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Intelligent Slime Mould Optimization with Deep Learning Enabled Traffic Prediction in Smart Cities

Manar Ahmed Hamza[1,*], Hadeel Alsolai[2], Jaber S. Alzahrani[3], Mohammad Alamgeer[4,5], Mohamed Mahmoud Sayed[6], Abu Sarwar Zamani[1], Ishfaq Yaseen[1] and Abdelwahed Motwakel[1]

[1]Department of Computer and Self Development, Preparatory Year Deanship, Prince Sattam bin Abdulaziz University, AlKharj, Saudi Arabia
[2]Department of Information Systems, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh, 11671, Saudi Arabia
[3]Department of Industrial Engineering, College of Engineering at Alqunfudah, Umm Al-Qura University, Saudi Arabia
[4]Department of Information Systems, College of Science & Art at Mahayil, King Khalid University, Saudi Arabia
[5]Department of Computer Science and Bioinformatics, Singhania University, Pacheri Bari, District Jhnujhunu, Rajasthan, India
[6]Department of Architectural Engineering, Faculty of Engineering and Technology, Future University in Egypt, New Cairo, 11835, Egypt
*Corresponding Author: Manar Ahmed Hamza. Email: Ma.hamza@psau.edu.sa
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Abstract: Intelligent Transportation System (ITS) is one of the revolutionary technologies in smart cities that helps in reducing traffic congestion and enhancing traffic quality. With the help of big data and communication technologies, ITS offers real-time investigation and highly-effective traffic management. Traffic Flow Prediction (TFP) is a vital element in smart city management and is used to forecast the upcoming traffic conditions on transportation network based on past data. Neural Network (NN) and Machine Learning (ML) models are widely utilized in resolving real-time issues since these methods are capable of dealing with adaptive data over a period of time. Deep Learning (DL) is a kind of ML technique which yields effective performance on data classification and prediction tasks. With this motivation, the current study introduces a novel Slime Mould Optimization (SMO) model with Bidirectional Gated Recurrent Unit (BiGRU) model for Traffic Prediction (SMOBGRU-TP) in smart cities. Initially, data preprocessing is performed to normalize the input data in the range of [0, 1] using min-max normalization approach. Besides, BiGRU model is employed for effective forecasting of traffic in smart cities. Moreover, the novelty of the work lies in using SMO algorithm to effectively adjust the hyperparameters of BiGRU method. The proposed SMOBGRU-TP model was experimentally validated and the simulation results established the model's superior performance in terms of prediction compared to existing techniques.

Keywords: Smart cities; traffic flow prediction; slime mould optimization algorithm; deep learning; intelligent models

1 Introduction

The tremendous growth experienced in the total number of automobiles in recent years, without any additional supporting means of transportation architecture, is one of the major issues in smart city development [1]. Due to countless number of cars on road, urban regions are overcrowded which in turn causes multiple effects such as increased air and noise pollution, reduced fuel proficiency and increased velocity of traffic. This scenario stimulates the intersection traffic by major alterations in pace control structures of metropolitan cities and towns [2]. Since these systems further disturb traffic signal control mechanisms and pollution control strategies, logistics and traffic management have become major issues to deal with. In earlier times, traffic signal controlling tools were used in traffic administration system whereas such tools are used for traffic management these days in smart cities. It plays a major role in ensuring the safety of people who experience traffic [3]. Traffic data accumulations act as a significant input in both management and understanding of the traffic. Traffic counting process is commonly executed these days while conventional city or state governments have certain ways to track the count of traffic such as microwave sensors, cameras, radar weapons, and speed guns [4]. Fig. 1 illustrates the structure of ITS.

