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International Journal of Artificial Intelligence and Machine Learning
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Research Paper
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Adaptive Graph Neural Network Model For Traffic Flow Prediction In Intelligent Urban Transportation Systems

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Abstract
Urban traffic flow is dynamic, influenced by temporal demand, roadway interactions, incidents, and fluctuating mobility patterns, creating challenges for accurate prediction and responsive transportation management. Existing approaches often inadequately represent evolving spatial dependencies and temporal variations across interconnected road networks. The research develops a Dynamic Cat Swarm Optimizer-tuned Adaptive Graph Neural Network (DCSO-AGNN) for accurate traffic flow prediction within Intelligent Urban Transportation Systems. The Los Angeles Metropolitan Traffic (METR-LA) dataset with 207 sensors and 34,272 observations and the Bay Area Performance Measurement System (PEMS-BAY) dataset with 325 sensors and 52,116 observations, recorded at 5-minute intervals, were used for traffic-flow prediction. Data pre-processing employs Savitzky–Golay Filtering to suppress sensor noise and preserve temporal traffic patterns, followed by Robust Scaling to normalize heterogeneous traffic variables. Feature extraction uses Principal Component Analysis (PCA) to derive representations while reducing redundancy, complemented by temporal lag construction to preserve traffic behaviour. Processed observations are organized as graph-structured inputs, and connectivity relationships form edges. AGNN learns changing spatial dependencies and propagates information across connected road segments to capture evolving traffic conditions. Dynamic Cat Swarm Optimizer (DCSO) tunes AGNN parameters to improve convergence, stability, and generalization. The integrated DCSO-AGNN predicts traffic flow by jointly learning spatial interactions and temporal patterns, supporting traffic monitoring. Overall, DCSO-AGNN achieved the lowest Mean Absolute Error (MAE) of 3.12, Root Mean Square Error (RMSE) of 5.52, and Mean Absolute Percentage Error (MAPE) of 7.94%, confirming improved traffic-flow prediction accuracy using python. The model supports traffic forecasting and strengthens decision-making for responsive, efficient, and sustainable Intelligent Urban Transportation Systems.

Keywords: Traffic Flow Prediction, Intelligent Transportation Systems, Urban Mobility, Traffic Forecasting, Smart Cities, Transportation Management.

1. Introduction

Urban transportation systems are integral to the functioning of modern cities—providing mobility that is essential for everyday life, economic activity and accessibility, and efficient movement of people in increasingly interconnected metropolitan areas around the world (Tao et al., 2023). Traffic flow prediction can be used in intelligent transportation systems to provide kind of forward-looking information that can enhance the operational awareness, transportation planning, network coordination and timely mobility management decision (Salla et al., 2026). Reliable traffic forecasting contributes to smoother urban mobility by helping transportation authority's anticipate changing traffic states and coordinate responses across interconnected roadway environments more effectively (Mrudula et al., 2024).

Accurate prediction plays an important part in adaptive signal coordination, route guidance, congestion detection, incidents handling, safety, and service reliability in transportation systems (Xu et al., 2024). Traffic conditions exhibit intricate relationships across neighbouring road segments because vehicle movements propagate through connected transportation networks and influence downstream and upstream traffic states dynamically (Musa et al., 2023). Road networks are graph-based systems, with road segments and intersections as nodes and the relationships between them reflecting network structure, making it a natural model for transportation networks (Skoropad et al., 2025). Graph Neural Networks (GNNs) have become very important in traffic prediction as they enable the exchange of information between interlinked regions and provide a representation that preserves the network relations in transportation (Chen and wan Zhang, 2024). Modern research has shown that adaptive graph learning can uncover hidden relationships apart from static connectivity, making it possible to represent evolving dependencies between traffic regions (Ali et al., 2025).

Time-dependent traffic behaviour includes both regular and evolving patterns that correspond to different travel cycles, commuting times, and demand changes in varied urban transportation infrastructures (Pan et al., 2025). Consequently, the integration of adaptive spatial models with temporal learning enables a more comprehensive analysis of traffic dynamics and the ability to forecast traffic flows in a network of interconnected road networks (Ramana et al., 2023). The adaptive GNN framework is an advanced tool for representing evolving traffic relations while preserving structural characteristics required for intelligent transportation systems (Mohsen, 2024). Therefore, the development of adaptive graph learning in traffic flow prediction would enhance intelligent transportation through responsiveness and sustainable decisions regarding mobility management and operations (Abdullah et al., 2023). The traffic flow prediction was explored in (Rajagopal et al., 2025). This approach combines the advantages of Neural Ordinary Differential Equations (NODEs). Results on Los-loop demonstrated strong predictive performance, while the method remains limited by computational complexity, scalability, and reliance on city-specific traffic data.

The existing approach faces limitations related to computational complexity, scalability, and dependence on city-specific traffic characteristics, which may restrict broader transportation applications. To overcome these drawbacks, the Dynamic Cat Swarm Optimizer-tuned Adaptive Graph Neural Network (DCSO-AGNN) model that facilitates the learning of evolving traffic relationships while effectively lowering computational demands and enhancing generalization performance across different urban transportation networks. The research key contributions as follows:

- The advanced DCSO-AGNN model is intended to give precise predictions of the traffic flow in Intelligent Urban Transportation Systems.
- The traffic flow data is gathered from the roadway sensor datasets, which include transportation measurements such as traffic volume, across different urban traffic scenarios.
- Robust Scaling and Savitzky–Golay Filtering are applied for data preparation, while Principal Component Analysis (PCA) and temporal lag construction generate informative representations of traffic behaviour.
- The DCSO-AGNN model combines Adaptive Graph Neural Networks (AGNNs) for modelling dynamic spatial interactions with Dynamic Cat Swarm Optimization (DCSO) for optimizing AGNN parameters and enhancing prediction accuracy.
- The results show MAE, RMSE, MAPE, computational efficiency, and convergence behaviour, demonstrating improved prediction accuracy, robustness, generalization, and transportation decision-support capability.

