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Original Article

AI-Intelligent Demand-Sensitive Transportation Scheduling with IoT-Crowd Prediction an Reinforcement Learning Optimization

Reshma N.R.[1], S. Gokila[2]

[1,2]*Department of computer applications, Hindustan Institute of Technology and Science, Chennai, Tamilnadu, India.*

[1]*Corresponding Author: reshmasibin1994@gmail.com*

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Abstract *- Efficient scheduling of transportation in smart cities is made difficult by the dynamic nature of passenger demand and crowd movements. Previous methods for scheduling, which use established timetables and explicit guidelines, struggle to adapt to real-time changes in demand, often resulting in long wait times for passengers, inefficient usage of transportation resources, and higher overall operating costs. This research presents a cluster-aware intelligent transportation framework that combines an approach to forecasting transportation demand with an adaptive scheduling process using data from IoT-based mobile signals. The use of DBSCAN to determine areal mobility clusters from the mobile signal data allowed a Cluster-Aware CNN-GRU model to learn complex patterns of spatial-temporal movement, resulting in the accurate prediction of the future demand for transportation. The proposed forecasting methodology achieved high levels of accuracy in its prediction of demand, with a MAE of 0.1033, and an RMSE of 0.1290. The forecasted demand was then utilized as input to a Deep Q-Network (DQN) scheduling module, which allocated transportation resources dynamically based on the forecasted mobility needs of the population. Analysis of the experimental data demonstrates that using the hybrid forecasting/scheduling framework led to a reduction in both passengers wait times and operational costs while also increasing vehicle utilization as compared to traditional scheduling methods. The combination of the Cluster-Aware CNN-GRU demand forecasting and DQN-based scheduling provides a scalable, efficient, and demand-responsive means for managing urban transportation systems.*

Keywords *- Adaptive systems, Smart transportation, Crowd prediction, Reinforcement learning, Internet of Things (IoT), Deep Q Network, Demand-sensitive scheduling.*

1. Introduction

The quickly changing nature of urbanization, population increases, and an ever-increasing number of devices generating data are causing tremendous changes in transport systems. The variability of travel patterns in cities is fundamentally random, with a strong influence of periodic patterns of usage and significant geographic variation in the urban structure. Unfortunately, most current transport systems rely on fixed schedules with limited route flexibility and heuristic-based methods for vehicle dispatch. These systems are not capable of responding to any of the temporal or spatial variability in travel demand that exists in real time [1].

This leads to persistent problems in urban transport systems such as severe overcrowding during peak hours, long waits for service and underutilized vehicles during off-peak hours. Traditional optimization methodologies, like linear programming and network flow models, typically produce structured responses to meet demand but are based on fixed assumptions and const'aints, and assume travel patterns will remain constant, making them ineffective tools for highly variable environments.

Continuous monitoring of large-scale mobility trends is now possible using IoT-enabled sensors (for example, data from mobile networks or location-based services such as GPS-enabled fleets). Meanwhile, two types of deep learning modelling techniques, namely CNNs and GRUs, have proven capable of predicting demand for large crowds by effectively modelling the complex spatio-temporal dependencies that exist between different locations at different points in time.

Despite the progress in recent years, there is evidence of a significant disconnect between predictive modelling and operational scheduling, primarily because most available research treats demand forecasting and scheduling optimization as separate entities. In addition to this, very few research articles make use of demand predictions as a basis for making decisions in real time. Consequently, even though demand predictions can be highly accurate, transportation

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efficiency cannot benefit from the use of accurate predictions that have been used for making better decisions.

Recent studies focus on finding adaptive and learning strategies to address dynamic decision-making concerns in transport systems, such as using reinforcement learning for adaptive scheduling. The DQN model is one such example of a model created for sequential control problems by learning by interacting with the environment. However, there are many reinforcement-learning methods that do not cover demand forecasting in relation to scheduling. Many of the existing methods also have simple representations of the states, limiting their effectiveness in capturing local demand fluctuations and dynamic development of the system [2]. Therefore, the research in connecting spatiotemporal demand forecasting with real-time scheduling is not well developed. Not much attention has been paid to closed-loop schedules, which are direct connection of local predicted demand and the adaptive vehicle allocation decisions. Contrary to current methods that largely consider predicting demand and scheduling based on reinforcement learning separately, the framework being proposed enables a direct prediction-scheduling relation. The novelty of the approach relies on using spatio-temporal demand according to cluster awareness in the DQN state for enabling the proactive assignment of vehicles when demand fluctuates. The suggested framework promotes the advancement of demand-responsive ITS through the conversion of spatio-temporal demands into constructive dispatching resolutions, which in turn facilitates dynamic transport allocation depending on the evolving dynamics of mobility management.

This paper presents a new way to implement demand-sensitive transportation scheduling with an integrated method. The proposed model combines spatio-temporal predictions of demand alongside reinforcement learning to optimize scheduling in one architecture. A key innovation in this framework is the cluster-aware representation of demand; a demand's spatial region is defined using DBSCAN and then processed into meaningful features to represent demand instead of just using raw labels. By using cluster-aware demand, the model can detect localized patterns of mobility and bring this information directly into the scheduling process [3]. The scheduling as a Markov Decision Process, where the agent observes predicted demand, availability of vehicles, and current system states to learn the most favorable actions related to vehicle allocation, route alterations, and frequency of service.

Regarding how it is executed, the framework is a closed loop, where the predicted demand will keep feeding back into the scheduler and allows for real-time optimization. The reinforcement learning model will also take into consideration multiple variables, such as minimizing passenger wait time, minimizing operating costs, and minimizing underutilization of vehicles, while still meeting all operational constraints (e.g., service). In contrast to typical optimization techniques, the proposed method will not use fixed assumptions and will learn policies that will generalize across different demand scenarios.

The major contribution of this research includes:

- Creating a prediction-to-scheduling pipeline that integrates spatiotemporal forecasting with real-time operational controls.
- Developing a new demand integration mechanism that allows for scheduling decisions to consider more spatially sensitive information through cluster awareness.
- Creating a reinforcement learning-based adaptive scheduling algorithm that is robust to uncertainty and can adapt to changes and dynamic environmental conditions.
- Completing a comprehensive implementation that outperforms traditional scheduling methods.

This research is an essential breakthrough in terms of development of intelligent transportation systems by creating a unified, data-driven, and adaptive scheduling approach instead of isolated optimization approaches, providing scalable and effective mobility management in the context of a smart city's operations. The proposed framework is based on a Unified Intelligence Transportation Architecture that combines the prediction of crowd movement with the scheduling of transportation. The first phase involves predicting future crowd mobility along with the anticipated need for transportation using both mobile signal data and spatial clusters identified through DBSCAN via a Cluster Aware CNN-GRU Model. The predicted demand information is then passed to a DQN-Based Adaptive Scheduling Module that allocates transportation resources based on expected crowd movement needs. Therefore, crowd predictions are a means of enabling transportation optimization; ultimately, the goal of the framework is to make transportation more efficient through scheduling decisions that are driven by demand.

2. Literature Review

The optimization-based approaches for urban transit scheduling have benefited from thorough research using various types of optimization-based solution methods, which can include mixed-integer linear programming, flow network optimization, shortest path algorithms and meta-heuristics [4]. These methods provide a fully mathematical representation of the problem along with an accurate representation of the many operational constraints faced by transit systems (e.g., Vehicle capacity; Route feasibility and Service coverage). Most of the existing research on urban transit scheduling has shown strong results with the assumption that transportation systems operate under controlled conditions. However, the computational complexity of the transit scheduling problem grows exponentially with the size of the transit network and the level of uncertainty with respect to the demand for transit services. Furthermore, most optimization-based urban transit

scheduling methods are limited by their deterministic assumptions and predetermined scheduling rules, resulting in a system that is not designed to adapt to the highly variable nature of urban transit mobility and the real-time fluctuations in transit demand.

The fast rollout of IoT infrastructures and mobile sensing technologies has resulted in a continuous supply of large-scale transportation data, thus advancing the integration of deep learning into mobility prediction. Earlier research has explored the methods of deep learning for urban crowd-flow prediction. The study discusses the methods of deep learning to learn spatial and temporal features from the data of crowd-flow [5]. These hybrid models yield less forecasting error and better predictive stability than both conventional machine learning techniques and standalone recurrent models. Further research has examined predictive methodologies using information from crowds and data-based modeling. Even with these improvements, deep learning studies to date are still predominantly focused on making predictions and do not evaluate performance other than through forecasting metrics. Moreover, the information produced from predicted demand is not typically incorporated into operational scheduling frameworks, resulting in a lack of connection between demand estimation and allocation of transportation resources.

Reinforcement learning is a more recent development that serves as an effective toolkit to enable ongoing learning and determination of optimal policies based on interaction with and in response to changing environments. There are successful applications of DQN-based approaches in optimizing traffic signals, ride-hailing systems, fleet management, and adaptability to vehicle dispatching. The utilization of techniques attributed to reinforcement learning has also been examined to determine their effectiveness in the intelligent decision-making process in dynamic circumstances, with the use of applications for human-aware navigation and trajectory prediction [7]. However, existing development of reinforcement learning models commonly utilize overly simplistic demand profiles, synthetic datasets, and pre-defined states that do not accurately reflect realistic spatio-temporal travel behaviors. Predictive demand information is rarely used directly in the reinforcement learning process, leading to sub-optimal scheduling decisions and inefficient use of the available data in transportation.

