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A Hybrid Deep Learning Method for Short-Term Traffic Flow Forecasting: GSA-LSTM

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Abstract

Objectives: The main objective of this study is to improve the accuracy and reliability of the short-term traffic flow forecasting method, while simultaneously addressing limitations in existing models and proposing a novel approach that enhances the quality of the traffic flow predictions. **Methods:** This study developed a long short-term memory (LSTM) neural network optimized by the gravitational search approach (GSA) to enhance prediction accuracy for short-term traffic flow. The gravitational search algorithm selects the best parameters for the long short-term memory neural network on a global scale. **Findings:** The proposed GSA-LSTM model exhibits significant superiority over the selected models when assessing performance through the evaluation metrics such as root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and correlation coefficient (r). Moreover, the average accuracy of the proposed model is higher as compared to other existing neural network models which depicted the effectiveness of the proposed model. **Novelty:** Tables and figures displayed that the performance accuracy of the proposed model is higher than the other selected models such as autoregressive integrated moving average (ARIMA), wavelet neural network (WNN), Gated Recurrent Unit (GRU), long short-term memory model (LSTM), GSA-GRU, ACO-LSTM, and PSO-LSTM model.

Keywords: Intelligent Transportation System; Deep Learning; Traffic Flow Prediction

1 Introduction

In the modern world, traffic congestion is one of the main issues that practically all cities experience and it is dramatically increased by a fusion of deficient road infrastructure and a rising number of registered vehicles. The ineffectiveness of transportation systems, particularly in India, becomes evident during rush hours when traffic congestion becomes a common issue due to the rising number of vehicles [(1)]. The main requirement to maintaining the demand for traffic flow is the development of additional road infrastructure, however, this is not a realistic solution to the issue, mainly because of financial limitations. Therefore, an alternative strategy involves adopting an intelligent transportation system (ITS) to reduce traffic congestion.

The effectiveness of traffic operations and the reduction of traffic congestion are the objectives of reliable real-time traffic flow forecasting, which is essential to the implementation of guidance and traffic management. However, precise and reliable prediction remains a difficult task due to the periodicity of traffic flow and the random behavior it exhibits when it is affected by outside forces. Traffic flow prediction models may generally be split into three categories: time series models, machine learning models, and deep learning models. Time series models include the "random walk", "historical average", and "autoregressive model". A simplistic yet effective technique for obtaining reliable traffic flow prediction was introduced, utilizing the fundamental traffic flow structures of the autoregressive integrated moving average (ARIMA)[2]. The structure of these types of models is based on the stability concept prohibits them from effectively handling intricate and nonlinear traffic flow patterns. Therefore, researchers used machine learning models to estimate traffic flow using complicated and nonlinear characteristics[3]. In this direction, Cai et al.[4] proposed a support vector machine regression model improved by the gravity search algorithm that outperforms the conventional support vector machine in terms of efficiency when used to estimate traffic flow.

Conversely, deep learning has recently gained popularity for examining complex and nonlinear traffic patterns[5–8]. Deep learning-based models such as artificial neural networks (ANNs), recurrent neural networks (RNNs), LSTM, and convolutional neural networks (CNNs) have been increasingly influential in various fields due to their ability to handle complex, high-dimensional data. Shuai et al.[9] introduced a hybrid model that dissects traffic flow into distinct components and utilizes various models for prediction based on their individual characteristics. A hybrid deep learning network model was introduced to anticipate short-term traffic flow that integrates convolution on graphs with RNN[10]. Long short-term memory (LSTM)[11], a specific type of RNN, was designed to accomplish the long-term dependencies and minimize gradient explosion/vanishing. Lu et al.[12] presented a deep learning architecture incorporating multi-diffusion convolution and LSTM to estimate traffic flow.