The article is organized as follows: introduction is presented in Section 1. Section 2 summarizes the related literature on traffic flow prediction transportation systems. In Section 3, the proposed methodology consists of data collection, data pre-processing, feature extraction, AGNN modelling, and DCSO. Experimental results and analysis are described in Section 4. Conclusions and future work are provided in Section 5.

2. Related Works

This section highlights previous research works done in the field of traffic flow prediction by reviewing the applied learning approaches, graphical models, key findings, and identified limitations in order to justify the need for the DCSO-AGNN model.

2.1 Spatial-Temporal Learning for Traffic Prediction

The traffic flow prediction in Transportation Cyber-Physical Systems (T-CPS) was investigated by (Ali et al., 2025). The method combines multi-scale feature extraction, and dual attention mechanism. Results on two real-world datasets showed superior prediction performance compared with existing methods. The drawbacks were their dependence on specific graph inputs, high computational complexity, and difficulty in modelling highly dynamic traffic environments. The speed prediction model based on modelling road segments along with their spatial-temporal relationships was introduced by (Sharma et al., 2023). This approach is based on the usage of GNNs with blocks using the architecture. Findings shows better prediction accuracy than other models. However, limitations include high computational costs and requirement for traffic data across the entire network. (Velez-Serrano et al., 2021) for enhanced short-term traffic flow prediction in peak-hour traffic congestion. The Convolutional Residual Neural Network (CRNN) uses residual convolutional learning to forecast traffic flow and is compared with classical time-series methods. Results show that CRNN achieves superior performance across the evaluated metrics while adapting effectively to holidays and potential sensor failures. Limitations include dependence on traffic sensor quality and the need for validation across additional cities and diverse traffic conditions.

2.2 Dynamic Graph Learning for Traffic Prediction

Ma et al., (2024) enhanced Unmanned Aerial Vehicle (UAV) based traffic flow forecasting through overcoming problems of over smoothing and dynamic traffic relations. In this approach, Neural Ordinary Differential Equations (NODEs) have been employed in conjunction with evolutionary Graph Neural Networks (GNNs), and the semantic adjacency matrix is updated continually. The results obtained from different real-world datasets demonstrated better performance. Limitations include computational complexity and dependence on UAV-derived traffic data. Ali et al., (2024) traffic flow prediction through learning the dynamic spatial-temporal relationships. The technique uses a Spatiotemporal Attention Unit (STAU) for aggregating the features of neighbouring nodes with edge-cloud infrastructure. Experimental results using data sets demonstrate that the method surpasses the existing state-of-the-art method. Limitations included with infrastructure, computation, and scalability arise. The Multi-step traffic flow prediction based on the identification of dynamic spatial interactions and effects of traffic incidents was examined in (Ye et al., 2023). The approach involves multiple graphs, dynamic graph updating. Results on two real-world datasets demonstrate improved prediction performance over baseline models. The drawbacks are data dependency and computational intensity.

2.3 Adaptive Graph Neural Networks for Traffic Forecasting

Xiong et al., (2024) examined the traffic-flow prediction by capturing dynamic spatial and nonlinear temporal dependencies. The approach combines expanded causal convolution, and channel attention. Results show improvements for 60-minute prediction, while limitations include computational complexity and generalization across diverse road networks. The short-term traffic-flow prediction by capturing hidden spatial and temporal relationships was developed by (Li et al., 2022). The GNN integrates temporal and spatial features through graph-based learning to identify their underlying interactions. Experimental findings from real-life datasets show enhanced speed prediction for traffic speeds relative to existing models, although there are drawbacks such as high dependency on fluctuating traffic data and wider validation required across multiple road networks.

2.4 Optimization-Based Traffic Flow Prediction

Traffic Flow Forecasting based on the Optimization of Spatial-Temporal Feature Learning was developed by (Choudhary et al., 2026). The methodology integrates GNN and parameter tuning of the network. The outcomes reveal better performance of the prediction and its scalability. Limitations involve the computational efficiency and difficulty with the parameter tuning. Traffic-flow forecasting with the help of real-time data was investigated (Brimos et al., 2023). Temporal Graph Convolutional Network (TGCN) and Diffusion Convolutional Recurrent Neural Network (DCRNN) capture the complex dependencies in traffic data. Results show that both models outperform baselines. Limitations include dependence on real-time OGD availability, data quality, and computational requirements for large-scale traffic networks.

2.5 Research gap

Existing methods suffer from limitations like high computational complexity, dependence on particular types of graphs. (Ali et al., 2025) observed that there were high computational complexities and dependence on specific graph input. (Sharma et al., 2023) stated that there was a need for traffic data in the whole network and computational complexities. (Xiong et al., 2024) noted there were complexities and lack of generalizability to various road networks. (Choudhary et al., 2026) observed there were limitations in terms of computational efficiency and parameter tuning. DCSO-AGNN mitigates these limitations with adaptive graph learning and DCSO-based parameter optimization, thus enhancing spatial dependency modelling, convergence stability, and traffic flow prediction accuracy in diverse road networks.

3. Methodology

Accurate traffic flow forecast in Intelligent Urban Transportation Systems through the proposed DCSO-AGNN model. Figure 1 shows the overall DCSO-AGNN framework for adaptive traffic-flow prediction and intelligent transportation applications. The METR-LA dataset with 207 sensors and PEMS-BAY dataset with 325 sensors are collected from roadway sensor datasets. Pre-processing applies Savitzky–Golay Filtering for reduce the sensor nodes and Robust Scaling for normalization. PCA and temporal lag construction extract informative spatial and temporal representations. The DCSO-AGNN model then learns dynamic spatial dependencies and optimizes network parameters for reliable traffic forecasting.