Another significant difficulty for intelligent transport systems is the modelling of spatial heterogeneity, as mobility demands are typically distributed unevenly over metropolitan areas. Density-based clustering analysis methods such as DBSCAN have become the facto standard for identifying areas with high levels of mobility and identifying clusters of mobility-related behaviors, and identifying patterns of transportation that are spatially related to each other. Studies have been conducted on deep learning models that utilize both convolutional and recurrent neural networks to predict crowd flow. This shows the need to model both the spatial and temporal dependencies together rather than separately, which these models were able to accomplish [8]. Unfortunately, most cluster data are only used in the preprocessing or visualization phase of an intelligent transport system and are rarely used for optimizing scheduling networks. As such, the spatial context needed to help facilitate real-time adaptive transportation decisions is largely lost prior to the beginning of operational optimization.

There has been a growing body of literature exploring how to use both machine learning and optimization approaches combined will improve the development of intelligent TMS. There has been considerable research into the use of machine learning techniques for understanding crowds, including evacuation studies and abnormality detection [9], which shows that these methods can be applied to data-driven analysis of crowd behavior and the detection of abnormal crowd circumstances. However, these methods do not consider the incorporation of predicted traffic demand into vehicle scheduling. While these studies demonstrate progress towards intelligent TMS, very few hybrid frameworks consider forecasting and scheduling as independent optimization problems rather than as part of an integrated decision-making framework. In addition, little attention has been paid to developing adaptive scheduling policies that incorporate cluster-aware spatial intelligence, which limits their effectiveness in rapidly changing heterogeneous urban environments.

The research literature shows that three different research gaps exist. The first gap is seen in how transportation demand forecasting and scheduling optimization are typically separated in the research literature; this lack of integration has limited the ability to fully utilize predictive information for making operational decisions. The second gap is how spatial intelligence, extracted from clustering techniques, is not commonly integrated into adaptive scheduling frameworks, even though it provides significant utility in helping to make better transportation allocation decisions. The third gap is that many existing reinforcement learning-based transportation systems do not represent real-world spatiotemporal demand impacts, therefore failing to adapt to changing urban mobility conditions.

The use of mobile-phone approaches has also been studied in the context of fine-grained crowd-distribution prediction, considering multi-order spatial relationships [10]. Such approaches show how mobile-phone data can represent the spatial variations of urban crowd distribution. The forecasting process itself is not directly integrated with a transportation scheduling system based on reinforcement learning. By combining predictive demand information with cluster-level mobility awareness and adaptive decision-making, the framework will enhance efficiency and resourcing utilization as well as speed up operational responsiveness within smart city settings.

3. Methodology

An integrated intelligent transportation system is presented in this section and consists of two phases. The first phase predicts future mobility of people in a city, as well as the transportation demand of those people, by using a Cluster-Aware CNN-GRU model that uses IoT-enabled mobile signal data and applies DBSCAN to create spatial clusters. In the second phase, DQN will use the predicted transportation demand to determine the optimal number of vehicles to allocate to meet that demand. This integrated approach provides for proactive scheduling of transportation services based on predictions and supports decision-making in dynamically changing urban mobility conditions.

3.1. System Configuration and Data Flow

Let the urban service area be discretized into N regions Z= {z_1…,z_N} and time into T equal periods (T = {t = 1, ..., T}). This model uses predictive input from a CNN-GRU model that generates predicted demand values for each spatial zone and time frame. These demand values will later be used as the input for the scheduling stage, where a DQN agent learns an adaptive transportation allocation policy based on the anticipated mobility demand rather than just the current observations. For each t, IoT raw observations (for example, mobile signal strength, time of day and geographic location) are processed into a feature tensor that is called Xt (where Xt ∈ $R^{(N*F)}$ - meaning that the Flow of the system is cyclic thus.

1. Create the features at X_t
2. Calculate the demand at dt (dt ∈ $R^{(N)}$) for the features in Xt
3. Augment dt with spatial context (which is dt ˜)
4. Form the state S_t
5. Select the action to be taken A_t
6. Deliver the action and measure the system response.
7. Update your policy based on feedback received from step 6. The cyclic flow of the system allows for continuous adaptation without the requirement that the system will provide consistent measurements over a period.

3.2. Spatio-Temporal Demand Representation

Where demand is defined at time 't' in zone 'z' Demand in zone Z and the time t is defined by the nonlinear mapping of the empirical data to the demand model. Therefore, the system function will be expressed as Equation (1):

$$d_{i,t} = f_\theta(X_{i,t}) \quad (1)$$

Where f_θ is a nonlinear mapping learned from the data.

For the spatio-temporal demand models in the system function, the input to the empirical functions would include:

- Temporal features -Time of the day and the day of the week cyclical encodings.
- Signal attributes - Proxies that are associated with Received Signal Strength (RSSI) and throughput metrics.
- Spatial context - Geocodes derived from latitude/longitude coordinates or from their zone coordinate embedding.

The input data are normalized prior to being fed into the empirical functions to reduce the large system-generated data CD-based variability that may exist because of large data differences:

$$\widehat{X_{i,t}} = \frac{X_{i,t}-\mu}{\sigma} \quad (2)$$

Demand models are that will be log-transformed prior to analysis, based on having a skewed demand distribution.

$$\widehat{d_{i,t}} = \log(1 + d_{i,t}) \quad (3)$$

Scaling sensitivity is minimized, and numerical stability is enhanced by normalizing all inputs as shown in Equation (2). Additionally, skewed demands can be log-transformed for further enhancement of numerical stability, as shown in Equation (3).

3.3. Spatial Context with Clustering

To model the differences in transportation demand across different geographical areas, the DBSCAN algorithm uses density-based clustering using the latitude/longitude location of each of the mobility observations. This analysis breaks the transportation network down into a set of spatially related zones or spatial mobility zones that contain the same type of mobility [11]. Each of these spatial mobility zones is assigned an associated cluster label, C_i. The following formula provides how average demand associated with cluster c at time t will be computed by aggregating the predicted demand associated with each zone in that cluster, as in Equation (4):

$$\overline{d_{c,t}} = \frac{1}{|S_c|}\sum_{i \in S_c} d_{i,t} \quad (4)$$

Where:

- S_C is the total number of zones in cluster c
- $|S_C|$ is the total number of zones in cluster c
- $d_{i,t}$ is the expected demand for zone i at time t

The demand computed by cluster is then assigned for each zone within cluster, thus creating a dimensionalized demand representation, as illustrated in Equation (5).

$$\widetilde{d_{i,t}} = \overline{d_{C_i,t}} \quad (5)$$

Using this dimensionalized demand representation allows the scheduling framework to consider local mobility patterns as opposed to simply relying on each zone's independent prediction. To also account for intracluster

variability, a relative demand deviation is calculated as shown in Equation (6).

$$\Delta d_{i,t} = d_{i,t} - \widetilde{d_{\iota,t}} \quad (6)$$

The demand deviation from the average demand of cluster will provide a measure of cluster relative versus demand cluster average. A positive demand deviation indicates an area of high demand within a cluster, while a negative demand deviation indicates that area has less than average demand compared to the overall average demand of that cluster. Using these measures, the scheduling model will have a better ability to target distribution resources towards patterns of demand or concentrations of demand that are occurring.

3.4. System Dynamics and Scheduling Variables

To depict scheduling operations for transportation, dynamic operational variables are presented to identify zoned service allocations, predicted passenger demand, fleet resources and whole system usage levels. Let, $x_{i,t}$ refers to the total amount of service provided in terms of number of vehicles, vehicles per transportation unit or maximum capacity of seats, allocated from zoned area Z_i at time t_1. Similarly, V_t refers to the total number of vehicles in the fleet available at time, while Cap refers to how much that vehicle can hold when utilized for transportation. The "actual demand" that was served in zone will be represented by minimum of allocated level of service & number of passengers predicted to demand service. The served demand will be determined using Equation (7) found as follows:

$$s_{i,t} = \min\left(x_{i,t}, d_{i,t}\right) \quad (7)$$

Where:

- $s_{i,t}$ is the number of passengers who were served in zone i at time t
- $x_{i,t}$ is the capacity assigned to zone i from vehicle
- $d_{i,t}$ is the number of passengers expected to be needed service in zone i at time t

To account for the possibility of transportation service demand exceeding the available capacity to serve the demand, an queuing system has been built to represent the unserved passengers. The queuing process has been modeled recursively according to the following Equation (8).

$$q_{i,t+1} = \max\left(0, q_{i,t} + d_{i,t} - x_{i,t}\right) \quad (8)$$

Where:

- $q_{i,t}$ is the number of pending Passengers in Zone i at Time t
- $q_{i,t+1}$ is the updated queue state in Zone i at the next time interval

Using this structure guarantees that there will not be any unmet demand is carried forward to the next scheduling interval. In this manner, the queuing effects of demand on the transportation system are captured over time.

The waiting time that passengers experience while waiting to be served by the transportation system has been calculated by determining the cumulative number of persons waiting to be served; the total measured wait time at Time, t is calculated using the following Equation (9).

$$W_t = \sum_{i=1}^{N} q_{i,t} \quad (9)$$

Where N is the total number of spatial zones in the transportation system. A longer wait queue indicates a longer wait time for Passengers and a lower transportation scheduling efficiency.

