A Machine Learning Model for Forecasting Traffic Speeds in Urban Environments

Rajeshwari Pawar[1], Prof. Snehlata Mishra[2]
Department of Computer Science and Engineering[1,2]
SAGE University, Indore[1,2]

Abstract: The potential for data collecting and analytics-based intelligent traffic systems (ITS) to improve traffic systems is now being investigation. Predicting how fast traffic will be moving is one of the most important uses for this technology. In order to improve traffic management and maximize the overall efficiency of urban mobility, intelligent transportation systems rely on machine learning for traffic speed forecasts. Several data sources are used in this procedure to forecast traffic speeds, including past trends, data from sensors in real-time, and environmental conditions. The ability of machine learning models to sift through mountains of data in search of hidden patterns and correlations and provide reliable forecasts makes them indispensable in this field.

A neural network model for traffic speed predictions based on Particle Swarm Optimization (PSO) is presented in this research. By using the PSO, the network weights may be adaptively updated, which is different from traditional neural network models. Both the MAPE and the Forecasting Accuracy metrics show that the suggested method is superior than the current baseline methods.

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

I. INTRODUCTION

The degree of congestion in cities may be assessed by intelligent traffic systems by means of traffic speed predictions. Gathering historical data is an important part of traffic speed forecasting since it shows how traffic has changed over time. In order to forecast future traffic conditions with confidence, machine learning algorithms may use this data to spot trends, recurrence, and seasonality. To further enhance the forecasting models' adaptability to evolving traffic conditions, real-time data from sensors, cameras, and other monitoring equipment is incorporated. When getting data ready for ML models, feature engineering is an essential first step. Traffic speeds may be greatly affected by pertinent characteristics such the time of day, weather, day of the week, and special events. With these additions, the model can better represent the intricate interplay of the elements influencing traffic flow. It is usual practice to use supervised learning algorithms like neural networks or regression models to predict traffic speeds. By analyzing past data, these models may learn which input parameters correlate with desired traffic speeds. To make sure the models are accurate and can respond to changing traffic patterns, they need to be validated and refined continuously. To overcome the shortcomings of individual models, ensemble approaches can improve forecasting accuracy by combining forecasts from several models. To improve the accuracy of traffic speed forecasts, methods such as bagging and boosting can be utilized. Additionally, models can improve their performance in dynamic traffic conditions by adapting to real-time input through the incorporation of reinforcement learning.

$$Speed = f(time, lane\ congestion, other\ variables) \quad (1)$$

In addition, it is used to calculate the annual average daily traffic (AADT) from a disaggregated source. For highway planning, trend research, and project prioritization, AADT at the network level provides a measure of total usage of highway facilities, which suggests the level of road service. sensors such inductive loop detectors, radar detectors, and continuous counting stations (CCS) are the primary sources for traffic count (volume) at present. Budget constraints make it difficult, if not impossible, to deploy sensors with extensive network coverage, which is particularly problematic in rural locations. The challenge of replacing the deployment of vast amounts of sensors with accurate geographical estimates of traffic volumes has thus been a fascinating one over the last ten years. Among the most common uses are:

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.

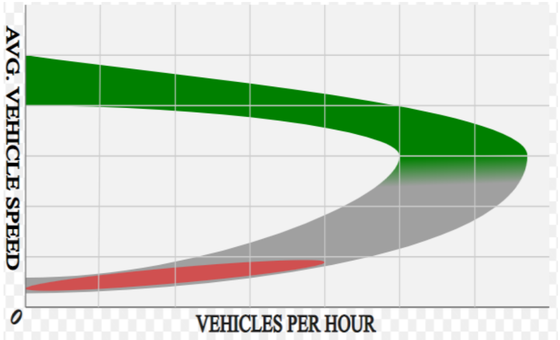

Fig.2 Speed-flow horseshoe diagram of traffic congestion

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

For transportation planners and traffic engineers, the speed-flow horseshoe diagram is a visual aid for understanding the connection between vehicle velocity and flow, especially when dealing with traffic jams. As congestion levels rise, this graphic shows how traffic conditions change. Central to the speed-flow horseshoe diagram is the idea that, when traffic is heavy, the inverse connection between speed and flow is best shown. Because traffic tends to slow down as quantities of vehicles rise, a horseshoe shape develops. One basic feature of traffic jams is that cars move at a slower pace as they try to negotiate the more densely packed roadways. On one side of the graphic you can see the number of cars moving through the system every hour, and on the other side you can see the speed of the traffic, usually expressed I n miles per hour or kilometers per hour. The curving contour of the horseshoe is a visual representation of the relationship between increasing traffic volume and decreasing speed. You may learn about the various traffic conditions by looking at the various areas of the horseshoe diagram. When traffic is light and cars may go at or near their target speeds, we see this situation reflected in the upper half of the horseshoe, which is called the free-flow region. The curve falls into the crowded area of the horseshoe as traffic flow climbs above a particular threshold, suggesting slower speeds despite increased traffic numbers.