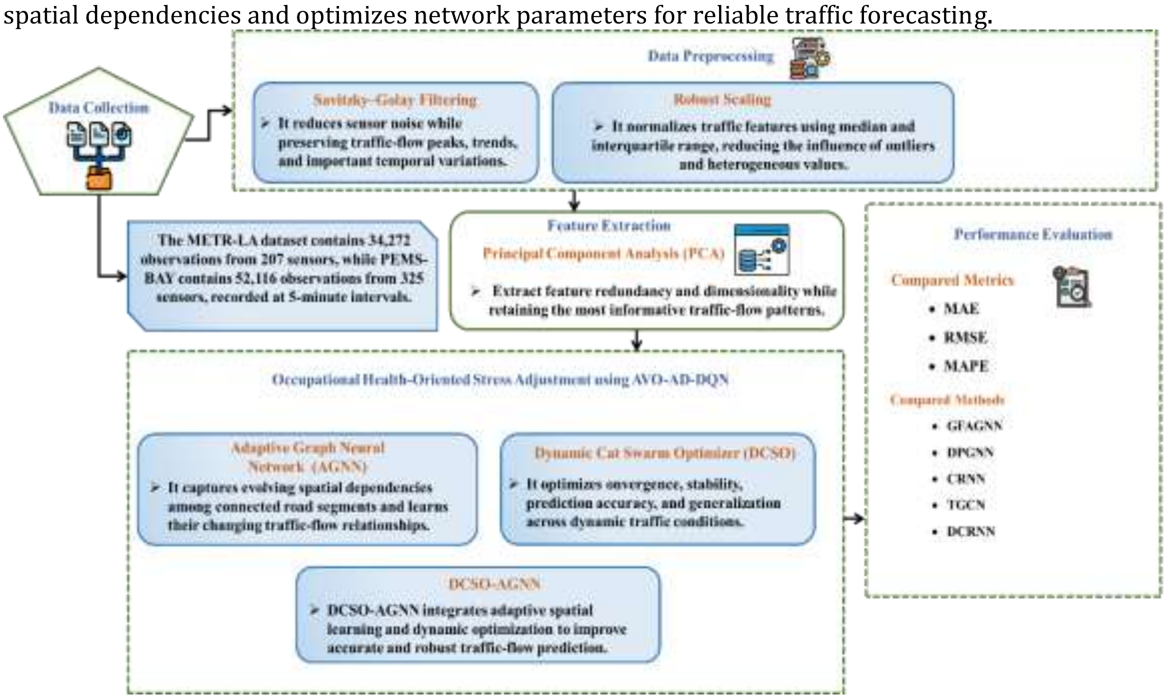


Figure 1. Overall DCSO-AGNN framework integrating adaptive graph learning, optimization, prediction, and intelligent transportation applications.

3.1 DCSO-AGNN Model for Adaptive Traffic Flow Prediction

The DCSO-AGNN integrates a DCSO with an AGNN to improve traffic flow prediction. The AGNN models temporal traffic variations in history, and captures the dynamic spatial relationships between interconnected road segments. The DCSO learns the optimal values of important AGNN parameters, such as the learning rate, dimension of the hidden layer, aggregation parameters and regularization constants, with a focus on minimizing the prediction error on the validation data. The feature-embedding layer transforms raw traffic features into compact hidden representations. The attention-based propagation layer assigns adaptive weights to neighboring road nodes. The adaptive graph-learning layer captures changing spatial dependencies. The output prediction layer maps the learned representations to traffic-flow estimates. This hybrid integration enables DCSO to systematically optimize AGNN hyperparameters through fitness-based evaluation, global-best-guided tracing, adaptive acceleration, local neighborhood search, and convergence-based selection, with the validation prediction error as the fitness objective, thereby identifying the parameter configuration that minimizes traffic-flow prediction error, and AGNN to learn adaptive spatial representations of traffic networks. The model thus enhances the accuracy of prediction, stability of convergence and adaptability in varying traffic conditions.

3.2 Adaptive Attention-Driven Graph Learning for Dynamic Traffic Flow Prediction

To improve traffic flow prediction by introducing an AGNN that extends the attention-based graph propagation mechanism to capture dynamic and heterogeneous relationships among interconnected road segments. Conventional graph neural networks generally employ fixed propagation patterns, which may not adequately represent the changing relevance and strength of neighboring road nodes under varying traffic conditions. Therefore, the attention-based propagation mechanism is adopted as the foundation and further improved into an AGNN, where the propagation weights dynamically adjust according to the learned states of neighboring traffic nodes. This adaptation allows for the model to give more weight to more pertinent road sections and less weight to less pertinent connections.

GCN and other graph neural networks generally use static propagation, which remains unchanged across layers, and non-adaptive propagation, which ignores node states. Such propagation cannot identify the varying relevance or strength of neighboring road nodes for predicting target-node traffic flow, particularly under dynamic traffic conditions. Therefore, the Attention-based Graph Neural Network is enhanced into an AGNN with dynamic and adaptive propagation. The sensors on the roads are denoted by nodes and the edges are built based on road connectivity as well as the proximity of the sensors. Road connections describe the direct interaction between traffic, but proximity describes spatial interaction between sensors. This set of edges provides AGNN the ability to learn the importance of the neighboring nodes in relation to the current traffic states.

The attention mechanism learns neighbor relevance from traffic-node states and assigns higher weights to more influential neighbors, while a single scalar parameter $\beta(t)$ at each intermediate layer maintains model simplicity. This mechanism enables layer-wise dynamic propagation, adaptive spatial-dependency learning, and improved representation of changing traffic-flow patterns. A feature-embedding layer maps the input traffic-flow features of road nodes into an averaged hidden representation, and the feature embedding $W^{(0)} \in R^{d_x \times d_h}$ is trained as a part of the model is represented as equation (1)

$$H^{(1)} = \mathrm{ReLU}(XW^{(0)}) \tag{1}$$

Here $H^{(1)}$generates the initial hidden representation of traffic nodes. Here, X denotes the input traffic-feature matrix, $W^{(0)}$ represents trainable embedding weights, H is the number of road nodes, and ReLU introduces nonlinearity. This is followed by attention-guided propagation layers, each parameterized by a learnable propagation parameter, as described in Equation (2).

$$H^{(t+1)} = P^{(t)}H^{(t)} \tag{2}$$

Here, $H^{(t+1)}$ is the current node representation, $P^{(t)}$is the adaptive propagation matrix, and $H^{(t)}$ is the updated traffic-node representation. The propagation matrix is also a function of the input states and is set to zero for absent edges, such that the output row vector of node i is expressed as Equation (3).