Operational costs associated with deployed transportation services include costs of allocating services to customers and relocating vehicles. Equation (10) defines the total operational costs of transportation:

$$C_t = c_v\left(\sum_{i=1}^{N} x_{i,t}\right) + c_r \cdot \text{RepositionCost}(A_t) \quad (10)$$

Where:

- c_v the cost of the vehicle(s) allocated to customer i,
- c_r is the coefficient (variable) for positioning the vehicle, and
- A_t is the scheduling operation at time t

The first term of the equation accounts for the resource costs of providing service to customers, while the second term provides more information about how much additional operational cost is a function of deploying vehicles dynamically or relocating individual vehicles. Vehicle utilization can also be used as an indicator of the efficiency with which a transportation service operates by measuring the ratio of actual customer demand served to available transportation capacity. Equation (11) describes how vehicle utilization measurements can be calculated:

$$U_t = \frac{\sum_{i=1}^{N} x_{i,t}}{\sum_{i=1}^{N} s_{i,t} + \epsilon} \times 100 \quad (11)$$

Here, ε is basically a small positive constant that is used to avoid division by zero and prevent any numerical instability of the utilization measure, U_t, which is worked out in percent terms, and the smaller number is given when a larger share of transportation capacity is in use. Such a situation leads to more efficient fleet resource allocation and higher effectiveness of scheduling decisions made under the existing demand conditions. This parameter, along with the parameters for demand and operational limitations described above, allows the scheduling framework to describe passenger demand,

fleet-capacity utilization, and operational efficiency at the same time [12].

3.5. A Multiple Objective Optimization Formulation

The transportation scheduling problem is modeled as a multipurpose optimization problem with the goal of optimizing three objectives: (1) minimizing passenger wait time (2) minimizing operational costs (3) minimizing unused capacity. The objective function is defined in Equation (12):

$$\min \sum_{t=1}^{T} (\alpha W_t + \beta C_t + \gamma U_t) \quad (12)$$

Where W_t is passenger wait time, C_t is operation cost, and U_t is unused capacity, respectively, where alpha (α), beta (β), and gamma (γ) are weights for their corresponding objectives.

Constraints on scheduling decision making will be respect to the fleet size constraints as expressed in Equation (13):

$$\sum_{i=1}^{N} x_{i,t} \leq V_t \cdot Cap \quad (13)$$

Where X_{it} is level of service provided by vehicle i during time t, V_t is the number of available vehicles at time t, and Cap is the vehicle's capacity.

And the non-negativity constraints will also apply as Equation (14):

$$x_{i,t} \geq 0 \quad (14)$$

The weight factors will allow the creation of a balance between service efficiency and total operating cost.

3.6. Formulation of Markov Decision Process

A Markov Decision Process (MDP) is modeled for the transportation scheduling problem. The predicted transportation demand from the Cluster-Aware CNN-GRU model will be incorporated into the scheduling state representation.

The DQN scheduler can then use this forecasted transportation demand, in conjunction with cluster aware spatial information, queue status and available fleet resources, to allow for proactive scheduling decisions versus traditional reactive scheduling. The tuple of the MDP is as follows: (S, A, P, R) where the agent learns optimal allocation of transportation resources (scheduling decisions) continuously from the transportation environment. The definition of the system state at time 't' is given below as Equation (15):

$$S_t = \left[d_t, \widetilde{d_t}, \Delta d_t, q_t, V_t, \phi_t\right] \quad (15)$$

Where:

- d_t represents the predicted demand for each zone
- $\widetilde{d_t}$ represents the cluster-aware demand
- Δd_t represents the intra-cluster demand deviation
- q_t represents the state of passenger queues
- V_t represents the resources of the fleet
- $\phi_t$represents the external traffic factors (e.g., congestion level, road conditions)

The action space contains possible allocation decisions for transportation across all zones, as expressed as Equation (16):

$$A_t \in R^N, \quad A_t \equiv x_{:,t} \quad (16)$$

Where $x_{:,t}$is the vector of service allocation decisions made at time 't.'

The action vector must be projected to the valid operational region to ensure that the scheduling decisions made are feasible, as shown in Equation (17)**.**

$$A_t \leftarrow \Pi(A_t; i \sum x_i, t \leq V_t \cdot Cap, x_i, t \geq 0) \quad (17)$$

The rules for the transition between states are based on the evolution of the passenger queue, the passenger allocation decision, and dynamic environmental factors. To minimize overall system inefficiency, a reward function is created, and as Equation (18):

$$R_t = -(\alpha W_t + \beta C_t + \gamma U_t) \quad (18)$$

The agent is motivated to reduce passenger wait time, operating costs, and unused capacity all at once by the negative reward motivating them to do so from three things together.

3.7. Value Function Approximation

The scheduling agent develops an optimal policy by approximating the expected future cumulative reward with a value function, which defines the action-value function under policy π as follows in Equation (19):

$$Q^{\pi}(S_t, A_t) = E\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k} \,\middle|\, S_t, A_t\right] \quad (19)$$

Where:

- γ is the discount factor ($0 \leq \gamma \leq 1$)
- $R_{t+k}$is the reward expected to be received at time t +k (or k periods in the future).

To approximate the optimal Q-function, a Deep Q-Network (DQN) is used and trained to optimize the neural network weights and biases (θ) by minimizing the temporal difference loss function in Equation (20):

$$L(\theta) = E\left[\left(y_t - Q(S_t, A_t; \theta)\right)^2\right] \quad (20)$$

Where y_t is calculated using the Bellman optimality update as in Equation (21)

$$y_t = R_t + \gamma \max_{A'} Q\,(S_{t+1}, A'; \theta^-) \quad (21)$$

where θ^- is the target network weight and bias values used in the learning algorithm for providing a stable learning environment.

3.8. Stabilization and Learning Strategy

To enhance stability and learning robustness, the following stabilization techniques have been included to help ensure better convergence:

- Application of ε-greedy exploration approach to allow exploration through reducing ϵ max and min values.
- Storing past transitions in experience replay memory D to limit the correlation of samples.
- Update target parameters by using periodic updates θ.
- Produce a stable training environment and accelerate reinforcement agent convergence using reward normalization.
- Control exploding gradients via gradient clipping.

3.9. Algorithmic Workflow

The overall learning process of the suggested reinforcement learning scheduler is shown in Algorithm 1. The agent learns optimal scheduling decisions about scheduling under a dynamic demand environment by continuously interacting with its environment [13].

Algorithm 1: Adaptive Transportation Scheduling Based on a Cluster-Aware Deep Q-Network (DQN).

1. Set up the parameters of the Q network θ.
2. Set up the parameters of the target network θ−.
3. Initialize the replay memory D.
4. For each episode of training:
5. Initialize the initial state of the environment S_t
6. For each time step t = 1, T:
   a. Generate a random value r ∈ (0,1).
   b. If r < ε then

      Select an action A_t randomly.

   c. Else:

      select Action A_t optimally
7. A_t = argmax Q (S_t, A; θ).
8. Project the action into the feasible scheduling region.
9. Execute the scheduling action A_t.
10. Gather the reward R_t from the scheduling action A_t and the next state $S_{\{t+1\}}$ resulting from state S_t after action A_t has been executed.
11. Store the transition (S_t, A_t, R_t, $S_{\{t+1\}}$) in the replay buffer D.
12. Randomly sample a mini batch from replay buffer D.
13. Using the last sampled transition, compute the target expression as follows:
14. Compute target Q-value:

    $y_t = R_t + \gamma \max Q\,(S_{\{t+1\}}, A'; \theta-)$.

15. Update the Q network by minimizing the following error:
16. $(y_t - Q\,(S_t, A_t; \theta))^2$.
17. Update the current state S_t={$S_{\{t+1\}}$}.
18. Periodically update the Q network target to maintain an up-to-date network every so often.
19. Target network θ− = θ;
20. End For.
21. Return the optimal schedule policy.

The workflow provides an interactive method of continuous improvement through adaptive learning and minimizing scheduling inefficiencies through feedback from the environment interacting with the transportation allocations.

3.10. Implementation Configuration

The framework proposed was built using TensorFlow and Keras for deep learning and reinforcement learning, respectively, to develop the models involved in the training process. Stochastic mini-batch optimization with experience replay is used to train the scheduling agent. The initial learning rate of the agent is set to $\eta = 10^{-3}$ and Discount factor γ=0.95 is used to define the level of financial importance that an agent places on future rewards when determining action choices.

Mini-batch sizes of between 32 and 64 are used during training to promote stable convergence. The capacity of experience replay memory is between $10^4 \leq |D| \leq 10^5$

indicating a range of scenarios that may exist within a transportation environment, and based upon different durations of the agent's training schedule. Training occurs in 100 - 500 episodes, and all state variables are feature normalized (normalizing each variable based upon its mean and standard deviation) to assist with convergence and improve numerical stability.

3.11. Computational Complexity

The computation complexity generated by the suggested structure includes both inference and training. The inference cost per decision step, a function of real-time scheduling, is given by Equation (22) as:

$$O(|A| \cdot H) \tag{22}$$

Where:

- |A| = Size of the action space
- H = Complexity of the hidden network.

When we consider the N zones within a transportation horizon and T scheduling intervals, the overall computation complexity of the system is given as Equation (23):

$$O(N \cdot T \cdot |A|) \tag{23}$$

On the other hand, the reinforcement learning training complexity is represented by the following Equation (24):

$$O(E \cdot B \cdot H) \tag{24}$$

Where:
E = Number of training episodes
B = Mini batch size.
H = Number of hidden network parameters.

Thus, even though train the scheduling model requires significantly more computation than the real-time performance of the deployed schedules, it allows the implementation of intelligent schedules in IoT-enabled transportation systems.

4. Experimental Setup and Dataset

Obtaining an Understanding of Experimentation, Dataset Characteristics, Preprocessing, Implementation Environment and Evaluation Methods and Evaluation Metrics Used to Evaluate the Effectiveness of Proposed AI-based Transportation Schedule. Experiments To Assess Prediction Accuracy of Demand by Crowd and To Assess Performance Under Dynamic Urban Transportation Conditions.

