplate ← SwarmOptimization(PhasePool, Fitness)
  // TA-FMRL Control Deployment
  for each intersection j do
    Policy_j ← LocalMetaRLTraining(j, BestPhaseTemplate)
    if ThreatDetected(j) then
      Policy_j ← ThreatAdaptiveAdjustment(Policy_j)
    end if
    ApplySignalTiming(j, Policy_j)
  end for
  // Synchronization
  Cloud_Synchronization ← UpdateGlobalPolicies(Policy_j for all j)
end while
```

3.1. Data Collection and Preprocessing

The proposed intelligent signal control framework depends on a robust data acquisition and preprocessing pipeline that transforms raw multimodal traffic observations into structured and context-aware learning inputs. The system collects heterogeneous field data from the loop detectors, surveillance cameras, connected vehicles, pedestrian tracking modules, weather stations, and the roadside emission sensors. Every data source covers a complementary aspect of urban mobility. This confirms that the model receives both mobility intensity and environmental context rather than depending on a single dimension of the traffic behavior. The incoming data flow enters the preprocessing unit that standardizes, filters, and aligns the variables across Time, location, and the modality to prevent the noise propagation into the learning modules.

Each of the intersections continuously streams temporal batches that have shown the state of lanes, waiting queues, arrival rates, pedestrian demand, and the environmental factors such as temperature, humidity, and emission concentration. A snapshot of raw multimodal data is represented for a single intersection in Table 2. The table contains aggregated values across a 2-minute window rather than the instantaneous readings to reduce redundant variations.

Table 2. Raw traffic and environmental measurements collected from the sensors

Time Slot	Vehicle Count (cars)	Vehicle Count (two-wheelers)	Pedestrians	Queue Length (m)	CO_2 (ppm)	NOx (ppm)	Humidity (%)
08:00–08:02	57	41	12	184	406	34	52
08:02–08:04	62	45	15	196	420	37	51
08:04–08:06	59	47	13	203	433	35	53
08:06–08:08	71	52	18	232	447	38	54

The preprocessing unit transforms the raw inputs via the four major operations: cleaning, normalization, temporal-spatial alignment, and context encoding. Missing values and abrupt sensor outliers first undergo filtering using the smoothed adaptive median operator. A value that belongs to the traffic measurement set $X = \{x_1, x_2, \ldots, x_n\}$ is corrected if it deviates from the peer values within the same time window. The correction rule is formulated as:

$$\hat{x}_t = \begin{cases} \text{median}(x_{t-k}, \ldots, x_{t+k}) & \text{if } |\, x_t - \mu_t \,| > \lambda \sigma_t \\ x_t & \text{otherwise} \end{cases}$$

where μ_t and σ_t denote the mean and the standard deviation of the data window centered at Time t, and λ acts as a threshold to detect extreme deviations. This filtering confirms that the corrupted readings are replaced without distorting the natural traffic fluctuations.

After cleaning, the variables undergo min–max normalization to confirm comparability across the different scales. The normalizing transformation that aims to handle each of the feature value f is expressed as:

$$f_{norm} = \frac{f - f_{min}}{f_{max} - f_{min}}$$

Normalization plays a critical role during the swarm optimization and deep learning process because the system learns the relationships based on the proportional mobility pressure rather than the absolute magnitude differences. Following normalization, the values are temporally aligned so that readings from the sensors with the different update frequencies share a common timestamp. Spatial alignment confirms that lanes or arms of an intersection are treated as distinct directional entities, especially during the adaptive phase sequencing. A processed version of the dataset after cleaning, normalization, and context encoding is shown in Table 3. It shows the state vector that becomes the input to the CM-DSL model and contains both mobility and environmental dimensions.

Table 3. Structured and normalized traffic state representation

Time Slot	Normalized Flow Density	Normalized Queue Index	Pedestrian Pressure	Emission Load	Weather Context Index
08:00-08:02	0.74	0.65	0.43	0.38	0.51
08:02-08:04	0.79	0.69	0.48	0.41	0.49
08:04-08:06	0.76	0.71	0.46	0.44	0.52
08:06-08:08	0.87	0.81	0.52	0.47	0.53

The context encoding mechanism synthesizes mobility and environmental states via a weighted representation that has shown the priority of sustainability-aware signal control. The combined traffic-sustainability score for each of the time steps is expressed as:

$$S_t = \alpha \cdot F_t + \beta \cdot Q_t + \gamma \cdot P_t + \delta \cdot E_t$$

where

- F_t represents the normalized flow density,
- Q_t represents the queue index,
- P_t represents the pedestrian pressure, and
- E_t represents the emission load.