$$H_i^{(t+1)} = \sum_{j \in N(i) \cup \{i\}} P_{ij}^{(t)} H_j^{(t)} \tag{3}$$

Here, $H_i^{(t+1)}$is the updated representation, $\sum_{j\epsilon}$ N(i) denotes neighboring road nodes, $H_j^{(t)}$is neighbor j's current representation, $P_{ij}^{(t)}$ is its adaptive attention weight, t and ∪ denotes the graph layer. The output layer has a weight $W^{(1)}$ is signified as equation (4)

$$Z = f(X, A) = \mathrm{softmax}\left(H^{(l+1)} W^{(1)}\right) \tag{4}$$

Here, Z denotes the output prediction, X represents input traffic features, A denotes the graph adjacency matrix, $H(l+1)$ is the final hidden representation, $W^{(1)}$is the trainable output weight matrix, and $softmax$ converts outputs into normalized prediction probabilities. $f(X, A)$ denotes the graph-based prediction function that maps the learned node representations and graph structure into the final traffic-flow prediction. The attention from node is formulated as equation (5)

$$P_{ij}^{(t)} = (1/C)e^{\beta(t)\cos(H_i^{(t)}, H_j^{(t)})} \tag{5}$$

Here, $P_{ij}^{(t)}$ is the attention weight, $1/C$ is the normalization constant, $e^{\beta(t))}$controls attention strength, $cosH_i^{(t)}$ and $H_j^{(t)}$ represent node states, and cosine similarity measures their traffic-feature similarity. The enhanced AGNN adaptively captures dynamic spatial dependencies among road nodes, assigns importance to influential neighbors, and generates robust traffic-flow representations, improving prediction accuracy under changing traffic conditions.

3.3 DCSO-Based Adaptive Optimization Mechanism for Traffic Flow Prediction Accuracy

The standard CSO algorithm may suffer from premature convergence because of limited population diversity and insufficient global-best guidance. The proposed DCSO addresses these drawbacks by using global-best guidance, adaptive acceleration parameters, modified velocity updates, and local neighborhood search which increases diversity, balances exploration and exploitation, prevents premature convergence, and efficiently finds optimal parameters for accurate dynamic traffic-flow prediction across interconnected road networks. To identify potential hyperparameters and optimize the convergence process, DCSO employs the global-best cat position as a basis to help cats learn through tracing. The total population size is 20 with 50 iterations. The parameter space is defined as follows: learning rate = [0.0001, 0.01]; hidden units = [32, 256]; dropout = [0.1, 0.5]; batch size = [16, 128]. Random cat initialization is employed in this range, and MAE on the validation data is used as the fitness function.The optimal global position of the cat is expressed by equation (6-7).

$$X_{j\,new}^{d+1} = (1-\beta) * X_j^d + \beta * p_g + V_j^d \tag{6}$$

$$V_{j\,new}^{d+1} = V_j^d + \beta\left(p_g - X_j^d\right) + \propto * \epsilon \tag{7}$$

Here, $X_{j\,new}^{d+1}$ is the new position, X_j^d is the current position, $1-\beta$ controls global-best influence, p_g denotes the global best position, and V_j^d represents the current velocity. The α parameter follows a decreasing function, whereas β follows an increasing function. $V_{j\,new}^{d+1}$ is the new velocity, V_j^d is current velocity, β controls global guidance, $\propto$ controls exploration, and ϵ is a random vector. d denotes the dimension index of the solution vector, and j represents the iteration index used to update the corresponding optimization variable. Their adaptive values are computed using the following equation (8-9)

$$\propto(t) = \propto_{max} - \left\{\frac{\propto_{max} - \propto_{min}}{t_{max}}\right\} * t \quad (8)$$

$$\beta(t) = \beta_{min} + (\beta_{max} - \beta_{min}) \sin\left\{\frac{\pi t}{t_{max}}\right\} \quad (9)$$

The equations (8-9) define the adaptive acceleration parameters used to balance exploration and exploitation. In Equation (8), $\propto(t)$ decreases from $\propto_{max}$ to $\propto_{min}$, where t is the current iteration and t_{max} is the maximum iterations. In Equation (9), $\beta(t)$ denotes the adaptive acceleration coefficient, while β_{min} and β_{max} represent its minimum and maximum values. These parameters regulate global-best guidance, balancing exploration and exploitation to identify AGNN hyperparameters that minimize traffic-flow prediction error. The term $\sin\left\{\frac{\pi t}{t_{max}}\right\}$ provides a smooth nonlinear variation of $\beta(t)$.

3.3.1 Local Search Method

A local search mechanism is incorporated into the tracing phase of DCSO to improve the quality of the selected hyperparameter configuration. The mechanism helps to steer the search to a good combination of parameters and minimizes the chance of being trapped in local optima, using the neighborhood information. In DCSO, the candidate solution is defined as equation (10-11)

$$Neighbor\ of[X_{gb}] = [X_{gbest} - r, X_{gbest} + r]^n \quad (10)$$

$$X_{gb}(k) = MIN\{X_{gb}^1(k), \ldots X_{gb}^L(k), \ldots, X_{gb}^n(k)\} \quad (11)$$

Here $Neighbor\ of[X_{gb}]$ represents the neighborhood of the current global-best solution, X_{gbest} denotes the best position, r defines the neighborhood boundary, and n is the population size. In $X_{gb}(k)$ denotes the best solution at iteration k, $X_{gb}^L(k)$ represents the Lth candidate solution, and MIN selects the minimum-fitness solution. DCSO efficiently explores promising parameter sets, balances exploration/exploitation, avoids premature convergence, and adapts traffic flow prediction between connected road networks under dynamic traffic conditions. Figure 2 shows DCSO-AGNN, which involves adaptive graph learning, guided attention propagation, and node updating of traffic features. The DCSO performs global and local search for AGNN hyperparameter optimization, leading to improved convergence, stability, generalization, and prediction accuracy.