4.1. Dataset Characteristics

Observations about mobility are being analyzed in the experimental study, using data from OpenCellID. The data source contains spatially cited mobile network captures in a span of time, where the data is found useful in describing the spatial and temporal behavior of mobile networks. Hence, it would not be suitable to interpret the dataset as a direct measure of passenger traffic or traffic flows, or public transport demand [14].

The data revert to four characteristics for analysis, namely latitude, longitude, time stamp, and signal strength. The latitude and longitude provide the location of the mobile observation, while the timestamp provides its timing. Furthermore, the signal strength is incorporated, showing the increase or decrease of mobile activity. Together, these four characteristics enable deriving a mobile signal-based proxy for mobility demand.

After the completion of data preprocessing and quality control procedures, a total of approximately 5000 observation records were selected for model development and evaluation. The spatial coordinates are first processed with the help of DBSCAN algorithm to obtain the spatial regions with geoclimatic coherency. Cluster labels then serve as spatial inputs in the forecasting stage. After that, Cluster-Aware CNN-GRU model is applied, where cluster data are combined with time and signal information to calculate the mobility activity for the regions given their coordinates as well as period.

The output of the forecasting phase is then directed to the scheduling phase, in the form of mobility demand was anticipated. DQN-based scheduling module uses these forecasts as a part of its state to allocate transportation resources accordingly. Thus, the data serve as a basis for obtaining mobility signals in both spatial and temporal domain while the anticipated mobility demand acts as a link between the DBSCAN-CNN-GRU forecast phase and the scheduling made by DQN.

4.2. Data Preprocessing

The actual IoT mobility datasets usually have many issues, including missing records, erroneous entries, duplicate records, and a wide variety of different scales for the variables in the datasets. As such, numerous steps will be undertaken to clean the data before the training of the models take place. First, any erroneous or missing observations will be deleted to assist in achieving a level of data cleanliness. The timestamp value will be converted to structured temporal representations, which will help us to identify sequential types of mobility behavior [15]. The latitude and longitude coordinates for both the location and the measurement will be converted to numeric values that are able to be used to optimize the deep learning method. DBSCAN clustering will be performed on the latitude and longitude coordinates of the combined dataset to assist with improving the representation of spatial data for building the models. DBSCAN clustering has an advantage over other clustering methods that are based on partitions in that it identifies dense areas of mobility (clusters) without a requirement to know beforehand how many clusters there are.

Therefore, it will enable us to automatically identify transportation hotspots or areas of atypical mobility. The Equation (25) is represented as the input feature vector at time step t:

$$X_t = [lat_t, lon_t, signal_t, cluster_t, time_t] \quad (25)$$

Where lat and lon refer to geographical coordinates; signal denotes signal-based mobile intensity measurements; cluster is used to reflect a spatial cluster index; and time represents temporal information within the mobility model.

For modelling temporal dependencies, the observations from previous time intervals are organized into sliding windows so that the historical observations can be sequenced into time-based sequences.

Through this sequencing technique, the CNN-GRU can learn to capture and predict both short-term and long-term patterns of mobile activity.

All feature variables are normalized using Min-Max scaling techniques to provide stability in optimizing a neural network model, as expressed as Equation (26):

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (26)$$

By use of this normalization procedure, the speed of convergence will improve, and the degree of instability of the training will decrease due to a lack of balance between the scales of the features being used for the learning.

4.3. Experimental Environment

The framework being proposed has been developed using TensorFlow, Keras and Scikit-learn in the implementation process using Python as a programming language. All experiments were carried out using a workstation powered by an Intel Core i7 processor, 16 GB of RAM and GPU acceleration to aid in the training of deep learning.

The Cluster-Aware CNN-GRU model was trained using an Adam optimizer with a learning rate of 10^{-3}. Mini-Batch Learning has been used with mini-batch sizes of between 32-64 to assist with convergence stability while using the reinforcement learning scheduler to optimize adaptive transport via experience replay, target network synchronization and ε-greedy exploration mechanisms [16]. This experimental procedure allows for efficient training and real-time inference for intelligent transport scheduling for dynamic transport conditions.

4.4. Comparison of Baseline Models

The present work provides a thorough comparative analysis to examine the validity of the proposed ITS under dynamic urban mobility patterns. The ITS integrates Spatio-Temporal Demand Forecasting with Reinforcement Learning-based Adaptive Scheduling; therefore, a performance evaluation shall be conducted that utilizes both prediction-centered Deep Learning architectures and Operational Transportation Scheduling methods [17]. Furthermore, the comparative analysis will focus on the contributions to Transportation Efficiency of using Spatial Clustering Techniques, Temporal Sequence Modeling, and Adaptive Decision Optimization Techniques.

Table 1. Scheduling strategies and baseline models

Model	Category	Functional Goal
GRU	Temporal Forecasting	Demand predictively through time
CNN-GRU	Spatio-Temporal	Learning how people will move based on location and time
Cluster -Aware CNN-GRU	Enhanced Forecasting	Predicting demand based on how the location is used at the same time as people use it.
Static Scheduler	Traditional Scheduling	Transportation permanent for a determined period.
Rule -Based Scheduling	Heuristic schedule	Allocate transportation adaptively based on predetermined thresholds
DQN-Based Adaptive Scheduling	RL-Based Scheduler	Use reinforcement learning to allocate transportation optimally

Three types of comparative models have been used to establish a good experimental benchmark, which are conventional temporal forecasting models, hybrid spatio-temporal deep learning architectures, and transportation scheduling methodologies with different levels of adaptivity. A methodology is utilized to assess if cluster-aware mobility representation and RL-optimized scheduling will improve scheduling performance. The first type of comparative model is the commonly used GRU-based temporal forecasting model used widely within intelligent transport systems. GRUs are good examples of how GRUs can model sequence behaviors with low computational cost compared to RNNs. They will learn sequentially evolving patterns of demand based solely on sequential observations, without taking into consideration

the use of explicit spatial information. These models perform adequately at doing sequence modeling. However, they lack in their sensitivity towards geospatially correlated mobility patterns and localized congestion events.

A hybrid CNN–GRU architecture is the second baseline and is one of the most widely used deep learning models for predicting spatio-temporal transportation. In this network, the convolution layers are used for detecting locally defined spatial patterns that represent mobility before using the GRU as a way of learning from the history of that mobility over time [18]. Compared to purely recurrent models, the CNN–GRU architecture provides an improved representation of the spatial patterns for the learning of these types of data points, thus providing an important baseline to measure the success of advanced transportation demand prediction models against. An extension to the traditional CNN–GRU framework has been developed by introducing cluster-aware spatial intelligence through density-based cluster analysis of the mobility patterns.

Instead of simply using the spatial representation based only on the coordinate level, the proposed architecture will utilize the cluster context information developed from DBSCAN as an input to learning. As a result, this method will be able to better identify transportation hotspots with high concentrations of usage, correlations in mobility between regions, and localized changes in demand over time. Additionally, demand variation modeling between and within clusters will enable the architecture to discern between high and low levels of transportation pressure in geographic regions that are related. Overall, these new spatially enriched contextual representations will provide significant improvements to the adaptability of the scheduling system to remain responsive to the heterogeneous mobility characteristics of urban transportation.

The proposed reinforcement learning scheduler has been evaluated for operational efficiency through comparative evaluations with other transportation scheduling methods, as well as predictive baselines. The first baseline for scheduling is a static allocation system that allocates transportation resources based on predetermined time intervals without accounting for real-time fluctuations in passenger use of the resources. These types of scheduling methods are very easy to implement from a computational perspective, but their responsiveness to rapidly changing levels of transportation demand can be very poor.

The second baseline for scheduling uses a rule-based adaptive allocation method that allocates transportation resources based on predetermined thresholds of passenger use and wait times. Compared to static scheduling methods, heuristic-based systems are not known for their level of responsiveness. They cannot learn autonomously and therefore cannot optimize long-term transportation efficiency in environments that are subject to highly complex dynamic mobility patterns.

The scheduling framework is based on deep Q-network reinforcement learning that learns adaptive allocation policies through reward-driven optimization while continuously interacting with the transportation environment. Through this novel approach to scheduling, the reinforcement learning agent will have the ability to dynamically modify the allocation of transportation resources by considering the changing predicted demand, current queue state, cluster-aware spatial context, fleet availability, and traffic conditions [19].

As a result, the proposed scheduling framework can produce adaptive real-time scheduling decisions in uncertain & dynamically evolving urban transportation networks. To ensure a thoroughly comprehensive assessment of the proposed scheduling framework, comparative evaluations are performed using both prediction and operational performance metrics. Prediction accuracy is evaluated using statistical regression methods that include MAE, RMSE, and R^2, whereas scheduling performance is evaluated using metrics such as reductions in passenger wait times, effective resource utilization, and reduced queuing intensity. This multi-faceted approach provides a rigorous assessment of both the forecasting performance and the feasibility of implementing the proposed intelligent transportation framework. Table 1 contains an overview of the baseline models and scheduling methodologies utilized in the comparative studies. Many baselines, including deep learning models and scheduling, will validate the proposed framework in terms of predictions and operations. The evaluation process allows a complete understanding of the use of cloud-based demand modeling and adaptive transportation scheduling through reinforcement learning for IoT-enabled smart cities.