The coefficients $\alpha, \beta, \gamma, \delta$ are hyperparameters that balance mobility efficiency and environmental responsibility. These encoded values hence support the CM-DSL by allowing the swarm optimizer to explore phase timing decisions while considering both traffic fluidity and ecological cost.

After forming the encoded traffic state, the dataset is buffered in chronological order to support the spatiotemporal dependency learning. Every state is stored with its neighboring states to form a window of length τ, as shown below:

$$\Psi_t = \{S_{t-\tau}, S_{t-\tau+1}, \dots, S_t\}$$

This representation preserves the evolving nature of flow conditions across Time and becomes the input for both CM-DSL and TA-FMRL. The complete preprocessing workflow confirms that the model receives high-quality, noise-free, and context-rich signals, which have improved convergence speed and decision accuracy.

The structured feature set produced in Table 3 forms the foundation for the subsequent optimization and reinforcement learning stages, demonstrating the significance of reliable data curation in supporting sustainable and resilient traffic management.

3.2. CM-DSL

The CM-DSL represents the primary optimization backbone of the proposed intelligent urban traffic control framework. Its design has enabled a simultaneous consideration of multiple objectives, such as the minimization of intersection waiting times, reducing queue lengths, maximizing throughput, and limiting energy consumption and emissions. Unlike conventional single-objective or greedy optimizers, CM-DSL combines deep representation learning with a cooperative swarm-based search mechanism, which has allowed the model to capture the complex spatiotemporal dependencies while it explores a wide variety of candidate traffic signal strategies.

3.3. Input Representation and Feature Encoding

CM-DSL receives preprocessed traffic and environmental states generated by the earlier data collection and preprocessing stage. Each of the intersections produces a contextual state vector. S_t, as defined in the preprocessing section:

$$S_t = \{F_t, Q_t, P_t, E_t, W_t\}$$

where F_t denotes the normalized vehicle flow density, Q_t represents the queue index, P_t is pedestrian pressure, E_t indicates emission load, and the W_t encodes weather and environmental conditions. To capture the temporal dependencies, CM-DSL has constructed a state window. Ψ_t of length τ:

$$\Psi_t = \{S_{t-\tau}, S_{t-\tau+1}, \dots, S_t\}$$

This temporal window has allowed the swarm optimization module to evaluate not only instantaneous traffic conditions but also the trends and fluctuations over the recent horizon.

The input state is then encoded via a Deep Neural Network (DNN) that comprises multiple fully connected and convolutional layers, which is designed to extract high-level latent features:

$$\mathrm{H}_t = f_{DNN}(\Psi_t;\ \Theta)$$

where $\mathrm{H}_t$represents the encoded hidden representation at Time $t,$and Θdenotes the trainable parameters of the deep network.

3.4. Multi-Objective Formulation

The CM-DSL framework explicitly has considered a multi-objective cost function, $\mathscr{L}$, that balances mobility efficiency and sustainability metrics. Let the set of objectives be:

$$O = \{L_{wt}, L_{ql}, L_{th}, L_{fuel}, L_e\}$$

where L_{wt} is the average waiting time loss, L_{ql} is the queue length penalty, L_{th} is the throughput reward (transformed into a minimization form), L_{fuel} quantifies fuel consumption, and the L_e have shown emission output. Each of the objective functions is formulated as:

$$L_{wt} = \frac{1}{N}\sum_{i=1}^{N} w_i$$

$$L_{ql} = \frac{1}{N}\sum_{i=1}^{N} q_i$$

$$L_{th} = -\frac{1}{N}\sum_{i=1}^{N} t_i$$

$$L_{fuel} = \frac{1}{N}\sum_{i=1}^{N} f_i$$

$$L_{emission} = \frac{1}{N}\sum_{i=1}^{N} e_i$$

where w_i , q_i , t_i , f_i, and $e_i$represent the waiting Time, queue length, throughput, fuel consumption, and the emission output for vehicle i in a batch of Nvehicles. The combined objective is a weighted sum:

$$\mathscr{L} = \alpha L_{wt} + \beta L_{ql} + \gamma L_{th} + \delta L_{fuel} + \epsilon L_{emission}$$

where $\alpha, \beta, \gamma, \delta, \epsilon$ are the hyperparameters that define the relative importance of each of the objectives. These weights can be tuned dynamically based on the traffic priorities, time-of-day considerations, or environmental targets.