The performance of each of the aforementioned deep learning models for predicting traffic flow is significant and notable. However, due to insufficient and poor training data, these models may enter a local minimum[13]. In deep learning networks, computational complexity increases significantly due to the iterative nature of parameter adjustments by driving the gradient descent algorithm by the concept of empirical risk reduction. To fine-tune the parameters for data-driven learning models more quickly and correctly, several researchers have turned to use heuristic algorithms. For example, a hybrid deep learning that combines a genetic algorithm and attention-based long short-term memory neural network was proposed to forecast traffic volume on urban roads[14]. Olayode et al.[15] introduced a hybrid algorithm known as ANN-PSO model to predict the flow of vehicles at a road intersection. Chen et al.[16] employed a particle swarm optimization (PSO) algorithm to address the issues of slow convergence and local optima in WNN prediction algorithm. For traffic flow prediction, a PSO-ELM model based on PSO was given[17] and this model combines the benefits of extreme learning machines with particle swarm optimization to quickly handle nonlinear relationships while searching for a global optimal solution. Furthermore, to improve the performance for forecasting short-term traffic flow, a gravitational search algorithm-optimized extreme learning machine (GSA-ELM) was developed[18]. Additionally, Xie et al.[19] presented a model based on the GSA-optimized Gated Recurrent Unit (GRU) method to attain a high-precision short-term prediction. A noise-immune extreme learning machine that combines an extreme learning machine to estimate traffic flow while implementing the gravitational search method to get the best overall solution was proposed[20]. A predictive model that combines PSO and LSTM techniques was developed to forecast the entire time series of road traffic speed, including its dynamics aspects[21]. As seen in the above literature, optimization techniques are often combined with machine learning and deep learning models to enhance the optimization and training process. Because optimization algorithms can be used to optimize hyperparameters of machine learning and deep learning models and find the optimal values for hyperparameters such as initial weights, bias, and learning rate can effectively improve the prediction performance of the models. Furthermore, GSA technique is designed to exhibit global exploration capabilities, enabling it to search across the entire solution space efficiently and this can make it more suitable for finding global optima in complex optimization problems, whereas other optimization techniques such as PSO, ant colony optimization (ACO), and genetic algorithm (GA) might get stuck in local optima.

Therefore, in the present research, we developed a long short-term memory traffic flow forecasting model which is optimized by a gravitational search algorithm and this model is termed as GSA-LSTM. The proposed GSA-LSTM model can significantly increase the traffic flow prediction accuracy and minimize the prediction time. Also, by analyzing the prediction performance of GSA-LSTM model and PSO-LSTM model, this study discovered that GSA has superior optimization capabilities than PSO in terms of optimizing the long short-term memory network for traffic flow forecasting. The following list summarizes our contributions to this paper:

- Firstly, the proposed work demonstrated that the gravitational search algorithm can increase the prediction accuracy of the long short-term memory model without making the model more complex.

- Secondly, a gravitational search algorithm-optimized long short-term memory model is introduced for accurate forecasting of short-term traffic flow.
- Thirdly, study analysis found that the predictive accuracy of proposed GSA-LSTM model is high as compared to PSO-LSTM model.
- Finally, appropriate experiments are conducted to establish the better performance of the GSA-LSTM model by comparing it with existing models in terms of evaluation metrics.

2 Methodology

2.1 Forecasting of Short-Term Traffic Flow

The traffic volume on the road has both spatial and temporal features. It is distributed differently according to location and time depending on the number of vehicles utilizing a particular segment of the road at a specific moment. Due to drivers' driving habits and the traffic laws on the routes they take, there are also specific guidelines and characteristics of the overall traffic flow.

Time and space, two-dimensional variables, are available in data on traffic flow forecasting. Analyzing the time-related data reveals that, during a specified time, traffic on a specific roadway segment maintains a consistent flow. Utilizing the historical average can offer an insightful perspective on the time-related aspect of the data. On the other hand, the space characteristic indicates a specific duration. The flow rates of the downstream and upstream sections that are adjacent to the road segment are related to the road segment. Traffic flow data is collected in a variety of ways (like loop detectors, video cameras, pneumatic tubes etc.). Collected traffic flow data may contain anomalies and therefore preprocessing becomes necessary before its utilization. Traffic flow forecasts are separated into long-term and short-term categories based on their length. The forecast's time horizon is short primarily because the phenomenon changes rapidly and lacks predictable patterns. Meanwhile, the prediction time for short-term traffic flow generally does not exceed 15 minutes (only in exceptional cases up to 30 minutes). For both automobiles and people, its precise predictions improve path planning.