4.5. Evaluation Metrics

There are two different metrics that can be used to evaluate the proposed framework for intelligent transportation scheduling based on prediction-related metrics and operational scheduling metrics. The evaluation method was designed to both evaluate the forecasting ability of the cluster-aware CNN-GRU model and measure the efficiency with which real-time scheduling is accomplished using reinforcement-learning-based transportation optimization. The need for two levels of evaluation is since forecasting the demand for transportation does not guarantee optimal scheduling of the transportation resources without creating adaptive allocation decisions (also evolving) at the same time. The predictive performance of the proposed spatio-temporal forecasting model was evaluated with MAE, RMSE, and R^2. The MAE measures the average absolute difference between the actual and predicted transportation demand values; it is given by the following Equation (27).

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{27}$$

The RMSE is an indicator of the spread of forecasting errors, with larger forecasting discrepancy errors accounted for more heavily than smaller errors in forecasting; therefore, this measure provides an indication of the accuracy of the forecasting methods under exceptional circumstances of rapidly changing travel conditions. The RMSE is calculated in accordance with Equation (28):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{28}$$

The statistical appropriateness of the regression model of the demand forecasting methodology above is assessed further by the Coefficient of Determination (R^2), which is calculated using the equation below in Equation (29). The R^2 is a measure of the variability in transportation demand accounted for by using the proposed forecasting methodology.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{29}$$

In the preceding equations, the variable y_i refers to observed transportation demand, the variable $\hat{y}_i$ is the forecasted or predicted demand, and the variable y refers to the average of transportation demand across all nodal, aggregate demand zones. To providing demand forecasts, the operational efficiency of the proposed scheduling system is evaluated by measuring transportation-oriented performance indicators. One important aspect of service quality is passenger wait time, which reflects the responsiveness of the scheduling system and accessibility to transportation services [20]. The total amount of time various passengers in every transportation zone had to wait before being served can be computed using Equation (30):

$$W_t = \sum_{i=1}^{N} q_{i,t} \tag{30}$$

Where $q_{i,t}$ represents the length of a queue of passengers at zone i at time t.

To evaluate the economic efficiency of the scheduling framework, an operational transportation cost is defined, which includes both vehicle deployment and route reassignment costs in Equation (31):

$$C_t = c_{v\sum_{i=1}^{N} x_{i,t}} + c_r \cdot \text{RepositionCost}(A_t) \tag{31}$$

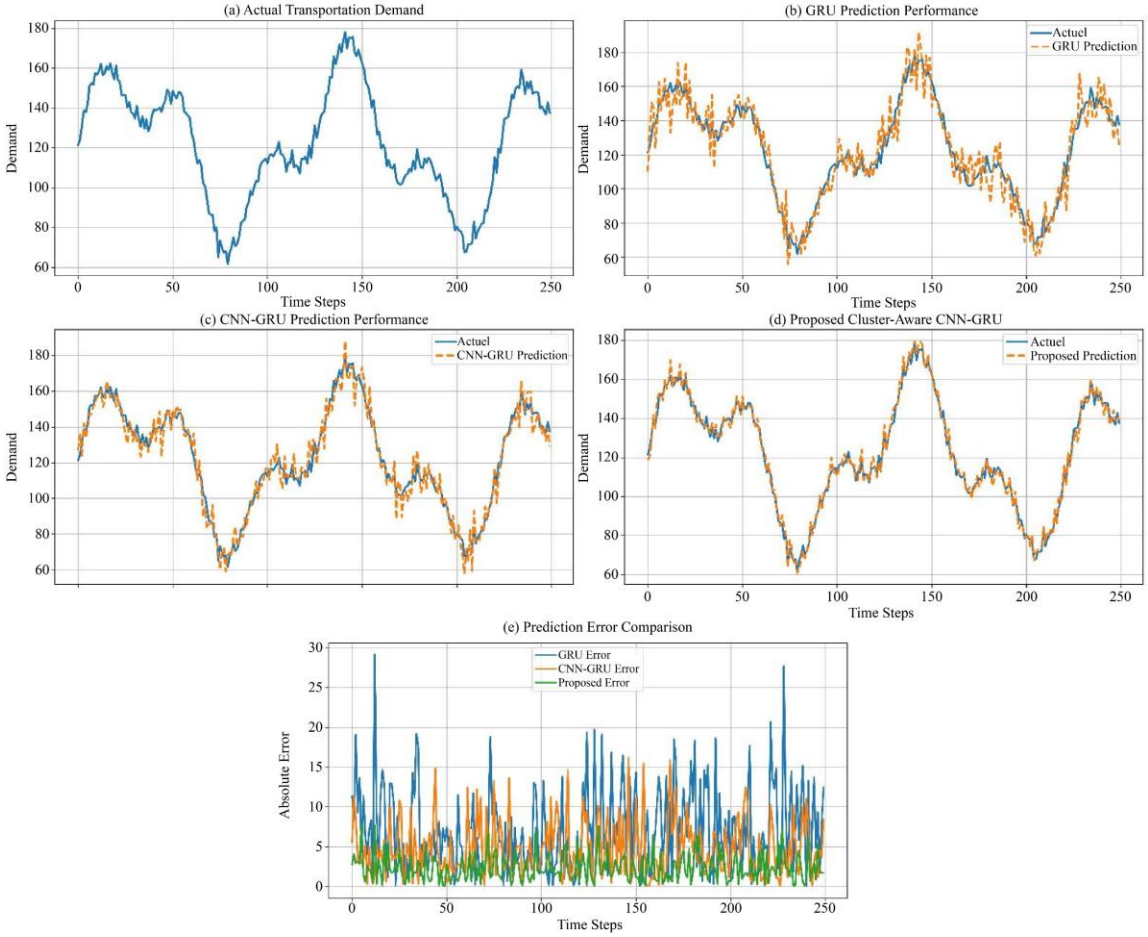


Fig. 1 Multiple perspectives of transportation demand prediction analysis

Where c_v and c_r are the transportation deployment and repositioning cost coefficients, respectively, and A_t is the scheduling action completed by the reinforcement learning agent. In addition to these quantifiable indicators, the queue reduction efficiency and the adaptability of the scheduling responsive to changing urban transportation demand will also be evaluated during comparative experiments to validate the effectiveness of the proposed framework operating under continuously changing urban transportation conditions. Improved services will be exhibited through lower queue wait times, higher fleet utilization and decreased operational costs. Combining statistical forecasting metrics and operational transportation metrics allows for a more comprehensive analysis of the proposed framework from both a machine-learning perspective and an intelligent transportation systems perspective [21].

5. Results and Discussion

The evaluation of the cluster-aware intelligent transportation scheduling framework under changing urban mobility conditions is the subject of this section. Analysis has two main foci: (1) how well transportation demand is predicted, and (2) how efficiently the scheduling of transportation is adapted to these predictions. To validate that the proposed framework works well in real-time intelligent transportation systems, experiments were conducted comparing it with conventional deep learning forecasting architectures and with traditional methods for scheduling transportation.

5.1. Prediction Performance Evaluation

The methodology for determining prediction performance is based on MAE, RMSE, and R^2. To assess how well transportation demand forecasting can be accomplished with spatial contextual integration, the experiments compared the MAE, RMSE and R^2 of the proposed cluster-aware CNN–GRU architecture vs. those obtained with traditional GRU and CNN–GRU architectures. The predicted performance results from the models discussed in Table 2.

Table 2. Comparative analysis of the predictive accuracy of deep learning techniques

Model	MAE	RMSE	R^2
GRU	0.1062	0.1324	0.0131
CNN-GRU	0.1037	0.1302	0.0455
Proposed Cluster-Aware CNN-GRU	0.1033	0.1290	0.0635

Table 2 states the errors based on the normalized demand scale, while errors regarding demand in the original units are shown in Figure 1 after applying the reverse transformation. While sequential modeling can capture temporal mobility dependency, it does not provide enough information to account for spatio-temporal variability in transportation demand. Thus, the ability to predict accurately decreases in highly heterogeneous urban mobility environments.

In contrast, the combination of the CNN and GRU model has been demonstrated to provide superior forecasting performance through convolutional extraction of spatially related features and learning local spatial dependencies prior to the temporal sequence modeling.

As a result, although the CNN–GRU model demonstrates lower error rates than the stand-alone GRU model, its spatial modeling remains limited to local feature extraction without a clear understanding of the overall region.

The CNN-GRU framework, designed with the cluster-aware feature, has improved forecasting by integrating a DBSCAN-based method to provide spatial clustering into the forecasting process. Thus, in addition to using only geographic coordinates, mobility representations at the cluster level are integrated to find similarities in transportation demand across geographically correlated urban neighborhoods; therefore, the additional context improves consistency in forecasting and reduces instability when sudden fluctuations in transportation demand occur.

The experimental results demonstrate that the suggested framework results in the lowest forecast error in comparison with the rest of the assessment models. In particular, the suggested Cluster-Aware CNN-GRU model has an MAE equal to 0.1033 and RMSE equal to 0.1290, while the obtained value of R^2 proves to be equal to 0.0635, which is higher than that of the GRU model and conventional CNN-GRU models.

This can be interpreted as the confirmation of the improvement of forecasting performance due to the use of mobility information, which is aware of spatial geometry. Nevertheless, a relatively low value of R^2 shows that there is still a significant part of the variance to be explained.

Forecasting behavior of the four deep learning architectures evaluated in this study is plotted with respect to dynamic transportation demand patterns as represented by the graphics in Figure 1. All four architectures were found to have greater consistency and lower forecast error at both normal and high demand levels of the mobile population. When integrated with the spatial clustering mechanism, the proposed architecture enhanced context learning capacity and improved resilience to variations of transportation demand.