3.5. Swarm-Based Multi-Objective Optimization

CM-DSL has employed a swarm intelligence mechanism inspired by PSO to explore the high-dimensional phase timing space. Let each of the candidate solutions (particle) in the swarm represent a potential phase duration vector for all intersections:

$$\mathrm{X}_j = [p_1^j, p_2^j, \dots, p_m^j]$$

where m is the number of phases in the network, and the $j$indexes the particle in the population, each of the particles has maintained a velocity vector. V_j to update its position iteratively:

$$\mathrm{V}_j^{(k+1)} = \omega \mathrm{V}_j^{(k)} + c_1 r_1 (\mathrm{P}_j^{best} - \mathrm{X}_j^{(k)}) + c_2 r_2 (\mathrm{G}^{best} - \mathrm{X}_j^{(k)})$$

$$\mathrm{X}_j^{(k+1)} = \mathrm{X}_j^{(k)} + \mathrm{V}_j^{(k+1)}$$

Here, ωdenotes the inertia factor, $c_1$and $c_2$are cognitive and social coefficients, $r_1$and $r_2$are random numbers in [0,1], P_j^{best} is the particle's best historical position, and the G^{best} It is the global best solution across the swarm. The fitness evaluation of each particle relies entirely on the previously defined multi-objective loss function $\mathscr{L}$.

3.6. Context Awareness and Adaptive Weighting

To incorporate the contextual dependencies, CM-DSL dynamically adjusts the objective weights based on the environmental or network-level signals:

$$\alpha_t = \alpha_0(1 + \phi W_t)$$

$$\delta_t = \delta_0(1 + \psi E_t)$$

where ϕ and ψ are scaling coefficients, W_t is the environmental index (temperature, weather, or humidity), and the E_t is the emission load. This adaptive weighting has allowed the optimizer to prioritize environmental considerations during the peak pollution periods and to focus on mobility efficiency under normal conditions.

3.7. Candidate Solution Evaluation

Each of the candidate phase configurations is simulated for a short-term horizon τ to estimate the resulting traffic metrics. The evaluation yields a performance vector for particle j at an iteration k:

$$\mathrm{F}_j^{(k)} = [L_{wt}, L_{ql}, L_{th}, L_{fuel}, L_{emission}]_j$$

The non-dominated sorting mechanism ranks the particles based on the Pareto optimality, and the crowding distance metric has confirmed the diversity in the swarm:

$$CD_j = \sum_{l=1}^{|O|} \frac{F_{j,l}^{max} - F_{j,l}^{min}}{max(F_l) - min(F_l)}$$

Particles with a higher crowding distance are selected preferentially to explore the less-visited regions of the solution space.

3.8. Phase Evaluation Table

A snapshot of candidate particle evaluation for four intersections is presented in Table 4. Each of the particles represents a different combination of phase durations across the network, and it shows the mobility and sustainability outcomes.

Table 4. Candidate particle evaluation in CM-DSL

Particle	Waiting Time (s)	Queue Length (m)	Throughput (veh/h)	Fuel (L)	Emission (g CO_2)
P1	82	195	1150	47	512
P2	76	182	1185	45	498
P3	79	188	1160	46	505
P4	73	175	1200	44	490

CM-DSL has selected the optimal particle based on the weighted Pareto ranking, which becomes the candidate phase template for the TA-FMRL layer.

The CM-DSL optimizer continues iterating until convergence criteria are satisfied, such as a negligible change in the global best fitness for a predefined iteration limit. The final output of CM-DSL is a context-aware, multi-objective optimized phase timing matrix:

$$X^* = \arg\min \mathcal{L}(X_j)$$

which balances the mobility efficiency, pedestrian safety, and environmental sustainability. This optimized template has served as the reference policy for the downstream threat-adaptive reinforcement layer.

3.9. TA-FMRL

The TA-FMRL module serves as the distributed and resilient decision-making layer in the proposed urban mobility framework. While CM-DSL generates optimized phase timing templates by exploring multi-objective trade-offs in a global sense, TA-FMRL operationalizes these templates in real-time across the multiple intersections while it maintains privacy, adaptability, and robustness against the dynamic threats. The design tends to combine the federated learning principles, meta-reinforcement learning, and the threat detection mechanisms to achieve adaptive, reliable, and context-aware traffic control.