Traffic flow prediction has become quite challenging, particularly for short-term traffic flow prediction due to uncertain factors (natural and human factors). Some conventional methods cannot satisfy the nonlinearity that is required for the prediction of short-term traffic flow. This challenge arises from the reduced forecasting horizon, which introduces substantial unpredictability and uncertainty, and the demand for highly accurate predictions. The development of highly accurate prediction techniques based on deterministic mathematical models is becoming more and more challenging. The idea of traffic flow prediction is to fully utilize the information collected by several traffic flow collection devices and to separate uniformity from randomness by analyzing appropriate methods. The fundamental procedure for the forecasting of traffic flow is as follows:

- Firstly, collect the required traffic data and extract the required input variables from the collected data.
- Secondly, analyze and clean/remove the data having incomplete information/errors.
- Thirdly, select the relevant model and supply the sample data to the model as input.
- Lastly, forecast the traffic flow for the next/upcoming period and compare the results with real field data.

Short-term traffic flow prediction models with features like accuracy, real-time, and dynamic feedback are efficient because it is essential for real-time data analysis. The above-mentioned features of traffic flow demonstrate that it needs formalization and is defined by complexity, uncertainty, and randomness. The statistical theory-based approach presents problems to resolve because of the complexity of the modeling process and the highly precise needs. Additionally, the adoption of specific mathematical models to forecast complex and nonlinear traffic flows is insufficient to meet the requirements. Consequently, researchers have shifted their focus from traditional statistical and mathematical approaches to the utilization of machine learning and deep learning methods. Recently deep learning has demonstrated beneficial results for capturing the non-linearity of traffic flow. In this article, LSTM model is combined with an optimization technique GSA to predict accurate traffic flow. The gravitational search algorithm is used to optimize the parameters of the long short-term memory model.

2.2 Gravitational Search Algorithm (GSA)

The "gravitational search algorithm (GSA)", was first invented by Rashedi et al. [22] in 2009. The fundamental inspiration for the gravitational search method is the physics law of gravity. In this algorithm, the optimal solution to the problem is considered to be a collection of space-moving particles. Then, as a result of all particles being attracted to one another by the force of gravity, they all travel in the direction of the objects with heavier masses. The position of the particle in the global search space improves as particle mass increases, resulting in the finding of the problem's optimal solution. GSA has good global search capabilities and is appropriate for the model's parameter optimization [23]. The formulation of this algorithm is as follows:

In a D-dimensional search space, with an initial group of N particles, the position of the kth particle is expressed as

$$P_k = p_k^1, p_k^2, \ldots, p_k^d, \ldots, p_k^D, k = 1, 2, \ldots, N \tag{1}$$

Assume that at time t the k^{th} particle's inertial mass $M_k(t)$ is

$$m_k(t) = \frac{Fit_k(t) - W_{worst}(t)}{B_{best}(t) - W_{worst}(t)} \tag{2}$$

$$M_k(t) = \frac{m_k(t)}{\sum_{l=1}^{N} m_l(t)} \tag{3}$$

where $Fit_k(t)$ is the fitness value for the k^{th} particle at time $t, B_{best}(t)$ and $W_{worst}(t)$ indicate the best and worst fitness values, respectively of the whole particle population at time t. The best and worst fitness for the problem of the least optimization are defined in the given Equations (4) and (5).

$$B_{best} \quad = \min_{l \in l, 2, \ldots, N} Fit_l(t) \tag{4}$$

$$W_{worst} = \max_{l \in 1, 2, \ldots, N} Fit_l(t) \tag{5}$$

The gravitational force between the l^{th} and k^{th} particles in d-dimensional space at time t is given as

$$F_{kl}^d = G(t) \frac{M_k(t) \times M_l(t)}{U_{kl}(t) + \delta} (p_l(t) - p_k(t)) \tag{6}$$

In this expression, $p_l(t)$ and $p_k(t)$ are the position of l^{th} and k^{th} particles in d-dimensional space at time t respectively, δ is a small constant value, $U_{kl}(t)$ is Euclidean distance between particle k and particle l at time t, and $G(t)$ is the gravitational constant at time t. The gravitational constant is calculated as

$$G(t) = G_0 e^{-vT} \tag{7}$$

where G_0 denotes the initial value of $G(t)$, v is mutually adjusted constant, and T indicates the maximum iterations.