5.2. Scheduling Performance Evaluation

The effectiveness of the proposed scheduling framework, based on reinforcement learning, was assessed under conditions of dynamically varying transportation demand [22]. The experimental set of analyses involved assessing the performance of the scheduling agent with respect to its ability to minimize passengers' waiting time; decrease queue congestion; maximize vehicle utilization and reduce operational costs, through adaptive allocation of transportation resources.

Table 3. Performance of scheduling under dynamic demand comparisons

Scheduling Method	Waiting Time (Min)	Queue Length (Passengers)	Vehicle Utilization (%)	Operational Cost (Cost Units)
Static Scheduling	18.4	142	63.5	2450
Heuristic Scheduling	12.7	96	74.2	2140
Proposed RL-Based Scheduling	7.9	51	89.6	1865

To establish the scheduling framework's capacity to perform real-time decision-making under dynamic urban mobility conditions, it was compared to conventional static scheduling and heuristically based scheduling techniques [23]. The results of scheduling procedures obtained from the different scheduling types evaluated were summarized in Table 3. When using static scheduling, people will have the longest time waiting while being able to accumulate queues.

This is because static scheduling policies that are based on fixed transportation can't adjust quickly enough to changing mobility demand patterns. As the transportation demand changes over space across different zones, the use of static scheduling results in inefficient resource allocation of transportation, which causes high levels of congestion among passengers during peak demand periods.

The heuristic scheduling method improves system responsiveness because it incorporates a set of predefined adaptive rules for how transportation will be allocated. Although the heuristic scheduling method has less waiting time and operational inefficiencies than a static strategy, it still faces limitations in decision-making due to its reliance on well-defined rule sets that cannot accommodate the great deal of variability in the mobility of individuals across space and time [24]. The scheduling system built from reinforcement learning showed better overall performance across all evaluation metrics than the other systems that were evaluated. The adaptive scheduling agent continually learns from environmental interactions, the best ways to distribute transportation, which remain continually updated based on what their predicted future transportation demands might be. Therefore, the scheduling system proposed can reduce passenger wait times and queue overflow while increasing the utilization of vehicles very significantly [25]. Tests demonstrate that the proposed scheduling system resulted in an average of 57% less wait time and 64% less queue build-up than when static scheduling was used. Increased vehicle utilization levels will also result from using a better distribution of transportation resources over areas with high levels of demand for mobility services.

The reduction in operational costs shows how much intelligent adaptive scheduling simultaneously improves the efficiency of transport operations while reducing unnecessary costs associated with the deployment of service-related equipment [26]. With the addition of demand forecasting to the scheduling via Reinforcement Learning, the integrated system can sustain a constant level of service for transportation systems in an environment of continuously changing conditions for movement, therefore confirming that Adaptive Intelligent Scheduling greatly increases the operational scalability and responsiveness of transportation systems operating in smart urban mobility.

In Figure 2, three different approaches used for scheduling in a changing transportation demand environment were compared on three criteria; static scheduling, heuristic scheduling, and the new adaptive scheduling framework developed using RL.

The RL-based framework produces better overall results than either type of scheduling method on all of the criteria evaluated (i.e., average waiting times and queue lengths, vehicle usage, and operational costs).

The reduced waiting times experienced by passengers as a result of using the RL-based adaptive scheduling is illustrated in Figure 2(a) through the use of real-time allocations made for available vehicles based upon the forecasted demand for transportation. The fact that the RL-based adaptive scheduling framework is effective for reducing the accumulation of people waiting for vehicles is demonstrated in Figure 2(b) through the active management of delivery resources among areas of high demand in response to changing conditions throughout the day.

Also, in the results in Figure 2(c), it can be seen that the framework has achieved higher efficiency in vehicle utilization than the traditional scheduling methods, which indicates better resource management and a decrease in wasted capacity in transportation. The Figure 2(d), there was a significant reduction in operational costs due to improved scheduling decisions and smarter redistribution of the fleet resources. Thus, the findings indicate that the use of demand-based RL, along with the use of cluster-based knowledge of predictions of mobility, improves transportation scheduling efficiency, scalability, and responsiveness significantly in multi-faceted urban transportation systems.

The dynamic nature of demand creates a variety of queue accumulation behaviors with the varying scheduling techniques shown in Figure 3. The static schedule accumulates queues continually through the scheduling horizon because there is no real-time adjustment to accommodate the ever-changing nature of passengers' mobility [28, 29]. The lack of dynamic resource allocation during peak demand times creates persistent congestion and long passenger queues.