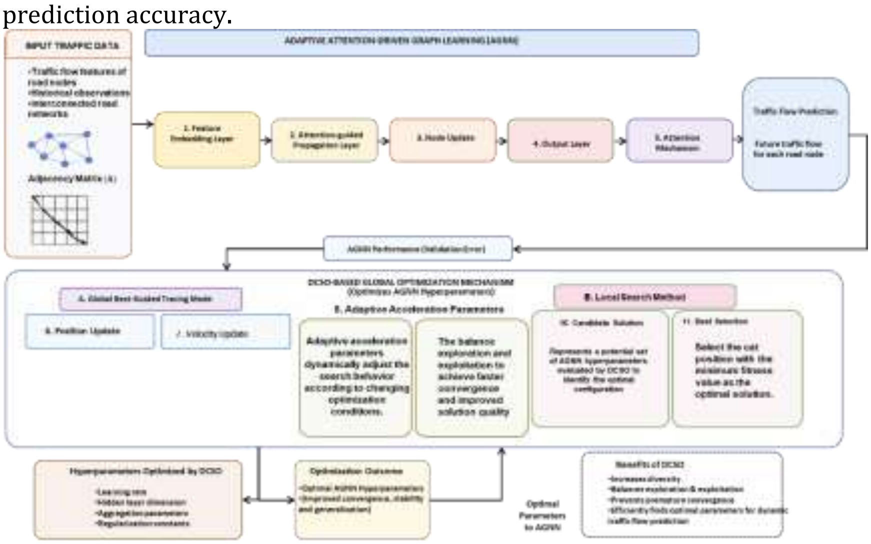


Figure 2. Architecture of DCSO-AGNN for adaptive traffic flow prediction and optimization

The proposed model DCSO-AGNN incorporates both adaptive graph-based spatial learning and parameter optimization using DCSO. AGNN detects the dynamic spatial dependencies and traffic relations between road sensors that are interconnected. DCSO discovers the optimal AGNN parameters. Algorithm 1 describes the proposed procedure of the DCSO-AGNN model used to predict traffic flow.

Algorithm 1: DCSO-AGNN for Adaptive Traffic Flow Prediction

Input:
$D \rightarrow Traffic - flow\ dataset$
$N \rightarrow Number\ of\ cat\ solutions$
$MaxIter \rightarrow Maximum\ DCSO\ iterations$
$X \rightarrow Traffic - feature\ matrix$
$A \rightarrow Road - network\ adjacency\ matrix$
$H \rightarrow Initial\ AGNN\ hyperparameters$
Output:
$M \rightarrow Optimized\ DCSO - AGNN\ model$
$Z \rightarrow Predicted\ traffic\ flow$
Begin
$Load\ traffic - flow\ dataset\ D\ and\ preprocess\ the\ traffic\ features.$
$Construct\ the\ road - network\ graph\ using\ X\ and\ A.$
$Initialize\ AGNN\ using\ hyperparameters\ H.$
$Generate\ initial\ traffic - node\ representations\ using\ H(1) = ReLU(XW(0)).$
$Apply\ adaptive\ attention\ propagation\ to\ capture\ spatial\ relationships\ among\ connected\ road\ nodes.$
$Initialize\ N\ cat\ positions\ Xjd, velocities\ Vjd, and\ global - best\ position\ Pg.$
For $iteration\ t = 1\ to\ MaxIter$
- $Evaluate\ the\ fitness\ of\ each\ cat\ using\ AGNN\ validation\ prediction\ error.$
- $Calculate\ adaptive\ \alpha(t)\ and\ \beta(t).$
- $Update\ cat\ positions\ using\ global - best\ guidance.$
- $Update\ cat\ velocities\ using\ global\ guidance\ and\ random\ exploration.$
- $Select\ the\ cat\ with\ minimum\ validation\ error\ as\ the\ global\ best.$
- $Generate\ neighborhood\ solutions\ around\ Xgbest\ using\ boundary\ r.$
- $Select\ the\ minimum - fitness\ neighborhood\ solution.$

End For
$Assign\ the\ optimal\ DCSO\ parameters\ to\ AGNN.$
$Train\ the\ optimized\ AGNN\ and\ generate\ traffic - flow\ prediction\ Z.$
$Evaluate\ M\ using\ RMSE, MAE, MAPE, and\ R2.$
$Output\ M\ and\ Z.$
End

The DCSO-AGNN adaptively learns dynamic spatial dependencies among interconnected road nodes while DCSO optimizes critical parameters, enabling robust representation of changing traffic patterns and improving accurate, reliable traffic-flow prediction under dynamic urban conditions.

3.4 Data Collection

The METR-LA data was collected from open-source Kaggle (https://www.kaggle.com/datasets/annnnguyen/metr-la-dataset). The dataset is a real-world dataset pertaining to traffic speeds, measured using 207 loop detectors deployed across highways in Los Angeles County. This dataset has a total of 34,272 temporal instances, measured every 5 minutes, giving about 7.09 million sensor time instances. The data were collected for about four months, starting from March and ending June 2012.

The PEMS-BAY dataset was collected from open source Kaggle (https://www.kaggle.com/datasets/scchuy/pemsbay). It is a realistic speed traffic dataset obtained from 325 sensors deployed in the San Francisco Bay area. There are 52,116 time instances captured every five minutes in the dataset, giving a total of roughly 16.94 million sensor-time instances. The period covered by the dataset spans roughly six months starting from January 2017 to June 2017.

A 70% training, 15% validation, and 15% testing split was applied chronologically to both datasets, ensuring temporal order and preventing data leakage.

3.5 Pre-Processing For Reliable Traffic Representation

Traffic data pre-processing ensures accurate traffic prediction through improved consistency, reduced measurement errors, and retention of realistic traffic patterns. Savitzky–Golay Filtering method is used to filter out sensor noise and ensure temporal continuity, while Robust Scaling is utilized to normalize traffic variables and limit the effect of outliers.

3.5.1 Savitzky–Golay Filtering (SGF) for Traffic Sensor Noise Reduction

After collecting the data, reprocessing is performed to improve data quality and generate reliable inputs for subsequent traffic flow prediction. SGF is used to smooth out high frequency sensor noise and fluctuations in measurements without altering the overall traffic-flow trends, local variations, and temporal characteristics. This filtering is done by fitting a low degree polynomial over a rolling window according to Equations (12).

$$c = (M^t M)^{-1} M^t \rho \tag{12}$$

Here c denotes the SG smoothing coefficient vector, M represents the polynomial design matrix, M^t is its transpose, and $(M^t M)^{-1}$ denotes the inverse matrix. ρ is the central-value selection vector, determining the filtered traffic-flow value from the fitted polynomial coefficients. SGF successfully reduces noise from sensors and measurement variations, maintaining temporal traffic patterns intact to generate smooth traffic representations.