Assuming in GSA that the acting forces given in Equation (6) of all other particles summed at time t is equal to the total acting force of the k^{th} particle in d-dimensional space and is given as

$$F_k^d = \sum_{l=1, l \neq k}^{N} r_l \, F_{kll}^d(t) \tag{8}$$

where r_l is a random number between 0 and 1. The acceleration of a particle at time t in the d-dimensional is defined as

$$a_k^d(t) = \frac{F_k^d(t)}{M_k(t)} \tag{9}$$

The equations for updated velocity and position of the particle are defined as

$$v_k^d(t+1) = r_k \times v_k^d(t) + a_k^d(t) \tag{10}$$

$$p_k^d(t+1) = p_k^d(t) + v_k^d(t+1) \tag{11}$$

where r_k is random number from the interval $[0, 1]$ and $v_k^d(t)$ is the velocity of k^{th} particle at time t in d-dimensional space.

- **Algorithm: Gravitational search algorithm (GSA)**

Input: Let N be the number of objects in d-dimensional space.
Output: The optimal solution is where the heaviest object is located.

1. Set up the population at random as given in Equation (1)
2. While termination condition does not get done
3. Compute the fitness for each object
4. Compute the inertial mass for each object using Equations (2) and (3)
5. Update gravitational constant using Equation (7)
6. Compute total acting force using Equation (8)
7. Update acceleration using Equation (9)
8. Update velocity using Equation (10)
9. Update position using Equation (11)
10. end while

2.3 Long Short-Term Memory (LSTM) Network

The term LSTM refers to a specific variant of Recurrent Neural Network (RNN) that is used to learn long-term dependencies and retains the recursion feature of RNN. LSTM effectively deals with time series data and addresses issues like gradient vanishing and exploding that are prevalent in RNNs. The LSTM structure basically consists of an input gate, forget gate, output gate, and memory unit. According to varying situations, the input gate i_t receives input data and modifies the memory unit's state. The forget gate f_t chooses the information to be discarded based on a certain condition. In accordance with the input data and the memory unit, the output gate o_t selects what will be displayed.

Suppose x_t for input, y_t for output, h_t and c_t can be referred to as short-term state and long-term state, respectively and $\widetilde{c}_t$ represents a candidate hidden state derived from the present input and prior hidden state. The construction of LSTM unit is illustrated in Figure 1.

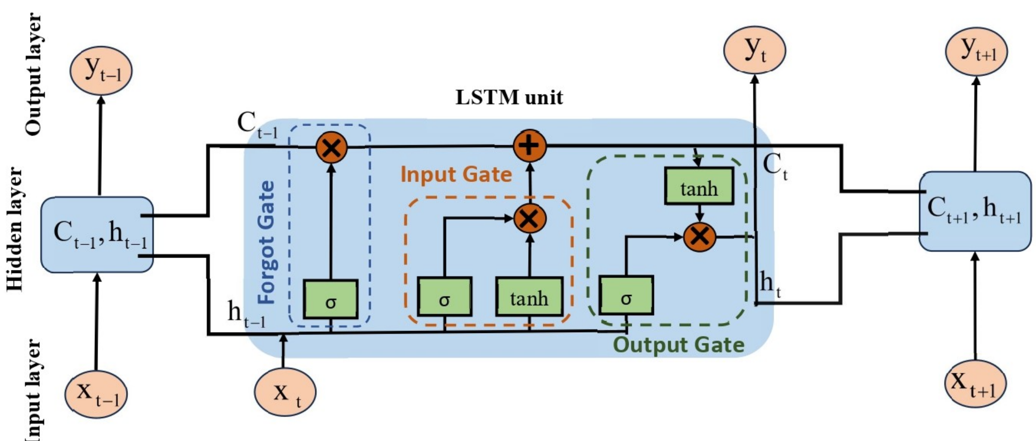

Fig 1. The framework of LSTM network

The forget gate f_t takes the current state x_t and the hidden layer state x_t from the previous moment at each instant, and through the activation function σ, outputs a value of $[0,1]$. To get the updated memory unit, the output of the forget gate f_t is combined with the nonlinear function's transformed input of the input gate i_t. Finally, after the execution of a nonlinear function, the output gate o_t can continuously regulate the output $h_t\,(y_t)$ of the LSTM in accordance with c_t.