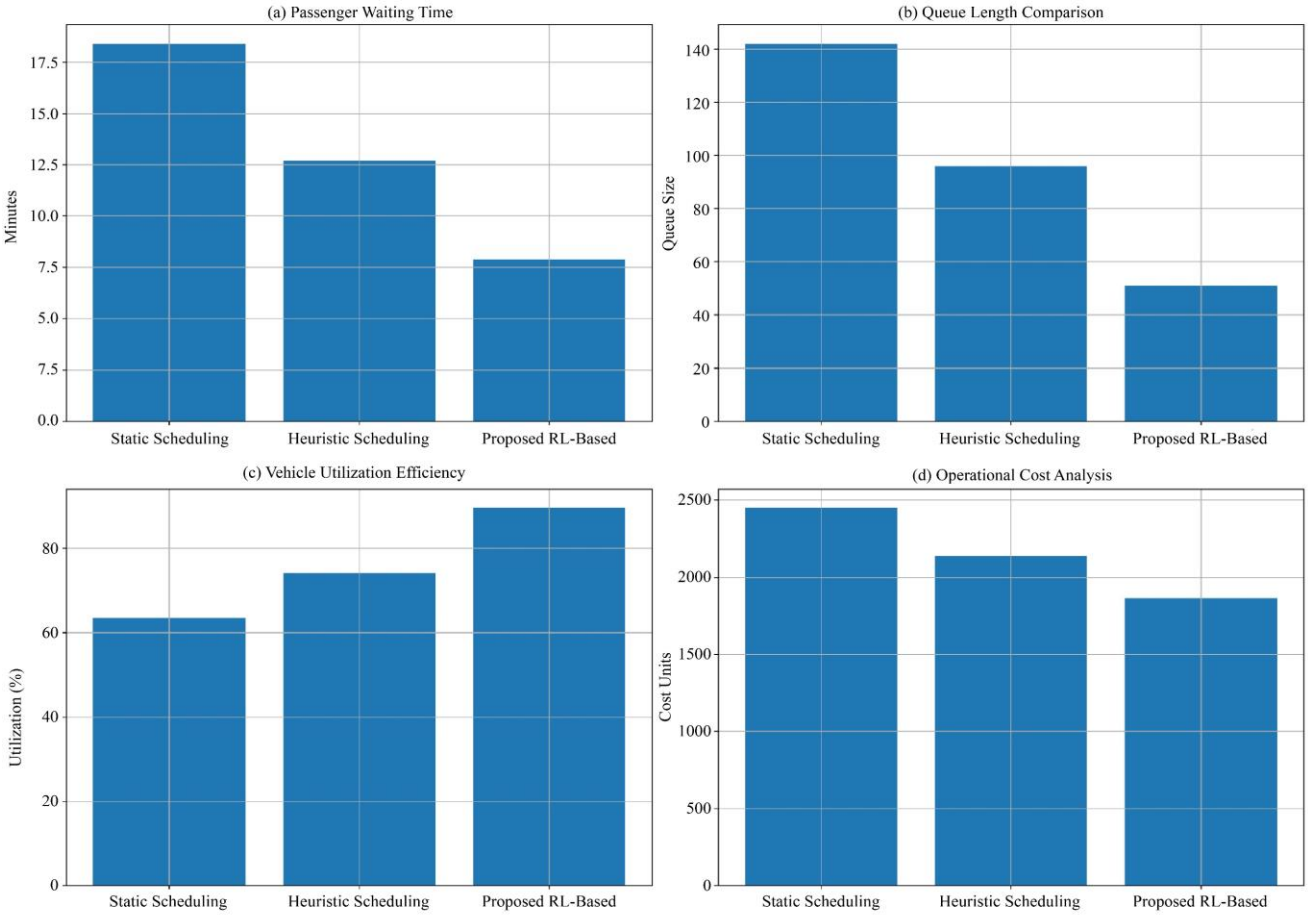


Fig. 2 Analysis of performance as per scheduling methods

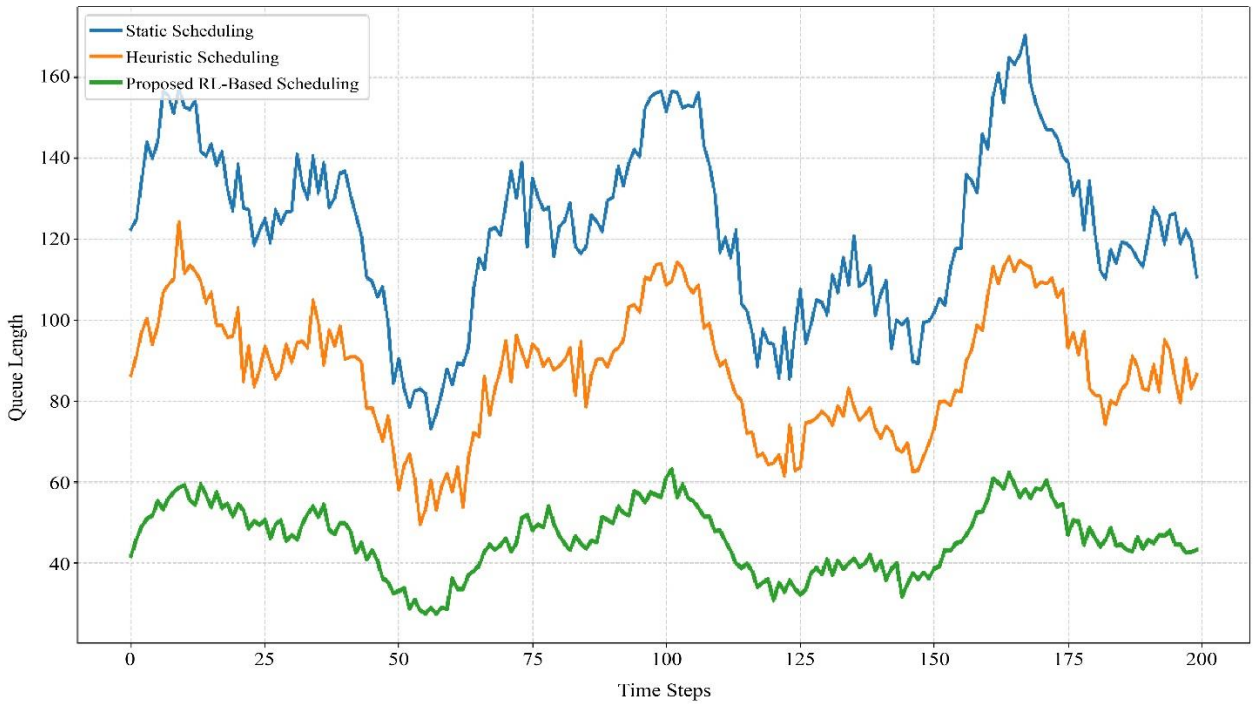


Fig. 3 Queue reduction performance

The heuristic schedule shows some improvement as it uses pre-defined schedule modulations and demand-aware resource allocation rules to provide some queue reduction compared to static schedules [30]. However, the heuristic schedule can still experience performance variability due to sudden demand changes, as it does not fully capture the complexity of the dynamic temporal-spatial mobility trends.

By contrast, the proposed reinforcement-learning-based scheduling framework consistently maintains lower queues over the evaluation period due to the real-time environmental adjustment of resource allocation policies by the adaptive learning algorithm [27]. As a result, this framework achieves significant reductions in congestion accumulation as well as increases in the stability of transportation flow for peak and a typical demand period.

Experimental observations confirm that the integration of Reinforcement Learning and intelligent scheduling based on demand. By finding the best routes, adding flexibility in prioritizing vehicles according to their demand as well as traffic congestion, it improves the ability to reduce congestion and responsiveness to transport needs overall, while increasing the efficiency of all operations.

5.3. Comparative Analysis

The main objective of this section is to provide insight into how individual architectural components of this proposed intelligent transportation system contribute to predictive capabilities using a comparative analysis. Compare the performance of three different forecasting architectures with three different scheduling methods, such as static, heuristic or Reinforcement Learning-based. In terms of forecasting performance in isolation, the GRU architecture has the best ability to learn long-term with limited space representation required when predicting in a complex urban transportation environment [31]. The CNN – GRU architecture improves local feature extraction and thus achieves better local prediction accuracy than GRU, however, does not show similar abilities to maintain regional flows.

The cluster-aware framework enhances the capability of the existing structure of CNNs and GRUs by using the clustered spatial context of travel behavior to inform learning of transportation demand consistency and to provide an additional layer of accuracy when forecasting trip demand in heterogeneous urban mobility scenarios

Static transportation allocation from a scheduling perspective does not handle changing mobility demand very well since the scheduling decision is not adaptable or flexible to changing conditions [33]. Adaptive heuristic scheduling offers some level of adaptability; however, the heuristic relies on manually created transportation allocation rules or logic for executing their action plan. A reinforcement learning-based scheduler continuously learns how to improve transportation allocation policies based on environmental feedback, resulting in superior long-term operational efficiency [32].

The experimental results show that the cluster-aware framework outperforms all other methods, especially in predicting and scheduling trip demand. The cluster-aware predictive capabilities of the system, along with an adaptive reinforcement learning-based scheduling system, provide balanced transportation network management, reduced congestion, improved fleet utilization and lower operational costs.

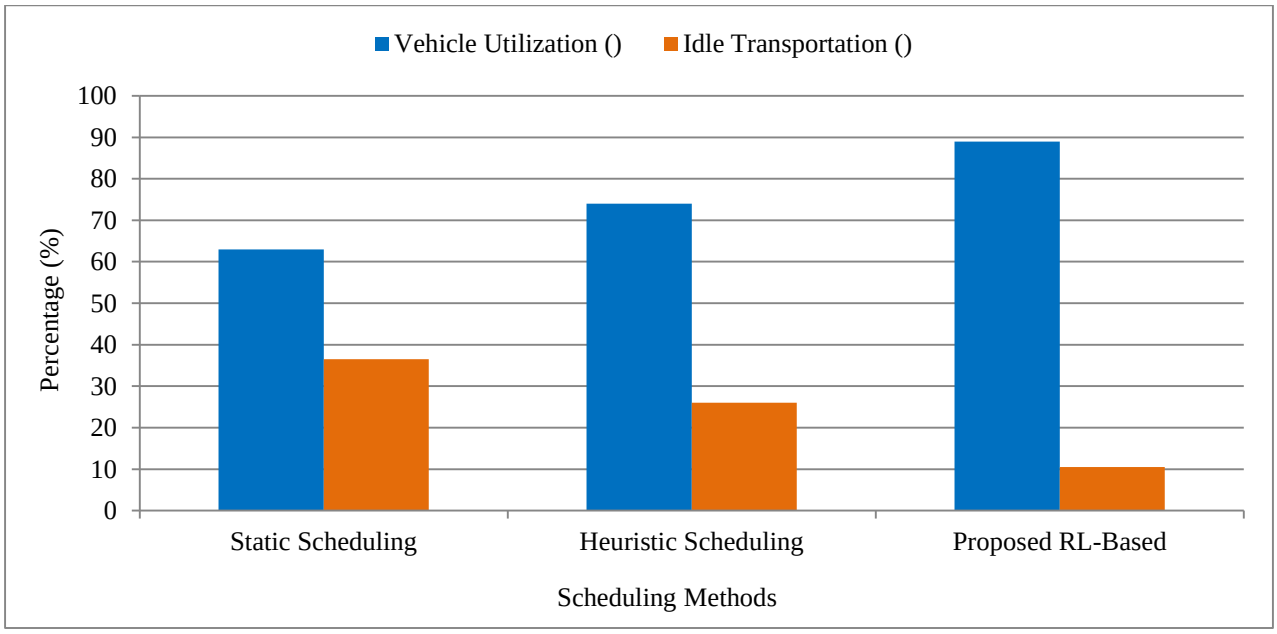


Fig. 4 Transportation resources utilization comparison

Figure 4 depicts the level of efficiency because of scheduling framework-based transportation resource utilization based on dynamic mobility demand. According to this figure, the proposed method of using reinforcement learning to schedule transportation resources has a greater level of active vehicle use along with a reduced level of unused transportation capacity than a static or heuristic-based method. Having the ability to allocate transportation resources based on the overall level of demand has allowed for a better balance of the fleet and more efficient distribution of transportation resources across high-demand urban areas, increasing overall operational scalability and efficiency of transportation services.

5.4. Ablation Study

An analysis of the periodical congruence between the two different broad groups of parameters is carried out as one method of evaluating the influence that the removal of an important component at a time has on predicting transportation demand and on scheduling efficiency under changing conditions of urban mobility. The improvement in performance has to do with the synergistic actions of the system elements.

Table 4. Ablation study results for the proposed intelligent transportation framework

Configuration	MAE	RMSE	Waiting Time (mins)	Utilization (%)
Without Clustering	0.1184	0.1469	11.8	76.3
Without RL Scheduling	0.1047	0.1328	13.6	72.5
Proposed Framework	0.1033	0.1290	7.9	89.6

The DBSCAN algorithm is a tool for understanding the peculiarities of demand in space, while the CNN-GRU recognizes relationships in the data over time. Demand patterns created using this predictive method are then used for scheduling based on DQN technology. This allows for planning vehicles in advance to meet demand. The ablation experiment results shown in Table 4 confirm that without any of these two technologies, namely spatial clustering and adaptive scheduling, the service will perform worse, thus validating the necessity of their integration for reducing waiting time and increasing fleet efficiency.

In the first ablation configuration, the DBSCAN-based spatial clustering is removed while the CNN–GRU forecasting model and reinforcement learning scheduling mechanisms remain intact. When there is no cluster aware spatial representation, the forecasting model produces greater prediction errors and has reduced stability when scheduling under conditions of high mobility heterogeneity. The experiments indicate that specifically learning the spatial context of the data improves the accuracy of demand estimation for public transit across correlated urban areas.

In the second ablation configuration, the reinforcement learning-based adaptive scheduling is replaced with fixed transportation allocation rules, but cluster aware forecast predictions remain. While the prediction accuracy remains relatively unchanged, the scheduling system has significantly longer wait times for passengers and lower overall usage efficiency of available transport. This illustrates that forecasting of demand does not alone allow for intelligent transportation optimizations without the ability to make adaptive decisions.

The full proposed architecture provides maximum overall performance on all forecasting and scheduling metrics. Combining a cluster-aware spatial demand model with a reinforcement learning-based adaptive scheduling approach results in improved response time to transportation needs, better fleet balance among multiple vehicles, and less congestion accumulation as demand for transportation changes dynamically from time to time.

The ablation studies suggest that both two components, such as spatial contextual integration and intelligent adaptive scheduling, are major contributors to achieving operational efficiency of the proposed architecture. These results also support the need for jointly optimizing both transportation demand prediction and scheduling policy learning through a single integrated architecture for intelligent transportation system optimization.

