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A Machine Learning Model for Forecasting Traffic Speeds for Intelligent Traffic Systems

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ABSTRACT

Intelligent traffic systems (ITS) are being explored to make traffic systems more efficient based on data collection and analytics. One of the major applications to avoid congestions in traffic speed forecasting. Traffic speed forecasting using machine learning is a crucial aspect of intelligent transportation systems, aiming to enhance traffic management and optimize the overall efficiency of urban mobility. This process involves the utilization of various data sources, such as historical traffic patterns, real-time sensor data, and environmental factors, to predict future traffic speeds. Machine learning models play a pivotal role in this domain, as they can analyze complex patterns and relationships within the data to generate accurate predictions.

This paper presents a Particle Swarm Optimization (PSO)-Neural network model for traffic speed forecasting. Contrary to conventional neural network models, the PSO is used to adaptively update the network weights. The results clearly indicate that the proposed approach outperforms existing baseline approaches in terms of MAPE and Forecasting Accuracy.

Keywords: Intelligent Traffic System (ITS), Particle Swarm Optimization (PSO), Artificial Neural Network (ANN), Mean Absolute Percentage Error, Regression.

I. Introduction

Intelligent traffic systems are utilizing traffic speed forecasts to evaluate the level of congestion in urban areas. One key element in traffic speed forecasting is the collection of historical data, which provides insights into traffic patterns over time. Machine learning models can leverage this data to identify recurring patterns, seasonality, and trends, enabling them to make informed predictions about future traffic conditions. Additionally, real-time data from sensors, cameras, and other monitoring devices contribute to the dynamic nature of the forecasting models, allowing them to adapt to changing traffic scenarios. Feature engineering is a critical step in preparing the data for machine learning models. Relevant features such as time of day, day of the week, weather conditions, and special events can significantly impact traffic speeds. By incorporating these features into the model, it becomes more capable of capturing the complexity of the underlying factors affecting traffic flow. Supervised learning algorithms, such as regression models or neural networks, are commonly employed for traffic speed forecasting. These models are trained on historical data, learning the relationships between input features and target traffic speeds. Continuous refinement and validation of the models are essential to ensure their accuracy and adaptability to evolving traffic patterns. Ensemble methods, which combine predictions from multiple models, can enhance forecasting accuracy by mitigating the limitations of individual models. Techniques like bagging and boosting can be applied to create a more robust and reliable traffic speed forecasting system. Moreover, the integration of reinforcement learning allows models to adapt to real-time feedback, improving their performance in dynamic traffic environments.

$$\boldsymbol{Speed = f(time, lane\ congestion, other\ variables)} \quad \textbf{(1)}$$

Furthermore, it is the dis- aggregated source for calculating annual average daily traffic (AADT). AADT at the network level offers a measure of overall utilization of highway facility, implies the level of service of roads, and can be used for highway planning, trend studies, and project prioritization currently, traffic count (volume) is mainly obtained from sensors

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such as inductive loop detectors, radar detectors and/or continuous counting stations (CCS). Yet installing sensors with large network coverage can be impractical and expensive given budget constraint, especially in rural areas. As a result, how to spatially estimate/predict traffic volume to substitute massive sensor deployment has been an intriguing topic over the past decade. Some typical applications can be:

1) Route Optimization & Navigation.
2) Smart Parking.
3) Lighting.
4) Accident Detection.
5) Road Anomalies.
6) Infrastructure Management.

Figure 1 depicts the horseshoe diagram for traffic congestion.

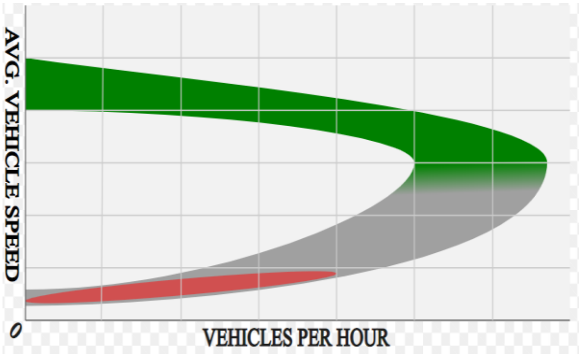

Fig.2 Speed-flow horseshoe diagram of traffic congestion

(Source:https://en.m.wikipedia.org/wiki/File:Speed-flow_horseshoe_diagram_traffic_congestion)

The speed-flow horseshoe diagram is a graphical representation used in traffic engineering and transportation planning to illustrate the relationship between traffic speed and traffic flow, particularly in the context of congestion. This diagram provides valuable insights into how traffic conditions change as congestion levels increase. At its core, the speed-flow horseshoe diagram depicts the inverse relationship between traffic speed and traffic flow during congested periods. The horseshoe shape emerges because as traffic flow increases, indicating higher vehicle volumes, the speed tends to decrease. This is a fundamental characteristic of congested traffic, where vehicles experience slower speeds as they navigate through denser traffic.