The efficiency and stability of traffic networks may be evaluated by transportation experts using the speed-flow horseshoe diagram. The graphic is useful for pinpointing possible bottlenecks or locations that can benefit from better traffic management, as well as for identifying prospective congestion hotspots. It also helps when trying to figure out how different interventions, like more lanes or better traffic signals, affected the overall link between traffic flow and speed. When it comes to planning and running operations, the speed-flow horseshoe diagram is invaluable. It helps traffic engineers comprehend the mechanics of congestion, develop more effective methods of traffic control, and plan transportation networks that can adapt to different demand levels with little interruption. When it comes to improving traffic performance in metropolitan settings, the speed-flow horseshoe diagram is still a vital tool for finding efficient solutions to traffic congestion.

II. NEED FOR TRAFFIC SPEED FORECASTING

Intelligent transportation systems rely on traffic speed forecasts to solve urban mobility problems by giving useful insights and solutions. Among the many uses and requirements for traffic speed forecasting are:

Traffic Management Efficacy: For effective traffic management, accurate speed forecasting is a must-have tool. Authorities in charge of transportation can manage traffic flow by anticipating future speeds and proactively implementing steps. To reduce congestion and increase traffic efficiency, this involves changing the timing of signals, controlling the structure of lanes, and using dynamic route guiding systems.

Limiting Delays and Congestion : Among the main goals of traffic speed forecasting is the reduction of congestion and the minimizing of delays. Authorities can adopt congestion pricing techniques, more equitable load distribution across the road network, and real-time traffic diversion interventions with precise traffic condition predictions. Congestion has a detrimental effect on travel times and the efficiency of transportation networks generally, but this preventative measure helps lessen that effect.

Improving Safety and Minimizing Accidents:: Reliable traffic speed projections contribute to enhanced road safety. To improve road safety and prevent accidents, authorities may impose speed restrictions, deploy changeable message signs, and allocate law enforcement resources to areas where they expect lower speeds or traffic congestion.

Enhancement of the efficiency of transportation planning: Forecasting traffic speed is essential for strategic transportation planning. Through the analysis of past traffic data and the projection of future traffic speeds, planners may make well-informed judgments on the development of infrastructure, expansion of roads, and improvements to public transportation. This facilitates the development of transportation systems that are both environmentally friendly and capable of withstanding present and future needs.

Assistance in the development of plans for responding to emergencies: Traffic speed forecasting plays a crucial role in enabling effective emergency response planning for unforeseen incidents or catastrophes, such as accidents, natural disasters, or road closures. Through the use of predictive analysis, emergency services may improve routes, efficiently manage resources, and guarantee prompt responses to crises by anticipating the impact on traffic patterns.

Urban Transportation Planning and Management: Forecasting traffic speed is advantageous for the purpose of public transportation planning and operations. By predicting traffic conditions, transportation agencies may optimize bus and rail timetables, control congestion at transit hubs, and enhance overall reliability. Accurate projections can also be advantageous for commuters, enabling them to optimize their travel plans.

Live navigation and up-to-date information for travelers: Integrating traffic speed predictions into navigation applications and traveler information systems empowers commuters to make well-informed choices on their routes and estimated journey durations. Providing users with up-to-date information enables them to select the most effective routes, resulting in shorter trip durations and more customer satisfaction.

Because of its many uses, traffic speed forecasting is essential for many reasons, including better public transportation operations, less congestion, increased safety, better transportation planning, easier emergency response, and real-time information for travelers. Better, more efficient, and more resilient urban transportation networks are a result of the combined efforts of these applications.

III. PROPOSED METHODOLOGY

The two methods that are combined in the suggested technique are:

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

Each of the approaches are explained next.