The formulas of forget gate, input gate, and output gate are illustrated in Equations (12), (13) and (14) respectively[24].

$$f_t = \sigma\left(U_f \otimes h_{t-1} + U_f \otimes x_t + b_f\right) \tag{12}$$

$$C_t = \sigma\left(U_i \otimes h_{t-t} + U_i \otimes x_t + b_i\right) \tag{13}$$

$$o_t = \sigma\left(U_o \otimes h_{t-1} + U_o \otimes x_t + b_o\right) \tag{14}$$

Here, $\sigma(.)$ represents the sigmodif function; U_f, U_i, U_o and b_f, b_i, b_o are the weight matrices and bias of forget gate, input gate and output gate, respectively, output gate and unit state control LSTM's final output.

Then, the values of c_t and h_t are then obtained using Equations (15), (16), and (17).

$$\widetilde{c_t} = tanh\left(U_c \otimes h_{t-1} + U_c \otimes x_t + b_c\right) \tag{15}$$

$$c_t = f_t \otimes c_{t-1} + i_t \otimes \tilde{c_t} \tag{16}$$

$$h_t = o_t \otimes tanh\left(c_t\right) \tag{17}$$

where U_c and b_c represent the weight matrix and bias of candidate state $\tilde{c_t}$ respectively, $\otimes$ represents element-wise multiplication operator.

2.4 GSA-LSTM

The accuracy of the model's predictions is significantly influenced by the parameters that are set. All of the generally used parameter optimizers, such as Adam, Adagrad, Stochastic gradient descent (SGD), etc., are based on the gradient of the loss function on parameters. Based on gradient descent algorithms, the basic idea behind these techniques is to employ the gradient to determine the best way for a parameter. Despite realizing quick model convergence and adaptive learning rate adjustment, it cannot ensure that the solution is found in the global solution space.

To address this issue, this research proposed a model in which a gravitational search algorithm is used to find better network parameters for the LSTM model. A model named GSA-LSTM is developed that incorporates the GSA to repeatedly generate the learning rate for LSTM and its structure is shown in Figure 2. To increase the accuracy of traffic flow forecasting, the proposed model uses an enhanced gravity algorithm that can perform global optimization to make the LSTM more advanced. The steps of the prediction process are given as

- First of all, normalize the input data.
- After that, initialize the parameters of the LSTM and GSA methods.
- Then calculate the initial fitness function of each particle.
- Particles are repeatedly updated to their individual and global optimal positions.
- After finding the optimal solution, traffic flow is estimated using the LSTM model in accordance with the optimized parameters.
- Additionally, the outcomes are denormalized.
- Finally, the predicted traffic flow is obtained.

Fig 2. The architecture of GSA-LSTM model

3 Results and Discussion

3.1 Data Description

The data used in this study were collected using video cameras at the Inner Ring Road, South Extension-II, Delhi, India from 24-02-2020 to 28-02-2020. During the periods of 8 am to 11 am and 4:30 pm to 7 pm, data were collected from both sides of the road. From the recorded videos, 678 sets of traffic data were extracted in intervals of five minutes. Training and testing data sets were selected from these 678 data sets at random.

3.2 Measures of Performance Evaluation

To examine the prediction performance of the suggested model, six performance measures, mean absolute error (MAE), mean absolute percentage error (MAPE), root mean squared error (RMSE), correlation coefficient (r), average accuracy (AA) and GEH statistics have been used in this article, which are defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum (Y_P - Y_A)^2} \tag{18}$$

$$MAE = \frac{1}{n}\sum |Y_P - Y_A| \tag{19}$$

$$MAPE = \frac{1}{n}\sum \frac{|Y_P - Y_A|}{Y_A} * 100 \tag{20}$$

$$r = \frac{n\sum (Y_P * Y_A) - \sum (Y_A) * \sum (Y_P)}{\sqrt{\left(n\sum (Y_A)^2 - (\sum (Y_A))^2\right)} * \sqrt{\left(n\sum (Y_P)^2 - (\sum (Y_P))^2\right)}} \tag{21}$$

$$AA = \left(1 - mean\left(\frac{|Y_P - Y_A|}{Y_P}\right)\right) * 100 \tag{22}$$

$$GEH = \sqrt{\frac{2*(Y_P - Y_A)^2}{Y_P + Y_A}} \tag{23}$$

where Y_P and Y_A indicate predicted and actual value and n is the number of data sets.