In the diagram, the horizontal axis typically represents traffic flow, measured in vehicles per hour, while the vertical axis represents traffic speed, often measured in miles per hour or kilometres per hour. The resulting horseshoe shape visually demonstrates that as traffic flow intensifies, the corresponding speed decreases, forming the curved outline of the horseshoe. Analysing the specific regions within the horseshoe diagram can reveal different traffic states. The top part of the horseshoe, known as the free-flow region, represents conditions when traffic is relatively uncongested, and vehicles can move at or near their desired speeds. As traffic flow increases beyond a certain threshold, the curve descends into the congested region of the horseshoe, indicating slower speeds despite higher traffic volumes.

Transportation professionals use the speed-flow horseshoe diagram to assess the efficiency and stability of traffic systems. The diagram helps identify critical points at which congestion may occur and provides insights into potential bottlenecks or areas where improvements in traffic management may be needed. Additionally, it aids in the evaluation of the impact of interventions, such as traffic signal optimization or lane additions, on the overall traffic flow and speed relationship. The speed-flow horseshoe diagram is a valuable tool for both planning and operational purposes. It allows traffic engineers to better understand the dynamics of congestion, optimize traffic control strategies, and design transportation systems that can handle varying levels of demand while minimizing disruptions and delays. As urban areas continue to face challenges related to traffic congestion, the speed-flow horseshoe diagram remains an essential tool for developing effective solutions to improve overall traffic performance.

II. Need for Traffic Speed Forecasting

Traffic speed forecasting is a critical component of intelligent transportation systems, providing valuable insights and solutions to address the challenges of urban mobility. Some of the major needs as well as applications of traffic speed forecasting are:

Efficient Traffic Management: Traffic speed forecasting is essential for efficient traffic management. By predicting future traffic speeds, transportation authorities can proactively implement measures to optimize traffic flow. This includes adjusting signal timings, managing lane configurations, and deploying dynamic route guidance systems to alleviate congestion and improve overall traffic efficiency.

Reducing Congestion and Delays: One of the primary objectives of traffic speed forecasting is to reduce congestion and minimize delays. By accurately predicting traffic conditions, authorities can implement real-time interventions to divert traffic, distribute loads more evenly across the road network, and implement congestion pricing strategies. This proactive approach helps mitigate the negative impacts of congestion on travel times and overall transportation network performance.

Enhancing Safety and Reducing Accidents: Accurate traffic speed forecasting contributes to enhanced road safety. By anticipating potential congestion points or areas with reduced speeds, authorities can implement safety measures, such as reduced speed limits, variable message signs, and targeted law enforcement, to prevent accidents and improve overall road safety.

Optimizing Transportation Planning: Traffic speed forecasting plays a crucial role in long-term transportation planning. By analyzing historical traffic data and predicting future traffic speeds, planners can make informed decisions about infrastructure development, road expansions, and public transit enhancements. This helps in creating sustainable and resilient transportation systems that can handle current and future demands.

Supporting Emergency Response Planning: During emergencies or unexpected events, such as accidents, natural disasters, or road closures, traffic speed forecasting is instrumental in facilitating efficient emergency response planning. By predicting how traffic patterns will be affected, emergency services can optimize routes, allocate resources effectively, and ensure timely responses to incidents.

Public Transit Planning and Operations: Traffic speed forecasting is beneficial for public transit planning and operations. By anticipating traffic conditions, transit agencies can optimize bus and train schedules, manage congestion at transit hubs, and improve overall reliability. Commuters can also benefit from accurate predictions, allowing them to plan their journeys more efficiently.