The PSO:

An evolutionary computer approach, the PSO algorithm takes its cues from the coordinated actions of a flock of birds. A swarm of particles in PSO represents several possible answers to the optimization issue. Particles stand for individual solutions. The Particle Stream Optimization (PSO) algorithm seeks, for a given fitness function, the optimal particle location. Each particle is "flown" through the multi-dimensional search space after being randomly assigned beginning parameters during PSO's startup phase. In order to improve their fitness, particles use data about their past best individual positions and global best positions to increase the likelihood that they will move towards a better solution space throughout each generation. According to the following equations, the candidate solution will be updated and the individual best fitness will be replaced when a fitness that is better than it is found:

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

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

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

By minimizing the performance function, the PSO adaptively updates the neural network's weights..

The ANN Model:

One of the most effective regression models, the ANN model has found repeated usage in traffic speed forecasts.

The ANN's mathematical model is shown in figure 1.

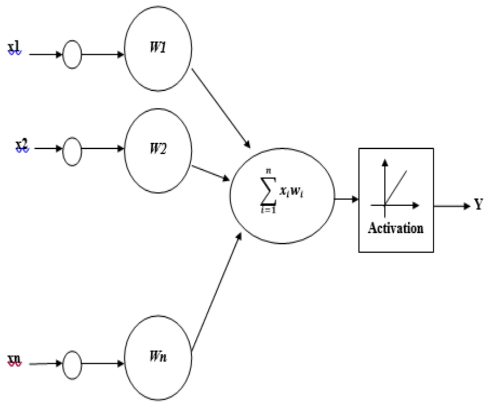

Fig.1 Mathematical Model of Neural Network

The output of the neural network is given by:

$$y = f(\sum_{i=1}^{n} XiWi \;+\; \Theta) \qquad (4)$$

Where,

Xi represents the signals arriving through various paths, Wi represents the weight corresponding to the various paths and Ɵ is the bias.

An technique that makes use of a neural network model based on back propagation is this one. In order to predict traffic speeds, a backpropagation neural network will normally have an output layer, a hidden layer, and an input layer. Factors like current weather, past traffic speeds, and time of day determine the amount of nodes in the input layer, which is utilized for prediction. Predicted traffic speeds are provided by the output layer, while nodes in the hidden layers learn and capture the complex patterns in the data. Applying the backpropagation algorithm repeatedly is what's required to train a backpropagation neural network. Training the network involves feeding it historical data and having the algorithm determine the discrepancy between the projected and real traffic speeds. Following this, the network feeds this mistake back into itself, modifying the connection weights and biases to reduce the prediction error. This procedure repeats itself until the network reaches a point where the error is reduced.

Integration of backpropagation neural network models for traffic speed predictions into traffic control systems is a viable option. By using the forecasts, these technologies optimize traffic flow, change signal timings in real-time, and give commuters precise information. Overall, traffic management in urban contexts is made more efficient with the inclusion of such models.

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

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

As a final performance statistic, the mean absolute percentage error is calculated as follows:

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

The accuracy of prediction is computed as:

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

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 suggested model is developed using MATLAB since it provides built-in mathematical capabilities for analyzing traffic volume. The data parameters utilized are:

1. Lane
2. Duration
3. Velocity of Traffic

Although there may be additional characteristics that are as relevant, a select few parameters are picked to create a simplified model. The findings are displayed thereafter.

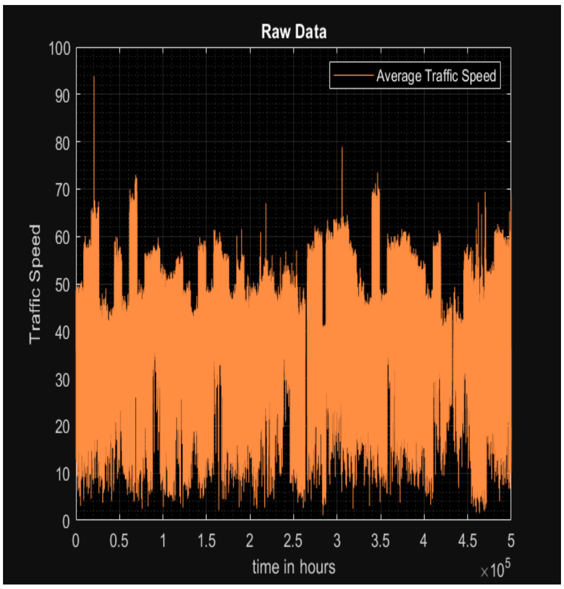

Fig.2. Raw Traffic Volume

Figure 2 Illustrates the unprocessed statistics on the amount of traffic over time.