3.3 Prediction Performance Analysis

The effectiveness of the proposed GSA-LSTM model is examined by contrasting it with various benchmark techniques, which consist of statistical methods, machine learning and deep learning techniques. Selected benchmark techniques in this study are: ARIMA, WNN, GRU, LSTM, GSA-GRU, ACO-LSTM, and PSO-LSTM.

For a valid comparison, all LSTM-based models employ the same parameters and were trained by an ADAM optimizer in MATLAB R2023a software. While this is going on, each model in the comparison uses the same test dataset to validate the prediction performance and the same training dataset to optimize the parameters.

Table 1 compared the selected models with the proposed GSA-LSTM model by using Equations (18), (19), (20) and (21). Compared with ARIMA, WNN, GRU, LSTM, GSA-GRU, ACO-LSTM, and PSO-LSTM, the values of RMSE, MAE, and MAPE for our proposed GSA-LSTM model are less as compared to other selected models. Additionally, the value of correlation coefficient is high in case of our proposed model which indicated favorable relationship between predicted and actual outcomes. Therefore, it is clear that the GSA-LSTM model performed well compared to other existing models in term of prediction accuracy. Using Equation (22), the average accuracy of ARIMA, WNN, GRU, LSTM, GSA-GRU, ACO-LSTM, PSO-LSTM, and GSA-LSTM are also compared as depicted in Table 1. From Table 1, it is concluded that the proposed model GSA-LSTM has higher accuracy as compared to other models.

Moreover, the difference between the model's results for short-term traffic flow forecast and actual traffic flow is then visually represented in Figure 3 and all profile of traffic flow in this figure are obtained using MATLAB R2023a. The actual traffic flow is represented by a blue line, and the predicted traffic flow is denoted by a red line. It is clear from Figure 3 that the fitting of real and predicted data is more close in case of the proposed GSA-LSTM model as compared to the other selected models. Equation (23) is used to determine the value of GEH statistics to examine the performance of forecasting results. Table 2 demonstrates the GEH statistics of the predicted results for several epochs. It is noted that GEH of the GSA-LSTM for each epoch is less than 5, as shown in Table 2. Thus, the GSA-LSTM model is regarded as having a good fitting performance under the GEH property.

Finally, we can say that proposed model is utilized for traffic flow prediction and it performs better than baseline models in terms of evaluation indicators as shown in Tables 1 and 2**,** and Figure 3.

Table 1. Analysis of the evaluation results of the various models

Experimental Model	RMSE	MAE	MAPE (%)	r	AA
ARIMA	136.6834	100.1617	20.6743	0.9685	75.7242
WNN	114.8104	93.5096	18.3028	0.9752	80.1153
GRU	97.3903	73.7078	16.1058	0.9769	85.9755
LSTM	93.3088	71.6502	15.3508	.9790	86.1904
GSA-GRU	92.0246	68.9631	15.2796	0.9801	87.2835
ACO-LSTM	91.2452	68.7413	15.1583	0.9804	87.2958
PSO-LSTM	87.2151	66.6821	14.6710	0.9819	87.5283
GSA-LSTM	85.1496	65.3748	14.1738	0.9827	87.7115