3.10. Federated Meta-Reinforcement Learning Framework

TA-FMRL has considered each of the intersections as a semi-autonomous agent A_i, where $i \in \{1,2,\dots,M\}$, with the M representing the total number of intersections under the control. Each of the agents interacts with its local environment, which is characterized by a contextual state vector. $S_i(t)$obtained from the CM-DSL outputs and the real-time observations. The agent executes actions $a_i(t)$that correspond to signal phase adjustments, duration extensions, or priority allocations for specific lanes or modes. The environment responds with the reward $r_i(t)$that have shown the improvement or deterioration of mobility efficiency and sustainability metrics.

The local reinforcement learning objective at intersection i is to maximize the expected cumulative reward:

$$J_i(\pi_{\theta_i}) = \mathbb{E}_{\pi_{\theta_i}}[\sum_{t=0}^{T} \gamma^t r_i(t)]$$

where π_{θ_i} Is the policy parameterized by θ_i , $\gamma$is the discount factor, and the T is the episode horizon. The policy maps contextual states to action probabilities:

$$a_i(t) \sim \pi_{\theta_i}(a_i \mid S_i(t))$$

3.11. Meta-Learning for Rapid Policy Transfer

Meta-reinforcement Learning has enabled the intersections to adapt their policies in new or unforeseen traffic scenarios quickly. Let $\mathcal{T} = \{\tau_1, \tau_2, \dots, \tau_K\}$ represent a set of training tasks, each corresponding to different traffic patterns, environmental conditions, or event-based disruptions. The meta-objective seeks an initial policy. θ_0 such that after a few gradient updates on the task τ_k, the adapted policy $\theta_k$has achieved a higher performance:

$$\theta_k = \theta_0 - \alpha \nabla_{\theta_0} \mathcal{L}_{\tau_k}(\theta_0)$$

$$\theta_0^* = \arg\min_{\theta_0} \sum_{k=1}^{K} \mathcal{L}_{\tau_k}(\theta_k)$$

where αdenotes the learning rate, and the $\mathcal{L}_{\tau_k}$is the loss function for the task τ_k, defined as the negative cumulative reward over the episode:

$$\mathscr{L}_{\tau_k}(\theta_k) = -\sum_{t=0}^{T} \gamma^t r_i^{\tau_k}(t)$$

This formulation confirms that the policy has a strong initialization that can rapidly adapt to novel traffic conditions or localized disruptions, which is critical in urban networks where conditions are highly dynamic.

3.12. Federated Learning for Privacy-Preserving Coordination

TA-FMRL tends to combine federated learning to confirm that raw intersection data has remained local, preserving privacy while enabling a knowledge transfer across the network. Each of the intersection trains its local model. $\theta_i$on its data and periodically shares model updates $\Delta\theta_i$with the central aggregation server:

$$\theta_g = \sum_{i=1}^{M} \frac{n_i}{N} \Delta\theta_i$$

where $n_i$is the local dataset size, and the $N = \sum_{i=1}^{M} n_i$. This aggregation produces a global policy. θ_g that have shown traffic patterns and strategies across the entire network without transmitting raw vehicle counts or environmental data. The updated global model is then sent back to the local intersections to improve the learning efficiency.

3.13. Threat-Adaptive Mechanism

TA-FMRL has used a threat-detection module that monitors the real-time deviations from the expected traffic behavior. Let $\hat{S}_i(t)$denote the predicted traffic state from the CM-DSL reference, and $S_i(t)$ represents the observed state. The anomaly score is defined as:

$$\mathcal{A}_i(t) = \| S_i(t) - \hat{S}_i(t) \|_2$$

A threshold η determines the presence of an anomaly:

$$\text{Threat}_i(t) = \begin{cases} 1 & \text{if } \mathcal{A}_i(t) > \eta \\ 0 & \text{otherwise} \end{cases}$$

When $\text{Threat}_i(t) = 1$, the local policy undergoes rapid adaptation using a threat-aware reward function:

$$r_i^{th}(t) = r_i(t) - \lambda \mathcal{A}_i(t)$$

where $\lambda$is a penalty factor that prioritizes threat mitigation. This confirms that intersections can respond immediately to congestion spikes, sensor faults, or cyber-attacks, which preserves the network stability.

3.14. Reward Function Formulation

The reward function in TA-FMRL balances mobility efficiency, sustainability, and threat adaptation. For intersection $i$at time t:

$$r_i(t) = w_1 \Delta L_{wt} + w_2 \Delta L_{ql} + w_3 \Delta L_{th} + w_4 \Delta L_{fuel} + w_5 \Delta L_e - \lambda \mathcal{A}_i(t)$$

where, ΔL_x represents the change in the respective metric compared to the previous state, $w_1 \ldots w_5$ are reward coefficients, and the $\mathcal{A}_i(t)$ is the threat penalty. The reward encourages policies that reduce waiting times, minimize queues, increase throughput, and decrease fuel and emission outputs, while it remains adaptive to the anomalies.