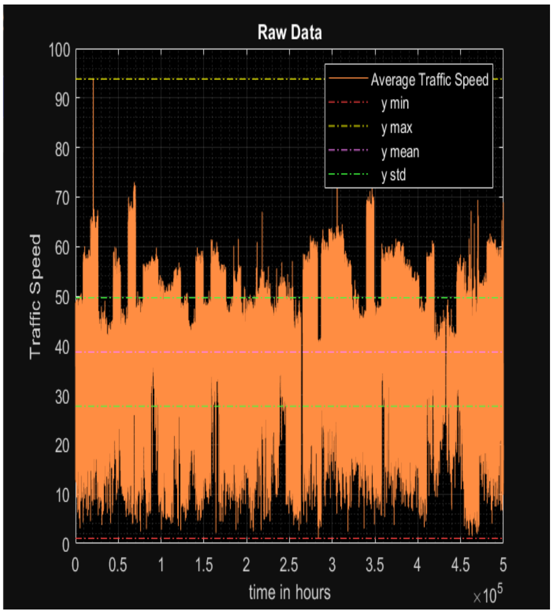

Fig.3 Statistical Data Parameters.

Figure 3 Illustrates the statistical indicators of the unprocessed data. Table 1 displays the statistical parameters.

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

Above, you can see the training details illustrated in the figure. Iterations, data division, the training function, and the built neural network are all clearly shown.

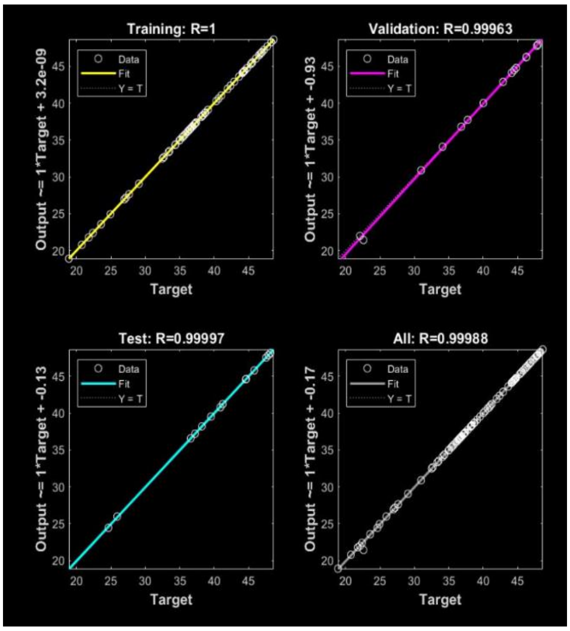

Fig.5 Regression

The suggested method yields a regression, which is essentially a measure of similarity between two random variables, as seen in the image above. Regressions up to unity, representing perfect resemblance, are permissible.

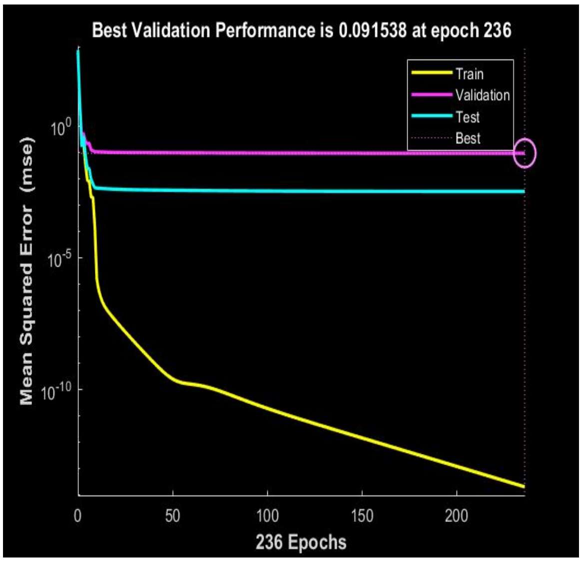

Fig.6 Performance Function

Ultimately, training is judged by the mean squared error (mse), a performance metric.