3.5.2 Robust Scaling for Consistent Traffic Data Representation

After using Savitzky-Golay filtering, robust scaling technique is used to standardize traffic variables such as volume, speed, and occupancy by median and interquartile range. It helps in reducing the effect of outliers and variation of traffic on traffic flow data but keeps the true distribution of traffic flow data. It is represented as equation (13)

$$x_{scaled} = \frac{x - Q_2}{Q_3 - Q_1} \tag{13}$$

Here, x denotes the original traffic observation, Q_2 represents the median, Q_1 and Q_3 denote the first and third quartiles, respectively, and x_{scaled} is the normalized value obtained using the interquartile range $Q_3 - Q_1$. Robust Scaling generates stable, comparable traffic representations by reducing outlier influence and scale differences, supporting reliable feature learning and improving the consistency of subsequent traffic flow prediction.

3.6 PCA for Informative Traffic Feature Extraction

After preprocessing, PCA is applied to transform the correlated traffic features into a smaller number of components, thereby retaining the variation in traffic data. This ensures that there is no redundancy in the features and enables succinct traffic prediction. The PCA transformation is represented as equation (14-15)

$$\sum = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x})^T (x_i - \bar{x}) \tag{14}$$

$$Y = X * W \tag{15}$$

Equation (14) calculates the covariance matrix, where $\sum_{i=1}^{N}$ denotes the number of observations, x_i represents the $i-th$ traffic feature vector, $\bar{x}$ denotes the mean vector, and T indicates matrix transposition. N denotes the total number of traffic observations, while $\sum$ represents the summation of the covariance contributions from all N observations. Equation (15) performs PCA transformation, where X is the normalized traffic feature matrix, W contains eigenvectors, and Y represents the transformed principal-component feature matrix. PCA provides compact and information-rich traffic representation through the elimination of redundancies and reduction of dimensionality while retaining the dominant traffic variations, facilitating effective feature extraction and accurate traffic flow prediction.

4. Evaluation Metrics

The following Assessment metrics like MAE, RMSE, and MAPE were considered for evaluating traffic flow prediction performance.

Mean Absolute Error (MAE) is defined as the average of the absolute differences between observed and predicted values of traffic flow. The smaller the MAE, the more accurate the predictions of traffic flows. It is expressed as equation (16)

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{16}$$

where $\sum_{i=1}^{n}$ means the over-all amount of traffic observations, y_i signifies the traffic-flow value, and $\hat{y}_i$ denotes the predicted value. The absolute term $|y_i - \hat{y}_i|$ calculates each prediction error magnitude, while $\frac{1}{n}$ averages all errors to indicate overall prediction accuracy.

Root Mean Square Error (RMSE) quantifies the size of prediction errors and penalizes larger errors more heavily. Hence, a lower RMSE could imply that the prediction for traffic flow is more accurate and stable, especially when the avoidance of large deviations in traffic-flow prediction are considered important. It is expressed as equation (17)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{17}$$

where n designates the full quantity of traffic explanations, yi characterizes the definite traffic-flow value, and $\hat{y}_i$ denotes the predicted value. The squared error$(y_i - \hat{y}_i)^2$ emphasizes larger errors, while $1/n$ and $\sum$ calculates their mean and the square root returns the error to the original scale.

Mean Absolute Percentage Error (MAPE) is the average prediction error, in percentage of the value of the traffic-flow. The smaller the MAPE is, the closer the predictions are to the actual traffic flows in relation to traffic-flow level. It is stated as equation (18)

$$MPAE = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{18}$$

where n denotes the total number of traffic observations, y_i represents the actual traffic-flow value, and $\hat{y}_i$ denotes the predicted value. The ratio $y_i - \hat{y}_i$ and $\sum_{i=1}^{n}$ calculates the relative prediction error, while $100/n$ converts the average error into a percentage.

5. Result And Discussion

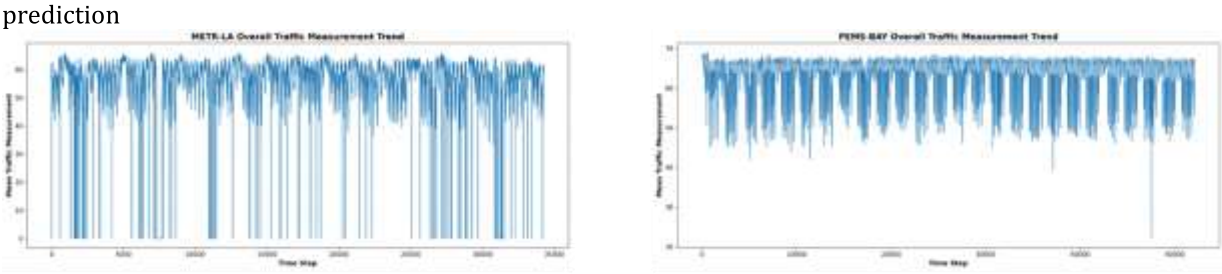
The DCSO-AGNN model is implemented using Python 3.11, PyTorch, PyTorch Geometric, Scikit-learn, NumPy, Pandas, NetworkX, Matplotlib and SciPy libraries. Experiments are conducted on Intel Core i9-13900K CPU, NVIDIA GeForce RTX 4090 24 GB memory GPU, and Windows 11 (64-bit) operating system. All the above traffic data preprocessing, construction of road networks graph, adaptive spatial-dependency learning, DCSO based hyperparameter optimization and traffic-flow prediction are supported by the experimental configuration. The effectiveness of DCSO-AGNN is measured by the traffic-flow prediction accuracy, comparative analysis, ablation analysis, convergence analysis, sensitivity analysis, and statistical significance testing with the existing graph-based and deep-learning models. The hyperparameters and training setting of the proposed DCSO-AGNN are shown in Table 1.