Real-Time Navigation and Traveler Information: Incorporating traffic speed forecasts into navigation apps and traveler information systems enables commuters to make informed decisions about their routes and travel times. This real-time information empowers individuals to choose the most efficient paths, contributing to reduced travel times and improved overall user satisfaction.

Thus, , the need for traffic speed forecasting arises from its diverse applications in optimizing traffic management, reducing congestion, enhancing safety, supporting transportation planning, facilitating emergency response, improving public transit operations, and providing real-time information to travelers. These applications collectively contribute to the development of more sustainable, efficient, and resilient transportation systems in urban environments.

III. Proposed Methodology

The proposed methodology presents an amalgamation of the following two approaches:

1. Particle Swarm Optimization (PSO)
2. Artificial Neural Networks (ANN)

Each of the approaches are explained next.

The PSO:

The PSO algorithm is an evolutionary computing technique, modeled after the social behavior of a flock of birds. In the context of PSO, a swarm refers to a number of potential solutions to the optimization problem, where each potential solution is referred to as a particle. The aim of the PSO is to find the particle position that results in the best evaluation of a given fitness function. In the initialization process of PSO, each particle is given initial parameters randomly and is 'flown' through the multi-dimensional search space. During each generation, each particle uses the information about its previous best individual position and global best position to maximize the probability of moving towards a better solution space that will result in a better fitness. When a fitness better than the individual best fitness is found, it will be used to replace the individual best fitness and update its candidate solution according to the following equations:

$$\mathbf{v_{id}(t) = w \times v_{id}(t-1) + c_1 Ø_1 (p_{id} - x_{id}(t-1)) + c_2 Ø_2 (p_{gd} - x_{id}(t-1))} \quad \mathbf{(1)}$$

$$\mathbf{x_{id}(t) = x_{id}(t-1) + v_{id}(t)} \quad \mathbf{(2)}$$

Table. 1 List of variables used in PSO equations.

v	The particle velocity
x	The particle position
t	Time
c_1,c_2	Learning factors
Φ_1 ,Φ_2	Random numbers between 0 and 1
p_{id}	Particle's best position
p_{gd}	Global best position
w	Inertia weight

The PSO is used to adaptively update the weights of the neural network based on the minimization of the performance function.

The ANN Model:

The ANN model is one of the most powerful regression models which has been used multiple times for traffic speed forecasting.

The mathematical model of the ANN is depicted in figure 1.

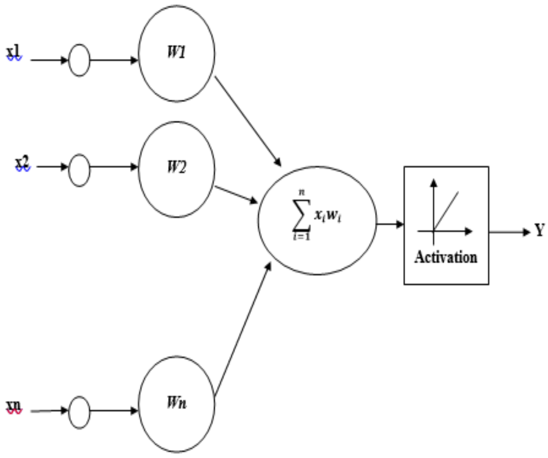

Fig.1 Mathematical Model of Neural Network

The output of the neural network is given by:

$$y = f(\textstyle\sum_{i=1}^{n} \mathbf{XiWi} + \Theta) \quad \mathbf{(4)}$$

Where,

Xi represents the signals arriving through various paths,

Wi represents the weight corresponding to the various paths and

Ө is the bias.

In this approach, the back propagation based neural network model has been used. A backpropagation neural network for traffic speed forecasting typically consists of an input layer, one or more hidden layers, and an output layer. The number of nodes in the input layer corresponds to the features used for prediction, such as historical traffic speeds, time of day, and weather conditions. The hidden layers contain nodes that learn and capture the intricate patterns within the data, while the output layer provides the predicted traffic speed. The training of a backpropagation neural network involves the iterative application of the backpropagation algorithm. During the training process, historical data is used to feed the network, and the algorithm calculates the error between the predicted and actual traffic speeds. This error is then propagated backward through the network, adjusting the weights and biases of the connections to minimize the prediction error. This iterative process continues until the network converges to a state where the error is minimized.