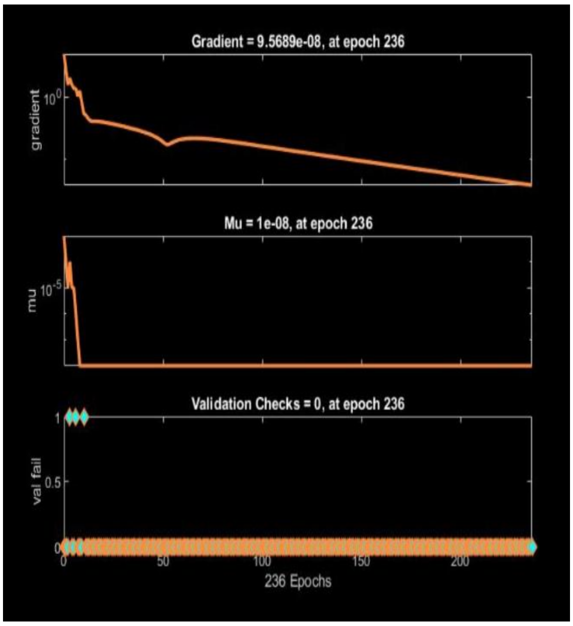

Fig.7 Training States

The picture above illustrates the training state parameters, including the gradient, combination coefficient, and validation checks.

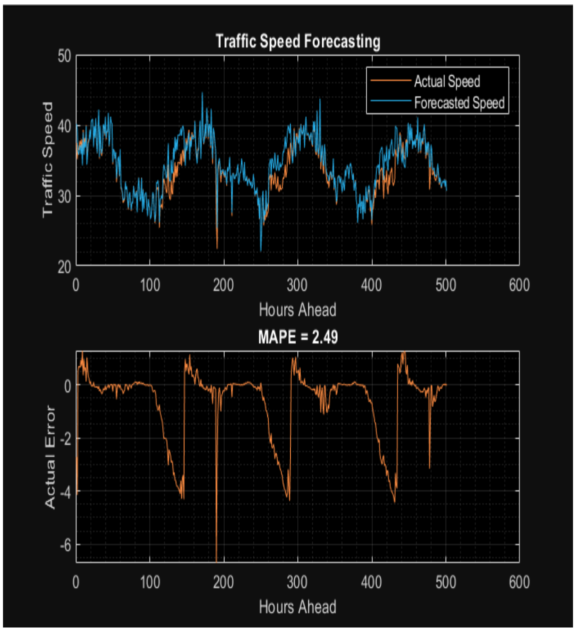

Fig.8 Actual and Modelled values

The provided diagram displays the Mean Absolute Percentage Error (MAPE) of the suggested system, with a value of 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)	2.5% (APPROX)
6.	MAPE (Previous Work)	4.013%
7.	Approach (Previous Work)	Attentive Graph Neural Process (AGNP)

The summary of findings is displayed in table 3. The suggested strategy demonstrates superior performance with a Mean Absolute Percentage Error (MAPE) of 2.49%, compared to the existing technique [1] which achieves a MAPE of 4.013% using the AGNP model.

V. CONCLUSION

The process of predicting traffic speed using machine learning is a complex and multifaceted task that encompasses data gathering, feature manipulation, model training, and continuous improvement. It is a highly significant utilization of intelligent traffic systems. The combination of historical and real-time data, along with modern machine learning algorithms, enables transportation authorities to make well-informed judgments, optimize the flow of traffic, and improve overall urban mobility. The continuous advancement of technology holds the potential to transform the field of intelligent transportation systems through the development of more precise and adaptable traffic speed forecasting models. The suggested study utilizes the ANN-PSO technique and achieves a Mean Absolute Percentage Error (MAPE) of just 2.49%. It surpasses other methods like graph neural networks and long short term memory (LSTM) networks in terms of accuracy and MAPE for forecasting purposes.

REFERENCES

[1] M Xu, Y Di, H Ding, Z Zhu, X Chen, H Yang, “AGNP: Network-wide short-term probabilistic traffic speed prediction and imputation”, Communications in Transportation Research, Elsevier 2023, vol.3, 100099.

[2] A Sharma, A Sharma, P Nikashina, V Gavrilenko, “A graph neural network (GNN)-based approach for real-time estimation of

traffic speed in sustainable smart cities", Sustainability, MDPI 2023, vol.15, no.5, pp.1-25.

[3] R Qaddoura, MB Younes, "Temporal prediction of traffic characteristics on real road scenarios in Amman", Journal of Ambient Intelligence and Humanized Computing, Springer, 2023. Vol.14, pp. 9751–9766.

[4] Y Zhang, T Zhao, S Gao, M Raubal, "Incorporating multimodal context information into traffic speed forecasting through graph deep learning", International Journal of Geographical Information Science, Taylor and Francis, 2023, vol.37, no.9, pp. 1909-1935.