Table 1. Hyperparameter Settings and Training Configuration of the DCSO-AGNN Model

Hyperparameter	**Value**
Dataset	*METR − LA dataset and PEMS − BAY dataset*
Optimized Parameters	*Learning Rate, Hidden Dimension, Aggregation Parameter, Regularization Constant*
Initial Learning Rate	0.001
Hidden Dimension	128
Batch Size	64
Number of Epochs	200
Activation Function	*ReLU*
Dropout Rate	0.5
Loss Function	*Mean Squared Error*
DCSO Population Size	30
DCSO Maximum Iterations	50
Local Search Boundary (r)	0.05
Fitness Function	*Validation RMSE*

5.1 Experimental Findings

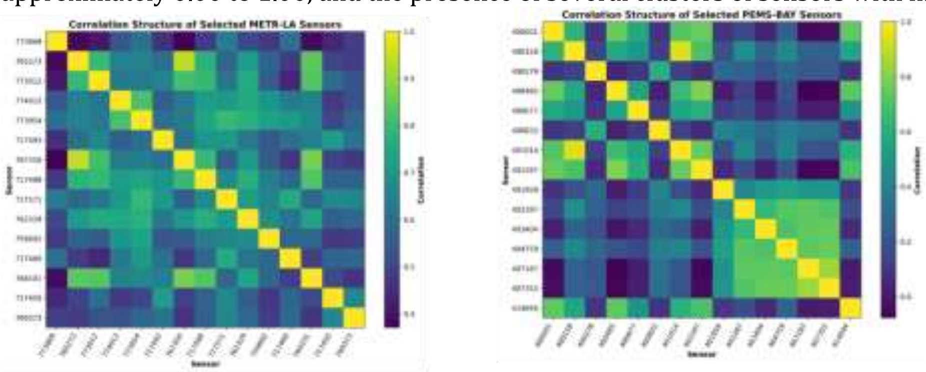
Experimental results demonstrate that DCSO-AGNN achieves improved traffic-flow prediction performance on both the METR-LA and PEMS-BAY dataset. The METR-LA measurements across approximately 34,000-time steps, mainly ranging from 50–65, with frequent drops toward 0 was shown in Figure 3 (a). Figure 3(b) presents PEMS-BAY measurements across approximately 53,000-time steps, predominantly ranging from 60–69, with intermittent declines to 40–50 and a minimum near 22, demonstrating substantial temporal variability. The METR-LA and PEMS-BAY traffic-flow graphs clearly show temporal variability, fluctuations, and abnormal drops, thus making noise filtering and traffic-flow prediction



(a) (b)

Figure 3. Traffic measurement trends for (a) METR-LA and (b) PEMS-BAY datasets across time steps recorded.

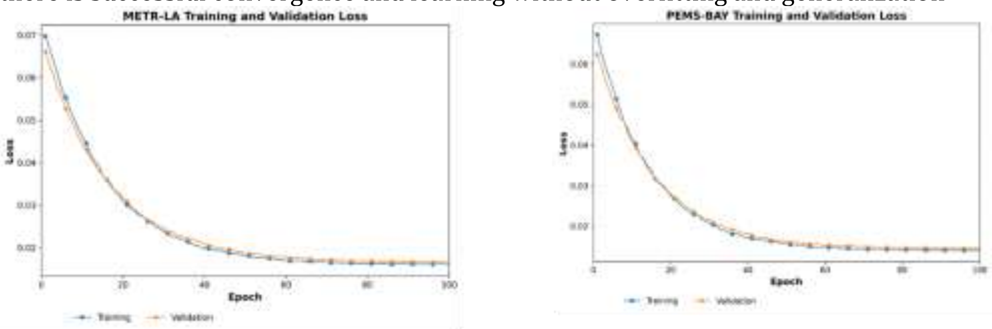
The correlation structure of selected METR-LA sensors, showing moderate to strong positive relationships ranging approximately from 0.4 to 1.00, was presented in Figure 4(a). The higher the correlation, the closer the traffic patterns and the higher the level of spatial dependence between road sensors that are connected. Figure 4(b) below shows the sensor correlations of the PEMS-BAY dataset, which are within the range of approximately 0.00 to 1.00, and the presence of several clusters of sensors with higher correlations.



(a) (b)

Figure 4. Correlation structures of selected sensors in (a) METR-LA and (b) PEMS-BAY datasets.

METR-LA Training and Validation Losses dropped progressively from 0.070 and 0.068 to 0.004, which is evidence of successful learning and convergence of the model, as shown in Figure 5(a). The relatively close training and validation loss curves indicate no obvious evidence of severe overfitting Figure 5(b) displays a similar trend for PEMS-BAY, as the training and validation losses dropped progressively from 0.065 to 0.015 before stabilizing. METR-LA and PEMS-BAY Training-Validation Loss Graphs depict the fact that there is successful convergence and learning without overfitting and generalization



(a) (b)

Figure 5. Training and validation loss convergence for (a) METR-LA and (b) PEMS-BAY datasets.

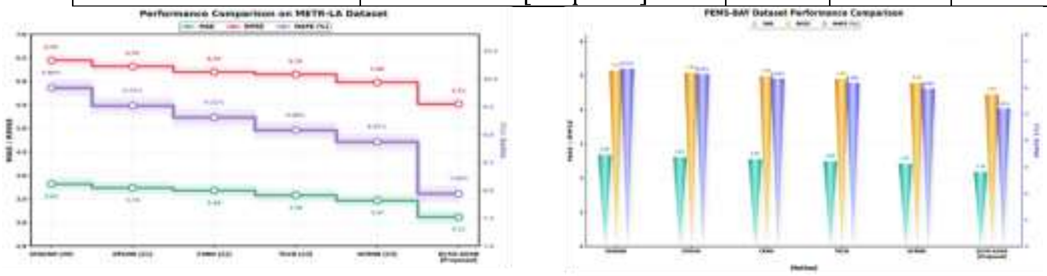
5.2 Performance Assessment On Traffic Flow Prediction Datasets

The Comparative analysis was conducted to compare the working of the proposed DCSO-AGNN with the other available models GFAGNN (Xiong et al., 2024) and DPGNN (Li et al., 2022) and CRNN (Velez-Serrano et al., 2021) and TGCN (Brimos et al., 2023) and DCRNN (Brimos et al., 2023) in the traffic-flow datasets METR-LA and PEMS-BAY. To ensure a fair comparison, all models were tested under the same experimental settings: The same preprocessing of the traffic features for the graph construction, the same training and test protocol, and the same evaluation settings. Three performance metrics, namely MAE, RMSE and MAPE were used to evaluate the performance and lower values signify a better prediction accuracy. The analysis shows the capability of DCSO-AGNN to identify dynamic spatial dependencies and enhance the traffic-flow prediction for both datasets.