Successful backpropagation neural network models for traffic speed forecasting can be integrated into traffic management systems. These systems leverage the predictions to make real-time decisions, such as adjusting signal timings, optimizing traffic flow, and providing accurate information to commuters. The integration of such models enhances the overall efficiency of traffic management in urban environments

The training is stopped based on the mean square error or mse given by:

$$mse = \frac{\sum_{i=1}^{n} e_i^2}{n} \quad (5)$$

The final computation of the performance metric is the mean absolute percentage error given by:

$$MAPE = \frac{100}{M} \sum_{i=1}^{N} \frac{E-E_i|}{i} \quad (6)$$

The accuracy of prediction is computed as:

$$Ac = 100 - \frac{100}{M} \sum_{i=1}^{N} \frac{E-E_i|}{i} \% \quad (7)$$

Here,
n is the number of errors
i is the iteration number
E is the actual value
E_i is the predicted value

IV. RESULTS AND DISCUSSIONS

The proposed model is implemented on MATLAB due to the availability of in built mathematical functions for analysis of traffic volume. The data parameters used are:

1. Lane
2. Time
3. Traffic Speed

While other parameters may also be important, the limited set of parameters are chosen to design a streamlined model The results are presented next.

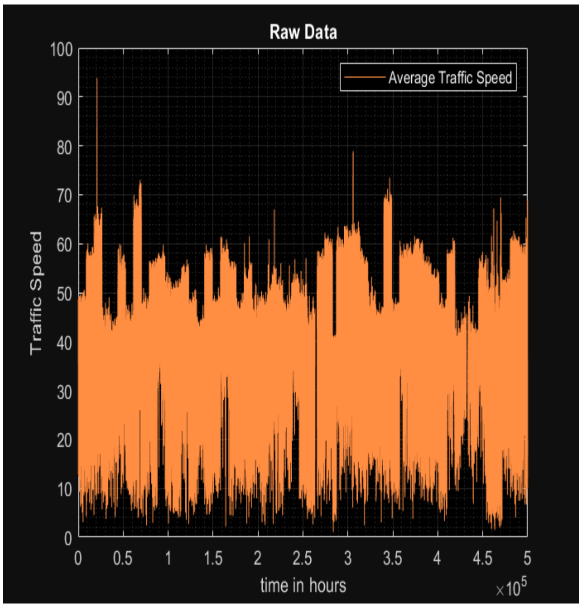

Fig.2. Raw Traffic Volume

Figure 2 depicts the raw traffic volume data as a function of time.

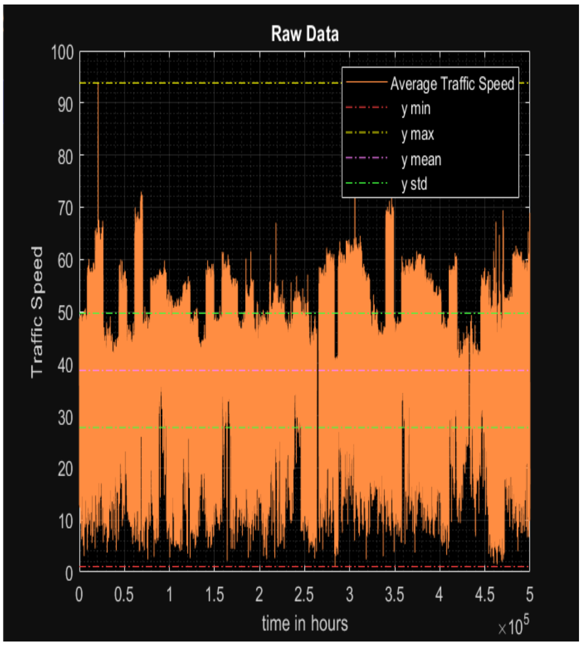

Fig.3 Statistical Data Parameters.

Figure 3 depicts the statistical markers of the raw data. The statistical parameters are presented in table 1.