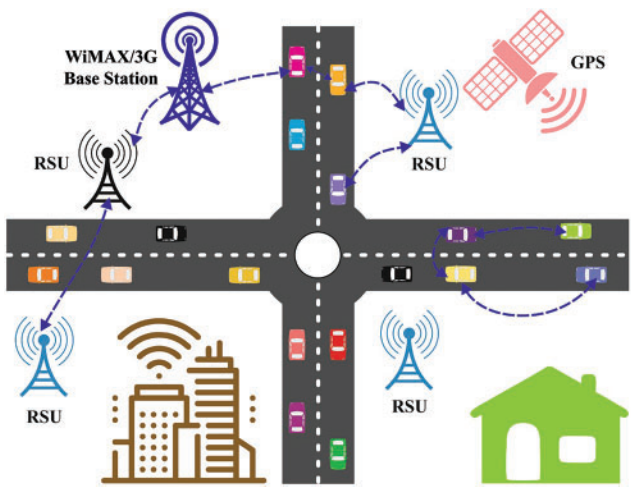

Figure 1: Structure of intelligent transportation systems

For a known period of time, researchers are working on automobile traffic prediction and proposed few models to achieve it. In specialized publications, various solutions have been proposed [5] which function in a fair and accurate manner under regular circumstances i.e., no unplanned incidents on road network. But, on many occasions, these methodologies are unprepared to find out the convoluted congestion propagation patterns. This lack of preparation results in erroneous predictions under severe conditions, although exact predictions are required during these important times [6,7]. Such serious conditions occur through multiple factors such as events, traffic threats, extreme weather conditions, and so on. Even though it is not easy to get rid of the suspicious element entirely from traffic estimation, it is possible to reduce the adverse effect of the blockage by considering exogenous data resources [8–10].

The advancements made in technology and unique ideas for smart cities have encouraged great deals of development in smart cities. The application areas of Artificial Intelligence (AI) such as big data, Deep Learning (DL), Machine Learning (ML), and Internet of Things (IoT) [11], have gained importance in assisting technological evolution of smart cities. Amongst them, ML approaches have endowed numerous applications in different fields such as air pollution monitoring and estimation, city planning, energy demand, consumption estimation, mobility management and monitoring of food supply and production estimation, resource distribution, etc. [12,13].

The current article introduces a novel Slime Mould Optimization (SMO) with Bidirectional Gated Recurrent Unit (BiGRU) model for Traffic Prediction (SMOBGRU-TP) in smart cities. Initially, the data is pre-processed to normalize the input data within a range of [0,1] using min-max normalization approach. Besides, BiGRU model is employed for effective forecasting of traffic in smart cities. Further, SMO algorithm is utilized for fine tuning the hypervariables involved in BiGRU design. In order to validate the superior prediction performance of the proposed SMOBGRU-TP model, numerous analyses were conducted and the results established the supremacy of the proposed model.

2 Literature Review

Vijayalakshmi et al. [14] projected an attention-based multi-stage predictive method named Convolution Neural Network(CNN)-Long Short Term Memory (LSTM). The suggested system used spatial and time-based traffic information extracted with the help of CNN and LSTM systems in order to enhance the accuracy of the model. Attention-based method assists in identifying the nearby traffic information, since the speed is an important parameter to forecast the upcoming values of the flow. In literature [15], the authors presented ML and optimization methods to empower an intelligent ecosystem. For validation purpose, a computation was executed in this study with multi-layer perceptron and Particle Swarm Optimization (PSO) approach.

Wang et al. [16] introduced a multi-task DL approach named 'Multitask Recurrent Graph Convolution Network (MRGCN)' which precisely forecasts the traffic data in smart cities. Especially, this study presented a multitasking architecture that consists of four major elements such as a task-specific decoder to forecast the traffic flow, a region flow encoding unit to model region flow dynamics, a transition flow encoding unit to explore transition flow correlation, and a context modelling module for contextual combination of two kinds of traffic flow. Khan et al. [17] aimed at developing a data fusion-related traffic congestion control scheme in smart city using DL method. A hybrid mechanism was utilized in this study based on CNN and LSTM frameworks for region-related traffic flow prediction in smart cities. CNN was employed here for spatial dataset categorization, whereas LSTM was applied for temporal dataset classification.

Kuang et al. [18] presented a traffic signal control method based on reinforcement learning using state reduction. At first, a reinforcement learning method was determined according to the previous traffic flow dataset. In addition to this, the study also presented a dual-objective reward operation that might improve the matching and degree decrease vehicle delay. Neelakandan et al. [19] developed a powerful IoT-based traffic predictive model with OWENN approach and traffic signal control scheme using Intel 80,286 microprocessor for smart cities. The presented technique comprised of five stages such as traffic signal control system, categorization, optimization of traffic IoT values, feature extraction and IoT data collection. At first, IoT traffic dataset is gathered from the information. Next, weather, direction, and traffic dataset are extracted. Followed by, the extracted feature is fed as input to the classification model that classifies the location as either heavy traffic or not.