Table 2. Comparative traffic-flow prediction performance of DCSO-AGNN against existing methods on METR-LA and PEMS-BAY datasets

Dataset	Method	MAE	RMSE	MAPE (%)
METR-LA dataset	GFAGNN	3.82	6.45	9.84
	DPGNN	3.74	6.32	9.52
	CRNN	3.68	6.20	9.31

	TGCN	3.58	6.15	9.08
	DCRNN	3.47	5.98	8.87
	DCSO-AGNN [Proposed]	3.12	5.52	7.94
PEMS-BAY dataset	GFAGNN	2.68	5.15	6.72
	DPGNN	2.61	5.08	6.51
	CRNN	2.55	4.98	6.34
	TGCN	2.49	4.90	6.18
	DCRNN	2.42	4.78	5.96
	DCSO-AGNN [Proposed]	2.18	4.45	5.21



(a) (b)

Figure 6. Performance comparison of DCSO-AGNN against methods on (a) METR-LA and (b) PEMS-BAY datasets.

Table 2 and Figure 6 (a) and (b) compares the forecasting performance of different models using MAE, RMSE, and MAPE. On the METR-LA dataset, the DCSO-AGNN model obtained the lowest MAE, RMSE, and MAPE scores of 3.12, 5.52, and 7.94%, respectively, better than those of DCRNN, which were 3.47, 5.98, and 8.87%, respectively. For PEMS-BAY, the values of MAE, RMSE and MAPE were 2.18, 4.45 and 5.21%, respectively, obtained by DCSO-AGNN. The proposed DCSO-AGNN model outperforms DCRNN values of 2.42, 4.78, and 5.96% on both benchmark datasets, showcasing superior forecasting accuracy.

5.3 Ablation Study For Model Component Validation

The ablation study was conducted to check the contribution of every part of the proposed DCSO-AGNN model using the METR-LA dataset for traffic-flow prediction. The configurations gradually introduce AGNN and DCSO and the individual and combined effect of adaptive graph learning and optimization are analyzed. The question is whether or not adaptive spatial representation and DCSO-based parameter optimization increase the prediction accuracy.

Table 3. Ablation Performance Comparison of DCSO-AGNN Components

Configuration	MAE	RMSE	MAPE (%)
w/o Savitzky–Golay Filter	4.21	6.83	10.47
w/o Robust Scaling	3.96	6.51	9.86
w/o PCA	3.78	6.28	9.42
w/o DCSO	3.64	6.11	9.17
GNN only	4.53	7.24	11.36
AGNN only	4.11	5.15	8.07
DCSO-AGNN [Proposed]	3.12	5.52	7.94

As illustrated in Table 3, the performance of the suggested DCSO-AGNN is the best for all the evaluation metrics where it yields the minimum values of MAE (3.12), RMSE (5.52), and MAPE (7.94%) as well, signifying the enhanced accuracy of traffic flow prediction. The results prove that the combination of adaptive graph learning with DCSO-based optimization successfully captures the dynamics of the traffic flow dependencies.

6. Discussion

Traffic-flow prediction accuracy was improved by integrating AGNN with DCSO for effective parameter optimization. The findings showed that AGNN was able to effectively capture dynamic spatial dependency whereas DCSO was capable of optimizing important parameters, which reduced the values of the MAE, RMSE, and MAPE and enhanced the accuracy and reliability of the traffic-flow prediction. The limitations of the existing methods can be summarized as follows: GFAGNN Xiong et al., (2024) may face limitations in adapting to rapidly changing traffic relationships; DPGNN (Li et al., 2022) can depend on effective graph representation; CRNN (Velez-Serrano et al., 2021) may struggle with long-term temporal dependencies; TGCN (Brimos et al., 2023) relies on predefined graph structures that may not fully capture dynamic spatial correlations; and DCRNN (Brimos et al., 2023) can be constrained by fixed graph topology, limiting its ability to represent evolving traffic dependencies. These limitations motivate adaptive graph learning and optimization. DCSO-AGNN addresses some of these limitations by incorporating adaptive spatial learning and optimization-based parameter tuning. The combination can help improve spatial representation, reduce prediction errors, improve adaptability of the system to traffic changes, and enhance robustness of the predictions using data.

6.1 Practical Implications

The DCSO-AGNN model may have applications in Intelligent Transport Systems (ITS) due to the capability of the proposed approach to improve traffic flow predictions within interconnected networks. Improved predictions mean that there will be more proactive ways to manage congestion, adapt traffic signals, develop routes, and predict travel times among other applications. In summary, both AGNN and DCSO models increase adaptability to varying traffic needs.

7. Conclusion

An enhanced traffic flow prediction model was constructed through the combination of AGNN and DCSO for spatial learning adaptation and effective parameter optimization. The data used were taken from METR-LA (207 sensors) and PEMS-BAY (325 sensors). Both the datasets were recorded at 5-minute intervals. Savitzky-Golay Filtering was used to remove the sensor noise, Robust Scaling for normalization of traffic variables, PCA for redundancy reduction, and temporal lag construction for preserving historical patterns. On the other hand, AGNN was used to capture the evolving spatial dependencies and DCSO for optimizing the critical parameters. Results predict the traffic flows effectively with MAE of 3.12, RMSE of 5.52, and MAPE of 7.94%. These findings indicated the possibility of using the model for traffic flow monitoring, signal coordination, congestion control, and efficient transportation management. The performance of the model may depend on the quality of the sensor data, connectivity of the graph, graph parameters, and computational requirements. Further improvements may include adding data related to the weather, incidents, events, and multimodal mobility.

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