Table.2 Statistical Parameters of Data

S.No.	Parameter	Value
1	Minimum	1.054
2	Maximum	93.83
3	Mean	38.69
4	Standard Deviation	10.96

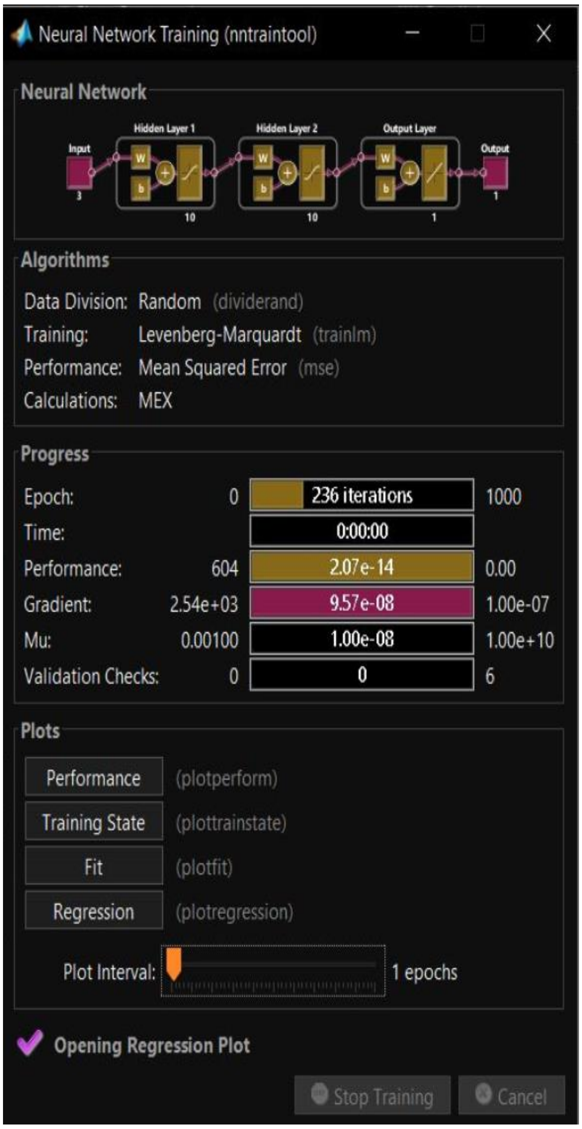

Fig.4 Model Design Parameters

The details of the training are depicted in the figure above, which clearly shows the designed neural network, the training function, the data division and the iterations.

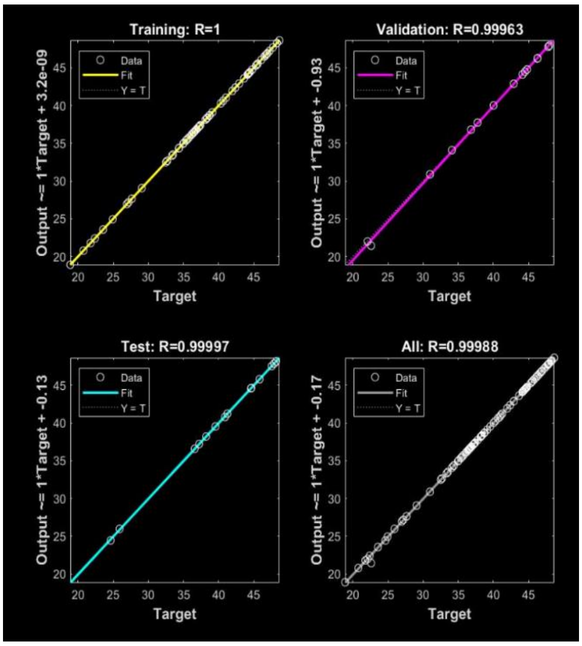

Fig.5 Regression

The figure above depicts the regression obtained in the proposed approach which is a sort of similarity among two random variables. The maximum allowable regression is unity depicting complete similarity.

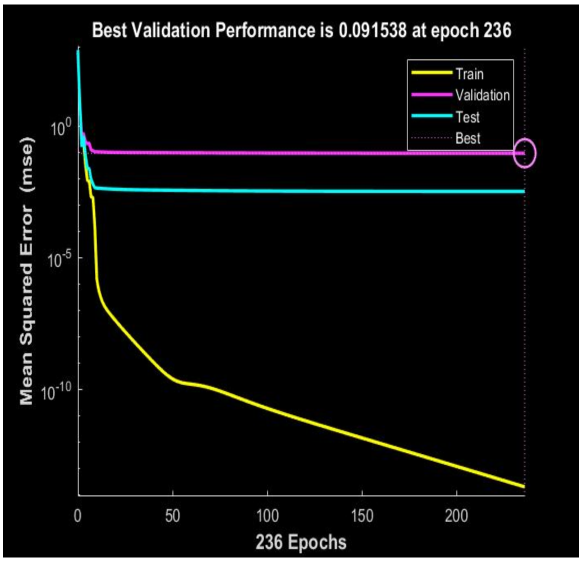

Fig.6 Performance Function

The performance function that decides the culmination of training is the mean squared error or mse.