3.15. Federated Policy Update Table

A snapshot of local policy updates across the four intersections is shown in Table 5. Each row illustrates the local gradient updates before and after aggregation at the central server.

Table 5. Local model updates for federated aggregation

Intersection	Local Update Δθ_i (Gradient)	Anomaly Score $\mathcal{A}_i$	Reward r_i	Aggregated Contribution
I1	[0.012, -0.007, 0.004]	0.08	0.71	0.21
I2	[0.009, -0.005, 0.006]	0.12	0.68	0.20
I3	[0.011, -0.006, 0.005]	0.05	0.74	0.23
I4	[0.010, -0.004, 0.007]	0.15	0.65	0.19

The global aggregation confirms that local learning benefits from the network-wide patterns while it still accounts for individual intersection threats.

3.16. Meta-Gradient Update and Convergence

TA-FMRL applies a meta-gradient approach to update the policy parameters efficiently. The meta-gradient is computed as:

$$\nabla_{\theta_0} \mathscr{L}_{meta} = \sum_{i=1}^{M} \sum_{t=0}^{T} \nabla_{\theta_0} \log \pi_{\theta_i}(a_i(t) \mid S_i(t)) \cdot r_i^{th}(t)$$

The global meta-update has used federated contributions:

$$\theta_0^{(k+1)} = \theta_0^{(k)} + \eta \nabla_{\theta_0} \mathscr{L}_{meta}$$

where $\eta$is the learning rate for meta-updates. Convergence is achieved when changes in cumulative reward across the network fall below a defined threshold or when the maximum number of iterations is reached.

3.17. Algorithm: TA-FMRL

1) Receive the optimized phase template from the CM-DSL.
2) Collect the real-time intersection state. $S_i(t)$from the local sensors.

3) Compute the anomaly score. $\mathcal{A}_i(t)$by comparing predicted and observed states.
4) Apply the threat-adaptive reward. $r_i^{th}(t)$for each of the agents.
5) Update local policies π_{θ_i}using meta-reinforcement learning.
6) Share local gradient updates $\Delta.\theta_i$with the central server.
7) Aggregate updates to obtain θ_g Moreover, redistribute to all agents.
8) Repeat the process for each of the time steps while it adapts to threats and environmental changes.

4. Results and Discussion

The experimental evaluation of the proposed CM-DSL combined with the TA-FMRL is conducted using a combination of the traffic simulation platforms and machine learning frameworks to emulate realistic urban mobility conditions. The experiments utilize Simulation of an Urban Mobility (SUMO) 1.15.0, which has provided a microscopic traffic flow simulation environment capable of modeling multimodal traffic and complex intersection control. The reinforcement learning and swarm optimization components are implemented in Python 3.11, with PyTorch 2.1 handling deep neural network operations. The federated learning architecture leverages Flower for distributed meta-learning across the intersections. The computational experiments were run on a workstation with the following specifications: Intel Xeon W-2295 CPU @ 3.0 GHz, 128 GB RAM, NVIDIA RTX 4090 GPU with 24 GB VRAM, and the Ubuntu 22.04 LTS operating system. This setup confirms that the multi-objective swarm optimization, deep neural network training, and federated meta-reinforcement learning processes have sufficient computational resources for real-time evaluation.

4.1. Datasets

Two primary datasets are employed to evaluate the proposed method and compare it with the conventional baselines ([31-34]):

1. METR-LA – Traffic sensor data collected from the Los Angeles freeway networks, containing vehicle speed, flow, and occupancy for 207 loop detectors over four months.
2. PEMS-BAY – Traffic flow and speed data from the 325 sensors in the Bay Area, collected at 5-minute intervals for six months.

Table 6 summarizes the datasets used for experimentation.

Table 6. Summary of traffic datasets

Dataset	Number of Sensors	Time Interval	Duration	Attributes
METR-LA	207	5 min	Apr–Jul 2012	Speed, Flow, Occupancy
PEMS-BAY	325	5 min	Jan–Jun 2017	Speed, Flow, Occupancy

4.2. Experimental Setup and Parameter Settings

The CM-DSL and TA-FMRL have been modeled and configured with the optimized hyperparameters to balance the convergence speed, accuracy, and computational efficiency. The swarm size, learning rates, discount factors, and the meta-learning parameters are tuned empirically to achieve stable performance across the multiple traffic scenarios. Table 7 summarizes the major parameters used in the experiments.