3 The Proposed Model

In current study, a new SMOBGRU-TP model has been proposed to forecast the flow of traffic in smart city environment. The presented SMOBGRU-TP model comprises of data pre-processing initially, during when the input data is normalized within a range of [0,1] using min-max normalization approach. Further, SMO-BiGRU model is employed for effective forecasting of traffic in smart cities.

3.1 Data Pre-processing

At this preliminary level, the presented SMOBGRU-TP model comprises of data pre-processing which is performed to normalize the input data within a range of [0,1] through min-max normalization approach from scikit library. In these experiments, the preceding traffic flow of an hour i.e., a time series of 12 data points, is considered. It is used in the prediction of traffic flow that approaches from the following five minutes. Here, the list is generally grouped into 13 readings and the lists are utilized for training and testing purposes.

3.2 Design of BiGRU Based Predictive Model

After data pre-processing, BiGRU model is employed for effective forecasting of traffic in smart cities. The benefit of utilizing DL approaches is its capability to learn abstract features under several hidden layers. Gated Recurrent Unit (GRU) method is different from LSTM since it combines forget as well as input gates to a single upgrade gate. Further, it also integrates the cell as well as hidden states [16]. Thus, the latest GRU technique is simple and fast compared to typical LSTM technique, particularly when training big data. It is stored for several times with small performance variance compared to typical LSTM method. Both GRU and LSTM maintain essential characteristics with several gates so as to make sure that these characteristics are not lost from long-term broadcast. Fig. 2 illustrates the structure of GRU technique.

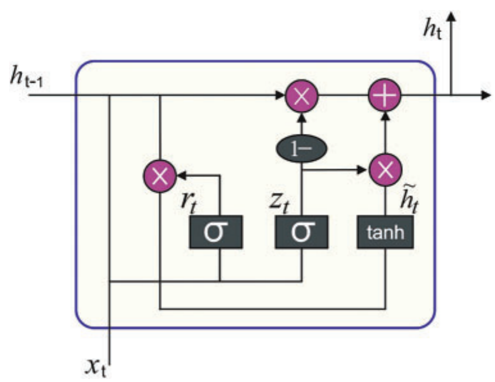

Figure 2: Structure of GRU

Whereas Z_t signifies the upgrade gate and r_t denotes the reset gate. At time t, GRU computes the novel state as follows.

$$h_t = Z * h_{(t-1)} + (1 - Z) * \tilde{h} \tag{1}$$

This is to compute a linear interpolation between the earlier state h_{t-1} and the existing candidate state $\tilde{h}_t$ with novel sequence data. The upgrade gate z_t resolves the issues like maintaining several past data and adding several novel data. It manages to an extent up to which the data of the preceding state is carried on to the existing state. The superior value of the state is denoted by z_t while the additional data of preceding state is taken forward. The state of z_t is upgraded as follows.

$$z_t = \sigma(W_Z.x_t + U_Z.h_{(T-1)} + b_Z) \tag{2}$$

Here, x_t refers to the instance vector at time t and $\tilde{h}_t$ denotes the candidate state which was calculated similar to the hidden layer of typical Recurrent Neural Network (RNN).

$$\tilde{h}_t = \tanh\left(W_h.x_t + r * U_h.h_{(t-1)} + b_h\right) \tag{3}$$

Here, r_t refers to the reset gate that controls several preceding states and gives to the existing candidate state, $\tilde{h}_t$. Lesser the value, lesser the contribution is, in the preceding state. When $r_t = 0$, it is forgotten as the preceding state. The reset gate is upgraded as follows.

$$r_t = \sigma\left(W_\gamma.x_t + U_\gamma.h_{(t-1)} + b_\gamma\right) \tag{4}$$

In case of several sequence modelling tasks, it is useful to gain access to upcoming and past contexts. But typical GRU network procedures perform sequence modelling in temporal manner and it disregards the future context altogether. Bi-directional GRU network expands the unidirectional GRU network by presenting an additional layer whereas the hidden-to-hidden associates flow from the opposite temporal sequence. This technique is capable of exploiting data from both past and the future. Similarly, GRUs provide a disappearing gradient issue by utilizing two gates such as update and reset gates. Essentially, these are two vectors that choose the dissemination of data to the output gate and these vectors are trained to retain the data even earlier. This permits it to pass the the applicable data down a chain of events so as to achieve optimum forecasts.