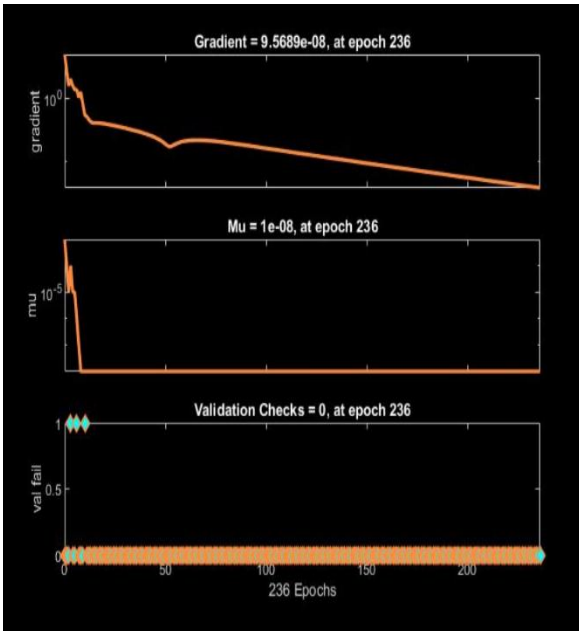

Fig.7 Training States

The training state parameters such as gradient, combination co-efficient and validations checks are depicted in the figure above.

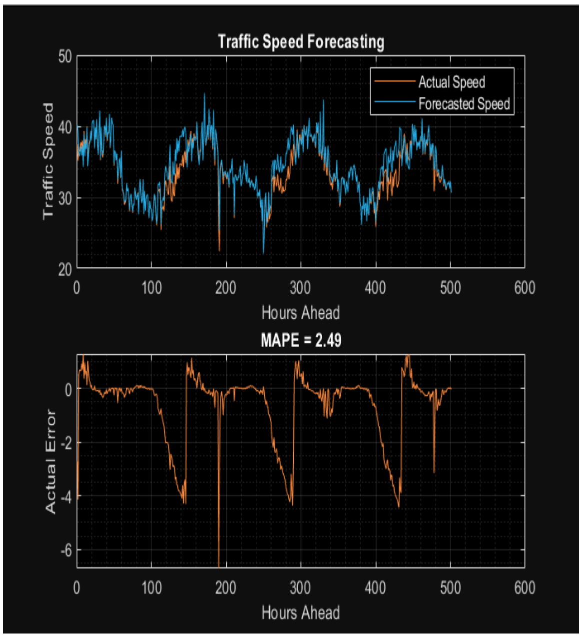

Fig.8 Actual and Modelled values

The above figure shows the MAPE of the proposed system which comes out to be 2.49%.

Table. 3 Summary of Results

S.No	PARAMETER	VALUE
1.	Samples	50,000
2.	Proposed Model	PSO-ANN
3.	Iterations	1000
4.	Regression	0.99988
5.	MAPE (Proposed Work)	2.49%
6.	MAPE (Previous Work)	4.013%
7.	Approach (Previous Work)	Attentive Graph Neural Process (AGNP)

The summary of results is presented in table 3. The performance of the proposed approach (MAPE of 2.49%) is found better compared to previously existing technique [1] which attains a MAPE of 4.013% using the AGNP model.

V. CONCLUSION

Traffic speed forecasting through machine learning is a multidimensional process that involves data collection, feature engineering, model training, and ongoing refinement. It is one of the most important applications of intelligent traffic systems. The synergy of historical and real-time data, coupled with advanced machine learning techniques, empowers transportation authorities to make informed decisions, optimize traffic flow, and enhance overall urban mobility. As technology continues to advance, the potential for more accurate and adaptive traffic speed forecasting models is poised to further revolutionize the field of intelligent transportation systems. The proposed work is a combination of the ANN-PSO algorithm and attains an MAPE of only 2.49% and outperforms baseline approaches such as graph neural networks and long short term memory (LSTM) networks in terms of forecasting accuracy and MAPE.

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