Table 2. GEH statistics of GSA-LSTM models

Epochs	200	250	300	350
GEH	3.8216	3.7747	3.5784	3.8938

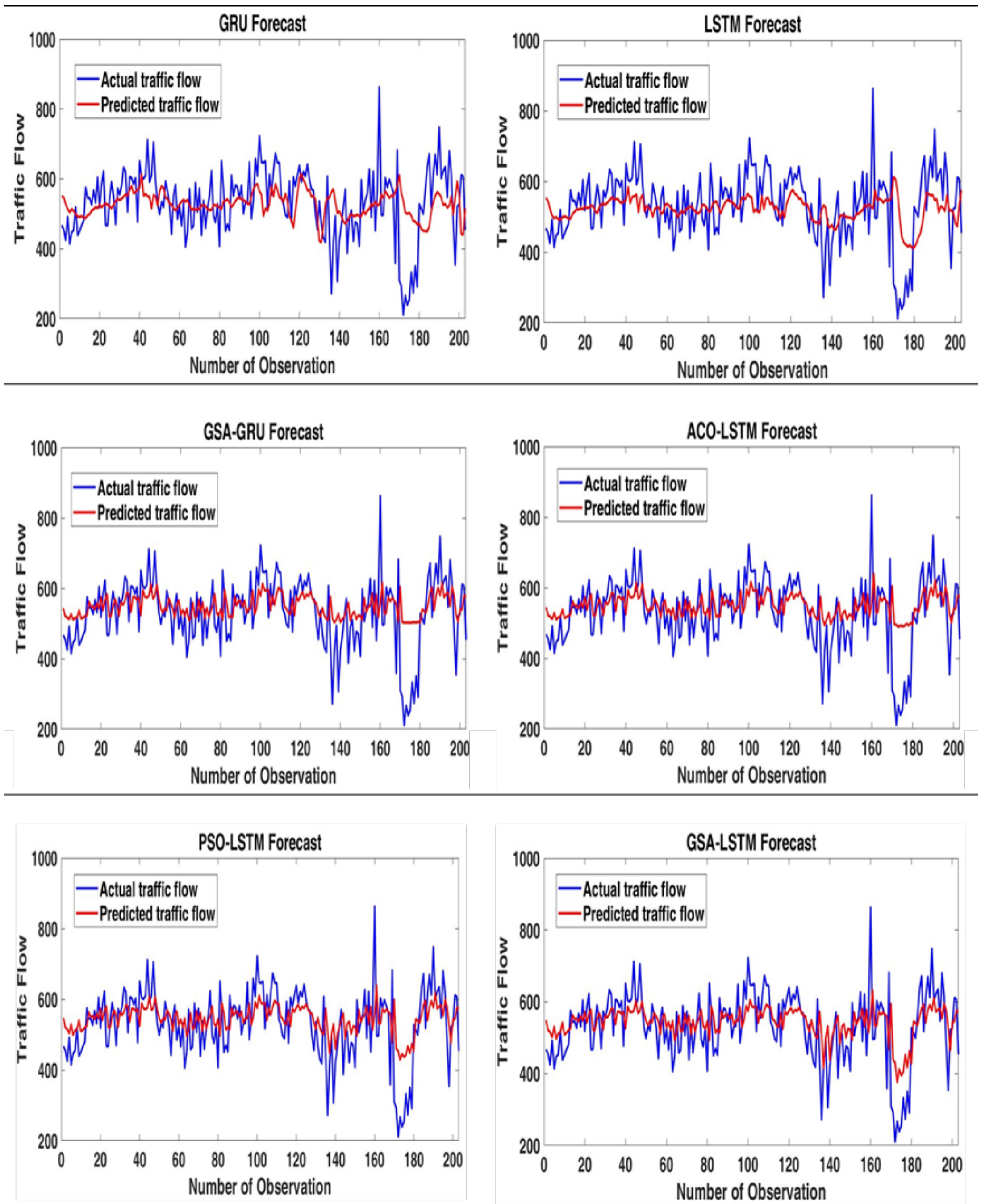

Fig 3. Traffic flow prediction performance for various models

4 Conclusion

A deep learning structure, named as GSA-LSTM, to predict traffic flow is proposed in this study. GSA-LSTM model utilizes the GSA to improve the predictive capabilities of LSTM model and GSA plays a crucial role in GSA-LSTM method, ensuring accurate short-term traffic flow predictions. In this study, the primary objective of GSA method is to achieve global optimization of the parameters for the LSTM model. Study outcomes indicate that the proposed model outperforms the selected models for various epochs in terms of evaluation metrics such as RMSE, MAE, MAPE, and r. Also, the prediction accuracy for the proposed model is higher as compared to PSO-LSTM, ACO-LSTM, GSA-GRU, LSTM, GRU, WNN, and ARIMA models. Consequently, proposed model is recognized as exhibiting strong fitting performance based on the GEH attribute. Additionally, when we examine the effectiveness of the GSA-LSTM model and the PSO-LSTM model in predicting traffic flow, we observe that GSA outperforms PSO in terms of improving the performance of the LSTM.

In conclusion, we can say that our proposed model performs well as compared to other chosen models in terms of traffic flow prediction. Future research will focus on the collection of more extensive data, potentially covering a full day's worth of information, to enhance the accuracy of traffic pattern predictions.

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Credit authorship contribution statement

Bharti Naheliya: Conceptualization, Methodology, Investigation, Writing – original draft. Poonam Redhu: Writing – review & editing, Supervision. Kranti Kumar: Writing – review & editing, Supervision.

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