3.3 SMO Based Hyperparameter Optimization

In this final stage, SMO algorithm is utilized for fine tuning the hyper-variables of BiGRU model [20–23]. Benabbou et al. [24] proposed SMO algorithm which is inspired from natural simulation as per the foraging and diffusion characteristics of slime mould. In current study, ‘slime mould’ (SM) represents *Physarum polycephalum* which is the major player in nutritious phase of SM. Here, the organic material in SM is accountable for travelling near the food, finding and digesting. The arithmetical model for the abovementioned stages is given below.

The individual objective optimization method is shown herewith.

$$\min f(X) \tag{5}$$

$$s.t. lb \le X \le ub$$

Here, $f(x)$ denotes the optimization function, and $lb, ub \in R^d$ indicate the upper and lower limits of the parameter, $\chi \in R^d$. For the abovementioned d dimension optimization issue, the initialized SM population with n individuals is represented by $n \times d$ matrix named $X(0) = \{X_1, X_2, \cdots, X_n$. All the individuals in this population are nothing but vectors with d components that can be calculated as follows.

$$X_i = lb + rand \cdot (ub - lb), i = 1, 2, \ldots, n \tag{6}$$

SM can approach the food based on the odor in air as given below.

$$X(t+1)\begin{cases} X_b(t) + vb \cdot (W \cdot X_A(t) - X_B(t)), & r < p \\ vc \cdot X(t), & r \ge p \end{cases} \tag{7}$$

Here, X signifies the location of SM, t indicates the existing iteration value, X_b denotes a separate location with maximum odor concentration, X_A and X_B indicate two individuals that are arbitrarily chosen from the population. Such behaviors are inspired by two variables, vb and vc, which lie within $[-a, a]$ and vc gets linearly reduced within [0,1]. W epitomizes the weight of the searching agents and r denotes the arbitrary value within [0, 1]. It can be expressed as per the literature [25]:

$$p = \tanh |S(i) - DP|, i = 1, 2, \ldots, n \tag{8}$$

Now, $S(i)$ signifies the fitness value of the existing individuals whereas DF signifies the optimum fitness value in existing iteration as shown in the following equation.

$$vb = [-a, a], a = arctanh\left(-\frac{2}{\max\_ t} + 1\right) \tag{9}$$

Here, $\max\_ t$ embodies the maximal number of iterations. Weight W is calculated as given below.

$$W(SmellIndex(i) = \begin{cases} 1 + r \cdot \log\left(\frac{bF - S(i)}{bF - wF} + 1\right), condition \\ 1 + r \cdot \log\left(\frac{bF - S(i)}{bF - wF} + 1\right), others \end{cases} \tag{10}$$

$$\text{SmellIndex} = sort(S) \tag{11}$$

In this equation, the condition indicates the initial half of the population while r indicates an arbitrary value within [0, 1]. SmellIndex denotes the series of fitness values arranged in the ascending order with minimal value issue and bF and wF indicate the optimum and worst values attained in the existing generation.

This phase mimics the contraction of venous tissues of the SM to search food. It alters the searching pattern based on the quality of food [26]. It is arithmetically formulated in the following equation,

$$X* = \begin{cases} rand \cdot (ub - lb) + lb, & rand < z \\ X_b(t) + vb \cdot (W \cdot X_A(t) - X_B(t)), & r < p \\ vc \cdot X(t), & r \geq p \end{cases} \tag{12}$$

Now, rand and r indicates the arbitrary values within [0, 1] and ub and lb indicate the maximum and minimum limits of the searching region, correspondingly. z represents a variable that balances both exploration and exploitation abilities. Further, distinct values are chosen based on certain problems. In current study, z is fixed to be 0.03. Fig. 3 demonstrates the steps involved in SMO.