5.5. Discussion

After an extensive evaluation of the Intelligent Transportation Framework and its use as a transportation demand forecasting and scheduling optimization tool in rapidly fluctuating urban mobility conditions, the experimental results confirm the effectiveness of the proposed framework. By combining spatio-temporal deep learning with reinforcement learning-based transportation scheduling, this new framework creates a common platform for all forms of intelligent decision-making regarding transportation demand forecasting and scheduling as it relates to current traffic conditions.

The forecasting results demonstrate the importance of spatially contextualized learning on transportation demand forecasting and how it has resulted in significant improvements to forecasting accuracy, as well as the ability to generalize forecasting accuracy, compared to other forecasting techniques used in large-scale smart transportation systems [34]. While time-series forecasting methods like the GRU model rely heavily on modeling the relationships between values at consecutive time periods, their ability to

model complex spatial relationships across spatially disperse geographic areas remains limited, while transportation demand prediction patterns across regions continue to show significant levels of heterogeneity and rapidly changing transportation distribution patterns [35]. As a result, although the CNN-GRU architecture can increase the extraction of local spatial features through convolutional operations, it does not have sufficient feature representation capabilities when applied to heterogeneous and quickly changing transportation distributions when it comes to modeling transportation demand relationships.

The novel cluster-aware forecasting mechanism improves on previous spatial representation learning approaches by integrating DBSCAN-derived regional mobility structures into the forecasting solution. Rather than treating transportation zones as independent entities, the framework integrating cluster-level regional mobility similarity and spatial continuity through cluster-based contextual aggregation to capture the interrelationship of regional transportation systems. This enhanced level of spatial awareness allows the forecasting model to provide a more accurate representation of the spatial concentration of transportation demand and localized congestion propagation across dense transportation hubs, as well as of correlated mobility patterns among adjacent urban regions. Therefore, the proposed framework produces lower forecasting errors and greater prediction consistency under both regular and peak transportation demand conditions.

From a scheduling perspective, the adaptive allocation strategy based on reinforcement learning provides significant operational advantages compared to current static and heuristic transportation scheduling methods. Static scheduling employs fixed transportation allocation policies that lack responsiveness to real-time variability in demand, resulting in excessive queue buildup, longer waiting times for passengers and inefficient utilization of transportation resources [36]. In contrast, heuristic approaches provide some level of adaptability through the implementation of pre-defined transportation allocation logic; however, manually designed scheduling rules do not offer the required flexibility within rapidly changing and highly non-linear urban transportation systems.

The reinforcement learning-based scheduling system continually adjusts its transportation allocation decisions because of interacting with the transportation system and optimizing policies based on rewards. The system adapts to its surrounding environment by considering current transportation demand forecasts, queue evolution, vehicle availability, and operational constraints to allocate available transportation resources based on current conditions at the time of transportation [37]. By using the adaptive learning capability of this scheduling framework, it is possible to enhance the ability to reduce congestion, manage the fleet of vehicles more effectively, and manage the flow of transportation resources more successfully during times of significant fluctuations in mobility.

The analysis of queue evolution during this proposed scheduling system shows the ability of this system to maintain transportation congestion stability throughout the scheduling horizon. In contrast to static scheduling methods which grow continuously during peak demand periods because of the inability to adjust transportation allocations rapidly, the proposed scheduling approach uses rapidly changing transportation allocation decisions to prevent excessive congestion from accumulating. The ability to maintain stable queues is further evidence of the effectiveness of this adaptive intelligent scheduling system for maintaining continuity of transportation services in large urban transportation networks.

In the transportation utilization analysis, the proposed framework provided improved operational efficiencies of resources. The active utilization rate of vehicles increased while the unused capacity of the fleet decreased, providing more even allocation of transportation resources against continually changing demand regions. Furthermore, the improvement in how transportation resources are allocated resulted in less operational overhead and improved scalability for large transportation operations.

The ablation study confirmed the importance of individual components of the framework and their overall effect on system performance. The removal of spatial clustering negatively affected the stability of forecasts and the model's ability to predict continuity of local transportation services. The exclusion of reinforcement learning-based scheduling had a similar negative effect in that it caused longer wait times for vehicles as well as decreased efficiency from a utilization perspective [38]. Thus, it is concluded that both spatial contexts based learning and adaptive optimization of scheduling are critical to achieving robust management of intelligent transportation systems.

The suggested framework is useful for technical applications in next-generation Internet of Things-enabled smart transportation/logistics infrastructures. For example, real-time scheduling for intelligent public transport, adaptive ridesharing, autonomous fleet management, congestion-aware transport planning, and demand-sensitive urban mobility optimization can all be achieved in denser metropolitan environments. Further, real-time Internet of Things sensing and adaptive artificial intelligence scheduling provide a scalable basis for future smart city transport ecosystems.

While the experimental results are encouraging, there are numerous outstanding issues to address through potential future research. In the real world, there will often be incomplete information from sensing about transport, noisy observations about mobility, latency in communication, and

potential disruption that will lead to lower accuracy in the forecast and provide stability in scheduling. The current implementation of this framework is also based on centralized optimization through reinforcement learning and may need to be expanded to include distributed multi-agent scheduling architectures for ultra-large-scale transport systems. Future work may also be able to take advantage of graph neural networks, attention-based spatio-temporal learning, federated transport intelligence and co-ordination between multiple modes of transport to provide further scalability, robustness and consistent adaptation to real-time intelligent transportation. Centralized DQN is suitable for use with small and medium-sized networks but becomes more computationally intense as the size of the network increases, due to the increased number of zones and vehicles involved. However, in the case of a metropolitan-scale deployment, regional agents can be formed, and they may use MARL techniques to distribute the scheduling among them, while still being able to coordinate the allocation of vehicles to the zones. Moreover, the practical IoT conditions were considered to evaluate the robustness of the proposed system, which included missing signal data between 10-30%, communication delay, and localized increases in demand. All these factors indicate a realistic disturbance in real-time transportation sensing and allow to test the reliability of the predictive and scheduling system.

6. Conclusion and Future Work

The research studies a unified intelligent transportation optimization framework that integrates cluster-aware spatial-temporal demand for transportation prediction and reinforcement learning-driven dynamic adaptive scheduling for urban mobility management in real-time. Unlike conventional approaches to managing transportation, which deal with predicting and scheduling tasks independently of each other, this proposed framework follows a closed-loop intelligent decision-making architecture so that the way to allocate transportation resources continuously adjusts based on changes in urban mobility demands.

For example, the forecasting portion of the overall framework utilizes convolutional spatial feature extraction with GRU-based sequential learning to provide highly effective transportation demand prediction in heterogeneous urban areas and employs DBSCAN-generated spatially contextualized representations to increase accuracy in predicting transportation demands. This enables the system to successfully account for both localized transportation dynamics and inter-regional continuity in the forecasted predictions of transportation demand as they change rapidly due to fluctuating demand.

To convert the anticipated demand for mobility into operational transportation decisions, an adaptive scheduling strategy has been developed that makes use of RL to allocate resources for transportation, considering both adaptive congestion and fleet coordination within the system. The RL scheduling framework interacts with its transportation environment on an ongoing basis, using reward-driven learning to continuously augment long-term transportation allocation policies. This ability to adaptively optimize resources allows for more efficient mitigation of congestion, less passenger wait time, more balanced use of the transportation resource, and improved scalability of operations relative to the constantly changing transportation conditions in urban areas.

Results from experiments show that the new adaptive scheduling framework consistently outperforms traditional GRU, CNN-GRU, static scheduling, and heuristic-based methods for both transportation resource allocation and scheduling. Integrating cluster-aware spatial learning into the overall scheduling process greatly enhances the consistency of forecasting demand for transportation, while using RL-based scheduling significantly improves responsiveness to demand for transportation and improves efficiency in resource allocation. In addition, ablation analysis shows that both the context of spatial representation as well as the intelligence associated with adaptive scheduling contribute significantly to the overall operations success of the framework.

The intelligent transportation system proposed by this framework provides operational scalability beyond just accurate forecasting. It represents the future of Integrated solutions providing intelligent transportation services within next-generation cities with smart, IoT infrastructures. Results from this new operational framework will provide for real-time coordination of transportation services, adaptive public transit scheduling, intelligent fleet management, optimization of mobility based on congestion, and demand-sensitive planning across large metropolitan areas. In addition, by learning and adapting continuously to the uncertain nature of transportation systems, this operating framework provides a viable foundation for future intelligent urban mobility systems.

Though there has been considerable promise in the results of this research framework for improving the performance of intelligent transportation systems; there are several research challenges still to be addressed in future research. Specifically, the operating framework currently assumes a centralized approach for transportation scheduling, as well as dependable IoT sensing data for measuring mobility. When transportation systems in the real world operate, there may be different levels of mobility observation data, either due to communication delays or poor performance of the IoT sensors, and there will also be significant fluctuations in environmental conditions and other elements that create uncertainty about the current state of transportation [39]. Therefore, in future research, the researchers will focus on the use of distributed multi-agent reinforcement learning architectures; spatio-temporal transportation modelling with graph neural networks;

federated intelligence applications for transportation; and the use of edge devices to assist large-scale scheduling optimization in real-time for smart transportation ecosystems. Future research may also include the integration of multiple modes of transportation between transportation providers; coordination of autonomous vehicles; developing energy-efficient schedules for transportation; and carbon reduction strategies in developing sustainable, scalable, and deployable intelligent transportation systems.

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