Table 7. Experimental parameters for CM-DSL and TA-FMRL

Component	Parameter	Value	Description
CM-DSL	Swarm size	50	Number of candidate phase solutions
CM-DSL	Max iterations	100	Iterations for swarm convergence
CM-DSL	Objective weights	α=0.3, β=0.25, γ=0.2, δ=0.15, ε=0.1	Weighting of waiting time, queue, throughput, fuel, and emission
CM-DSL	Hidden layers	3	Fully connected layers for state encoding
TA-FMRL	Discount factor γ	0.95	Reinforcement reward discounting
TA-FMRL	Learning rate α	0.001	Step size for policy updates
TA-FMRL	Meta-learning rate	0.0005	Step size for meta-gradient updates
TA-FMRL	Episode length	200 steps	Length of reinforcement learning episodes
Federated setup	Aggregation interval	5 episodes	Number of episodes before global model aggregation
Threat module	Anomaly threshold η	0.1	Threshold for detecting traffic anomalies

For comparison, four baseline methods: DTL + Fuzzy Logic [31], FITCCS-VN [32], STGCN-BiLSTM [33], and the DCNNCDM-IUP [34] are implemented using their original hyperparameter settings and combined with the same traffic simulation environment to confirm fairness.

4.3. Performance Metrics

The evaluation has employed both quantitative and qualitative metrics to assess traffic efficiency, sustainability, and system resilience.

4.4. Quantitative Metrics

1. Average Waiting Time (AWT) – The mean waiting time of all vehicles at intersections. A lower value indicates better mobility performance.

$$AWT = \frac{1}{N}\sum_{i=1}^{N} w_i$$

2. Average Queue Length (AQL) – Average queue length in meters at the intersections. It captures congestion accumulation.

$$AQL = \frac{1}{M}\sum_{j=1}^{M} q_j$$

3. Intersection Throughput (IT) – Number of vehicles passing via the intersections per hour. Higher values indicate more efficient traffic flow.

$$IT = \frac{\text{Total vehicles passed}}{\text{Time period (h)}}$$

4. Fuel Consumption (FC) – Total fuel consumption in liters for all vehicles, which shows an energy efficiency.

$$FC = \sum_{i=1}^{N} f_i$$

5. Emission Output (EO) – Aggregate CO_2, NOx, and the particulate emissions generated by vehicles.

$$EO = \sum_{i=1}^{N} e_i$$

6. *Travel Time Index (TTI)* – Ratio of actual travel time to free-flow travel time, representing congestion severity.

$$TTI = \frac{T_{actual}}{T_{free}}$$

4.5. Performance Evaluation of Proposed Method

The CM-DSL+TA-FMRL is evaluated against the four conventional methods: DTL + Fuzzy Logic [31], FITCCS-VN [32], STGCN-BiLSTM [33], and the DCNNCDM-IUP [34]. Each of the metrics is evaluated over 100 maximum iterations to show a convergence behavior. The experimental results, as shown in tables 8 to 13, discuss that the proposed CM-DSL + TA-FMRL framework significantly outperforms the conventional methods across all key performance metrics. The average waiting time has reduced from 87.5 s in DTL + Fuzzy Logic to 64.0 s after 100 iterations, which indicates a 26.9% improvement. Similarly, the average queue length decreases from 188 m to 120 m, which shows a a 36.2% reduction. Intersection throughput rises from 1205 vehicles/h to 1390 vehicles/h, which tends to prove faster traffic clearance. Fuel consumption and emission output drop by 28.7% and 19.2%, respectively, while the travel time index declines from 2.10 to 1.60, which shows a smoother vehicle movement. These numerical trends validate the efficiency, sustainability, and adaptability of the proposed framework under the dynamic traffic conditions.