In this work, SMO algorithm is applied to appropriately fine-tune the hyperparameters involved in BiGRU model so as to minimize MSE. MSE is calculated as follows.

$$MSE = \frac{1}{T}\sum_{j=1}^{L}\sum_{i=1}^{M}\left(y_j^i - d_j^i\right)^2, \tag{13}$$

Here, M and L define the resultant values of layers and data correspondingly whereas y_j^i and d_j^i signify the attained and suitable magnitudes for j[th] unit from the resultant layer of network, at time t.

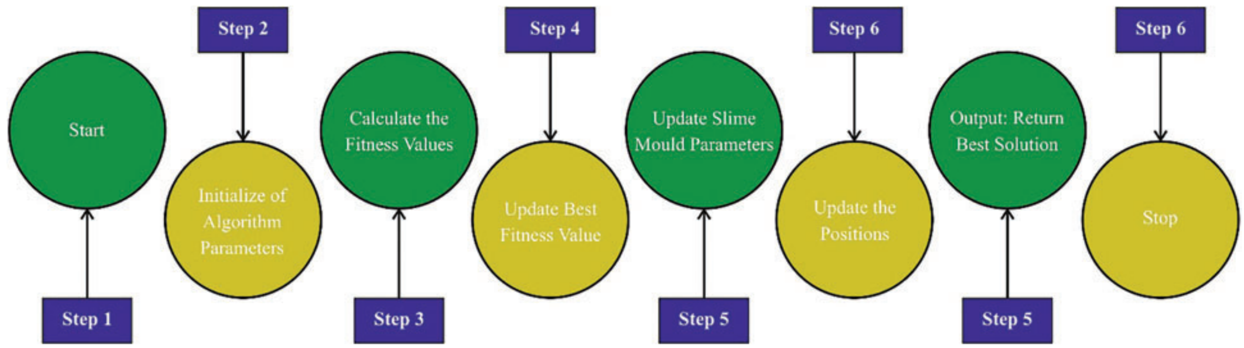

Figure 3: Steps in SMO

4 Experimental Validation

In this section, the TFP outcomes of the proposed SMOBGRU-TP model were analyzed under several aspects. Tab. 1 and Figs. 4 and 5 provide a detailed overview on TFP performance outcomes achieved by the proposed SMOBGRU-TP model and other existing models under different measures. The experimental results indicate that Radial Basis Function (RBF)+Principal Component Analysis (PCA)+PIM and RBF+PCC+PCA+PIM models reached ineffectual outcomes compared to other methods. At the same time, RBF+PIM and RBF+PCC models accomplished slightly enhanced results. Though AT-TFP model reached a Mean Absolute Percentage Error (MAPE) of 21.364%, Mean Square Error (MSE) of 299.636, and Root Mean Square Error (RMSE) of 17.310, the proposed SMOBGRU-TP model attained the least MAPE of 18.560%, MSE of 256.350%, and RMSE of 16.011.

Table 1: Results of the analysis of SMOBGRU-TP technique under distinct measures

Algorithms	MAPE (%)	MSE	RMSE
Radial Basis Function+PIM	21.996	310.867	17.631
Radial Basis Function+PCC	23.509	333.776	18.270
Radial Basis Function +PCA+PIM	20.537	418.009	20.445
Radial Basis Function +PCC+PCA+PIM	24.268	428.065	20.690
AI-TFP Model	21.364	299.636	17.310
SMOBGRU-TP	18.560	256.350	16.011

Tab. 2 and Figs. 6 and 7 provide a detailed overview on predictive outcomes accomplished by the proposed SMOBGRU-TP model and other recent models. The experimental outcomes infer that RNN-LSTM and RNN-GRU models reached ineffectual outcomes with maximal error values. Followed by, the cascaded LSTM, cascaded GRU, and autoencoder methodologies produced slightly lesser error values. Though NN, AE-RBF, and AI-TFP models accomplished reasonable error values, the proposed SMOBGRU-TP model attained an effectual performance with a minimal MAPE of 9.523%, MSE of 142.265, and RMSE of 11.927.