[5] Y. Gao, C. Zhou, J. Rong, Y. Wang and S. Liu, "Short-Term Traffic Speed Forecasting Using a Deep Learning Method Based on Multitemporal Traffic Flow Volume," in IEEE Access, vol. 10, pp. 82384-82395, 2022.

[6] C. Ma, Y. Zhao, G. Dai, X. Xu and S. -C. Wong, "A Novel STFSA-CNN-GRU Hybrid Model for Short-Term Traffic Speed Prediction," in IEEE Transactions on Intelligent Transportation Systems, vol. 24, no. 4, pp. 3728-3737, April 2022.

[7] X. Xu, T. Zhang, C. Xu, Z. Cui and J. Yang, "Spatial–Temporal Tensor Graph Convolutional Network for Traffic Speed Prediction," in IEEE Transactions on Intelligent Transportation Systems, vol. 24, no. 1, pp. 92-103,2023.

[8] C Xu, A Zhang, C Xu, Y Chen, "Traffic speed prediction: spatiotemporal convolution network based on long-term, short-term and spatial features", Applied Intelligence, Springer, 2022, vol.52, pp. 2224–2242.

[9] Z Zhang, Y Li, H Song, H Dong, "Multiple dynamic graph based traffic speed prediction method", Neurocomputing, Elsevier, 2021, vol.461, pp. 109-117.

[10] A. Abdelraouf, M. Abdel-Aty and J. Yuan, "Utilizing Attention-Based Multi-Encoder-Decoder Neural Networks for Freeway Traffic Speed Prediction," in IEEE Transactions on Intelligent Transportation Systems, 2021, vol. 23, no. 8, pp. 11960-11969.

[11] J. J. Q. Yu, C. Markos and S. Zhang, "Long-Term Urban Traffic Speed Prediction With Deep Learning on Graphs," in IEEE Transactions on Intelligent Transportation Systems, 2021, vol. 23, no. 7, pp. 7359-7370.

[12] YL Hsueh, YR Yang, "A short-term traffic speed prediction model based on LSTM networks", International Journal of Intelligent Transportation Systems Research, Springer 2021, vol.19, pp. 510–524.

[13] M. Cao, V. O. K. Li and V. W. S. Chan, "A CNN-LSTM Model for Traffic Speed Prediction," 2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring), Antwerp, Belgium, 2020, pp. 1-5.

[14] X. Yang, Y. Yuan and Z. Liu, "Short-Term Traffic Speed Prediction of Urban Road With Multi-Source Data," in IEEE Access, vol. 8, pp. 87541-87551, 2020.

[15] X. Meng et al., "D-LSTM: Short-Term Road Traffic Speed Prediction Model Based on GPS Positioning Data," in IEEE Transactions on Intelligent Transportation Systems, 2020 vol. 23, no. 3, pp. 2021-2030.

[16] W. Lu, Y. Rui and B. Ran, "Lane-Level Traffic Speed Forecasting: A Novel Mixed Deep Learning Model," in IEEE Transactions on Intelligent Transportation Systems, 2020, vol. 23, no. 4, pp. 3601-3612.

[17] J Yu, MEJ Stettler, P Angeloudis, S Hu, "Urban network-wide traffic speed estimation with massive ride-sourcing GPS traces", Transportation Research: Part: C, Elsevier 2020, vol.112, pp. 136-152.

[18] Y Gu, W Lu, L Qin, M Li, Z Shao, "Short-term prediction of lane-level traffic speeds: A fusion deep learning model", Transportation Research: Part: C, Elsevier 2019, vol.106, pp. 1-16.

[19] W Zhang, Y Yu, Y Qi, F Shu, Y Wang, "Short-term traffic flow prediction based on spatio-temporal analysis and CNN deep learning", Transport Science, Taylor & Francis, 2019, vol.15, no.2, pp. 1688-1711.

[20] D Yu, C Liu, Y Wu, S Liao, T Anwar, W Li, "Forecasting short-term traffic speed based on multiple attributes of adjacent roads", Knowledge-Based Systems, Elsevier, 2019, vol.163, 472-484.

[21] A Emami, M Sarvi, S Asadi Bagloee, "Using Kalman filter algorithm for short-term traffic flow prediction in a connected vehicle environment", Journal of Modern Transportation, Springer 2019, vol.27, pp. 22–232.