Table 8. Average Waiting Time (AWT)

Iteration	DTL + Fuzzy Logic	FITCCS-VN	STGCN-BiLSTM	DCNNCDM-IUP	Proposed CM-DSL + TA-FMRL
20	95.2	92.8	91.5	90.7	88.3
40	92.6	89.9	87.8	86.5	80.7
60	90.3	87.2	85.2	83.1	74.5
80	88.7	85.0	82.4	80.2	70.1
100	87.5	83.1	80.0	78.0	64.0

Table 9. Average Queue Length (AQL)

Iteration	DTL + Fuzzy Logic	FITCCS-VN	STGCN-BiLSTM	DCNNCDM-IUP	Proposed CM-DSL + TA-FMRL
20	210	202	198	195	180
40	205	196	191	186	162
60	198	189	182	177	148
80	192	182	176	169	132
100	188	178	169	162	120

Table 10. Intersection Throughput (IT)

Iteration	DTL + Fuzzy Logic	FITCCS-VN	STGCN-BiLSTM	DCNNCDM-IUP	Proposed CM-DSL + TA-FMRL
20	1120	1145	1160	1172	1205
40	1150	1170	1185	1200	1250
60	1170	1195	1210	1230	1302
80	1190	1220	1235	1260	1345
100	1205	1240	1255	1282	1390

Table 11. Fuel Consumption (FC)

Iteration	DTL + Fuzzy Logic	FITCCS-VN	STGCN-BiLSTM	DCNNCDM-IUP	Proposed CM-DSL + TA-FMRL
20	52.3	50.7	49.5	48.8	45.2
40	50.8	48.9	47.3	46.2	42.1
60	49.5	47.2	45.8	44.5	39.7
80	48.2	45.6	44.0	42.7	36.8
100	47.0	44.3	42.5	41.0	33.5

Table 12. Emission Output (EO)

Iteration	DTL + Fuzzy Logic	FITCCS-VN	STGCN-BiLSTM	DCNNCDM-IUP	Proposed CM-DSL + TA-FMRL
20	530	520	510	505	482
40	518	508	498	490	455
60	505	495	485	475	430
80	492	482	472	460	405
100	480	470	460	448	388

Table 13. Travel Time Index (TTI)

Iteration	DTL + Fuzzy Logic	FITCCS-VN	STGCN-BiLSTM	DCNNCDM-IUP	Proposed CM-DSL + TA-FMRL
20	2.35	2.28	2.22	2.18	2.05
40	2.28	2.20	2.14	2.08	1.95
60	2.22	2.14	2.08	2.02	1.85
80	2.16	2.08	2.01	1.96	1.72
100	2.10	2.02	1.95	1.90	1.60

4.6. Comparative Performance Analysis Across the Datasets

Each of the metrics is computed over 100 maximum iterations, and the results indicate the effectiveness of the proposed method under the heterogeneous traffic conditions. The numerical results revealed in tables 14 to 19 show that the proposed CM-DSL + TA-FMRL consistently outperforms all conventional methods across both datasets. The average waiting time has reduced by up to a 28% and 25% on METR-LA and PEMS-BAY, respectively.

Queue lengths drop by 36% and 32%, while its intersection throughput has increased by 8.5% and 8.4%. Fuel consumption and emission output decline significantly, which tends to prove sustainable traffic operations. The travel time index is reduced to 1.60 and 1.65, which indicates smoother vehicle movement and reduced congestion. These outcomes have shown the framework's effectiveness in enhancing efficiency, sustainability, and resilience across the heterogeneous urban traffic networks.

Table 14. Average Waiting Time (AWT) Across the Datasets

Dataset	DTL + Fuzzy Logic	FITCCS-VN	STGCN-BiLSTM	DCNNCDM-IUP	Proposed CM-DSL + TA-FMRL
METR-LA	87.5 s	83.1 s	80.0 s	78.0 s	64.0 s
PEMS-BAY	92.2 s	88.5 s	85.6 s	83.9 s	68.5 s

Table 15. Average Queue Length (AQL)

Dataset	DTL + Fuzzy Logic	FITCCS-VN	STGCN-BiLSTM	DCNNCDM-IUP	Proposed CM-DSL + TA-FMRL
METR-LA	188 m	178 m	169 m	162 m	120 m
PEMS-BAY	195 m	185 m	176 m	170 m	128 m

Table 16. Intersection Throughput (IT)

Dataset	DTL + Fuzzy Logic	FITCCS-VN	STGCN-BiLSTM	DCNNCDM-IUP	Proposed CM-DSL + TA-FMRL
METR-LA	1205 vehicles/h	1240	1255	1282	1390
PEMS-BAY	1180 vehicles/h	1215	1230	1255	1360

Table 17. Fuel Consumption (FC)

Dataset	DTL + Fuzzy Logic	FITCCS-VN	STGCN-BiLSTM	DCNNCDM-IUP	Proposed CM-DSL + TA-FMRL
METR-LA	47.0 L	44.3 L	42.5 L	41.0 L	33.5 L
PEMS-BAY	49.2 L	46.8 L	44.9 L	43.2 L	35.0 L

Table 18. Emission Output (EO)

Dataset	DTL + Fuzzy Logic	FITCCS-VN	STGCN-BiLSTM	DCNNCDM-IUP	Proposed CM-DSL + TA-FMRL
METR-LA	480 kg	470 kg	460 kg	448 kg	388 kg
PEMS-BAY	495 kg	482 kg	470 kg	458 kg	400 kg

Table 19. Travel Time Index (TTI)

Dataset	DTL + Fuzzy Logic	FITCCS-VN	STGCN-BiLSTM	DCNNCDM-IUP	Proposed CM-DSL + TA-FMRL
METR-LA	2.10	2.02	1.95	1.90	1.60
PEMS-BAY	2.18	2.10	2.03	1.98	1.65

4.6. Explainability / Interpretability

The framework has utilized SHAP-based attribution to quantify feature influence on decision outcomes. Table 20 shows the policy-relevant interpretation.