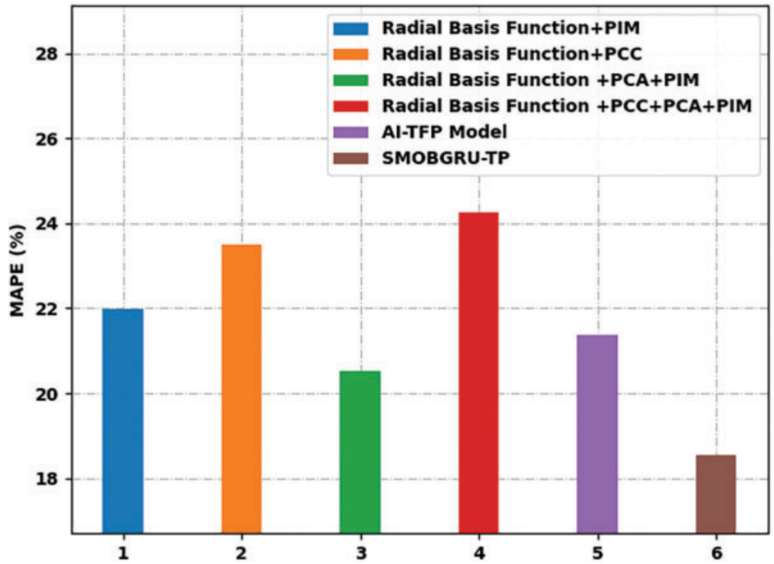

Figure 4: Results of the analysis of SMOBGRU-TP technique in terms of MAPE

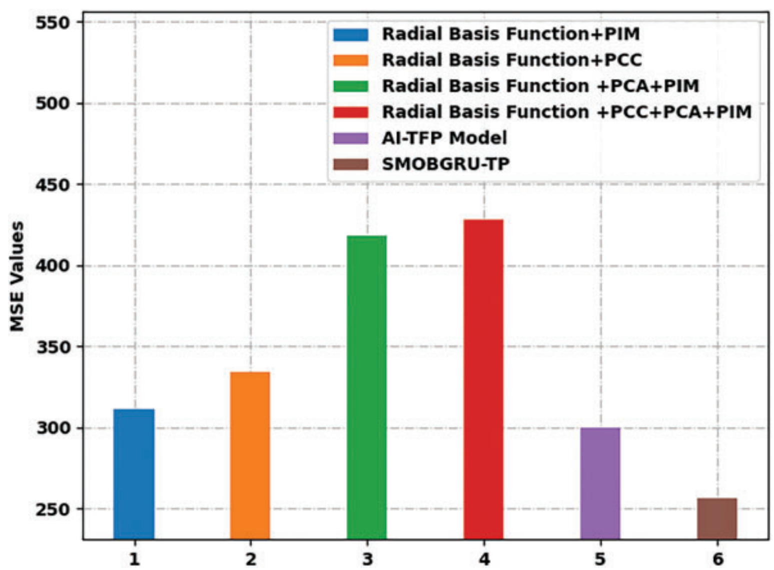

Figure 5: Results of the analysis of SMOBGRU-TP technique in terms of MSE

Table 2: Predictive analysis results of SMOBGRU-TP technique and other existing approaches

Algorithms	MAPE (%)	MSE	RMSE
RNN-LSTM	15.894	188.626	13.734
RNN-GRU	13.023	182.593	13.513
Cascaded LSTM	11.533	175.741	13.257
Cascaded GRU	11.148	175.382	13.243

(Continued)

Table 2: Continued

Algorithms	MAPE (%)	MSE	RMSE
AutoEncoder	11.113	165.035	12.847
Neural Networks	10.924	164.913	12.842
AutoEncoder-RBF	10.898	162.353	12.742
AI-TFP Model	10.528	157.846	12.564
SMOBGRU-TP	09.523	142.265	11.927