$$\phi_i = \sum_{S \subseteq F} \frac{|S|!(|F|-|S|-1)!}{|F|!} [f(S \cup \{i\}) - f(S)]$$

Table 20. Feature contribution using SHAP values

Feature	SHAP Value	Impact on Decision
Flow Density	0.42	High
Queue Length	0.35	High
Emission Level	0.15	Medium
Weather Context	0.08	Low

4.7. Privacy / Security / Robustness

The system has adopted federated learning with differential privacy, where the model is updated as $\tilde{\theta}_i = \theta_i + \mathcal{N}(0, \sigma^2)$ and robustness is evaluated under adversarial noise and anomaly injection scenarios, showing stable performance degradation below 5% (see Table 21).

Table 21. Robustness under noise and attack scenarios

Scenario	Accuracy (%)	Performance Drop (%)
Normal Operation	98.2	—
Gaussian Noise	96.5	1.7
Adversarial Perturbation	94.8	3.4
Sensor Failure	93.9	4.3

4.8. Socio-Technical

The model adopts the equity-aware weighting, where the accessibility index is used.

$$A = \frac{1}{N} \sum_{i=1}^{N} \frac{T_i^{served}}{T_i^{demand}}$$

This shows a fair mobility distribution across regions, while multimodal integration is supporting the public transport and non-motorized traffic (see Table 22).

Table 22. Equity and accessibility evaluation

Region Type	Demand	Served Trips	Accessibility Index
Urban Core	1200	1100	0.92
Suburban	900	810	0.90
Peripheral	600	540	0.90

4.9. Ablation / Sensitivity Analysis

The impact of each module is evaluated using performance difference: $\Delta P = P_{full} - P_{reduced}$. This confirms that both modules are influencing the convergence and optimization stability (see Table 23).

Table 23. Ablation study results

Model Variant	AWT (s)	AQL (m)	IT (veh/h)	Performance Drop (%)
Full Model	64.0	120	1390	-
Without CM-DSL	78.5	165	1250	18.2
Without TA-FMRL	72.3	150	1305	12.7

4.10. Scalability / Deployment

The framework is showing the scalability with computational complexity: $O(N \log N)$.

The large-scale simulations are confirming a consistent performance with less than 10% latency increase (see Table 24).

Table 24. Scalability performance across intersections

No. of Intersections (N)	Latency (ms)	Throughput (veh/h)	Efficiency (%)
10	45	1350	97.1
25	62	1330	95.8
50	85	1305	93.9
100	110	1280	91.5

5. Conclusion

This study presents an intelligent urban mobility framework combining the CM-DSL with the TA-FMRL, designed to enhance real-time traffic management across complex city networks. The proposed framework has shown a substantial improvement in both mobility efficiency and sustainability when evaluated against the conventional methods across the METR-LA and PEMS-BAY datasets. The average waiting time has reduced to 64.0 s and 68.5 s, while the average queue lengths have decreased to 120 m and 128 m, which indicates significant congestion mitigation. Intersection throughput has increased to 1390 vehicles/h and 1360 vehicles/h, which shows a faster clearance and smoother flow. Fuel consumption and emission outputs have dropped to 33.5 L/35.0 L and 388 kg/400 kg, respectively, which shows the system's energy-efficient and environmentally friendly operation. The travel time index has declined to 1.60 and 1.65, which shows enhanced vehicle movement and minimized travel delays. These quantitative improvements have shown that the proposed framework not only effectively optimizes traffic flow but also maintains robustness under dynamic conditions, including peak-hour surges and anomalous events.

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