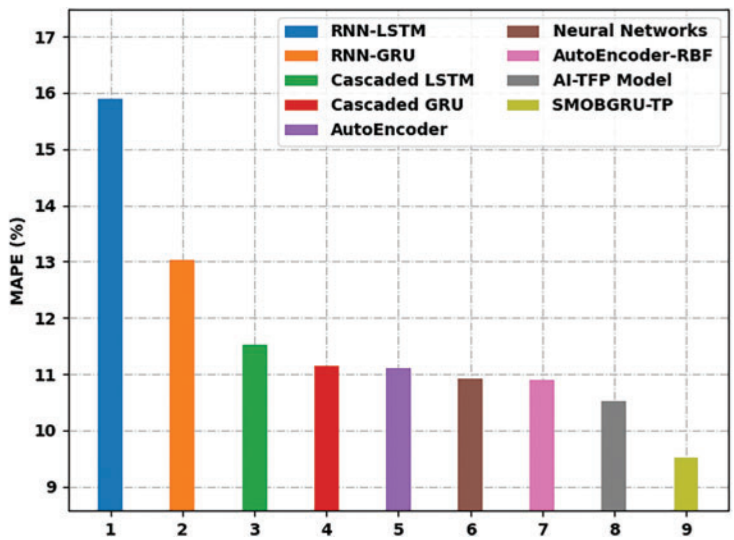

Figure 6: MAPE analysis results of SMOBGRU-TP technique and other existing approaches

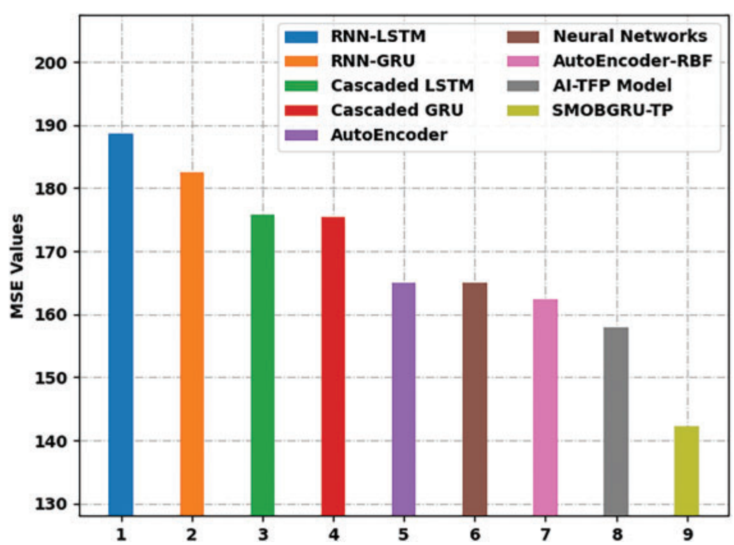

Figure 7: MSE analysis results of SMOBGRU-TP technique and other existing approaches

Tab. 3 and Fig. 8 shows the predictive results achieved by SMOBGRU-TP model and other recent models under distinct time durations [27–29]. The experimental results exhibit that the proposed SMOBGRU-TP model accomplished the least MAPE under all-time durations. For example, with a time duration of 5 mins, SMOBGRU-TP model provided the least MAPE of 15.894%, whereas RNN-LSTM, RNN-GRU, cascaded LSTM, cascaded GRU, AE, NN, AE-RBF, and AI-TFP models reached high MAPE values such as 15.894%, 13.023%, 11.533%, 11.148%, 11.113%, 10.924%, 10.898%, and 10.528% respectively. Along with that, with a time duration of 30 mins, the proposed SMOBGRU-TP method provided a low MAPE of 17.820%, whereas RNN-LSTM, RNN-GRU, cascaded LSTM, cascaded GRU, AE, NN, AE-RBF, and AI-TFP techniques reached high MAPE values such as 25.073%, 24.995%, 22.787%, 22.174%, 21.761%, 21.656%, 20.957%, and 17.820% correspondingly.

Table 3: MAPE analysis results of SMOBGRU-TP technique and other recent algorithms under distinct time durations

MAPE (%)						
Algorithms	Time (min)					
	5	10	15	20	25	30
RNN-LSTM	15.894	18.448	20.113	21.284	23.371	25.073
RNN-GRU	13.023	15.798	18.500	20.762	22.386	24.995
Cascaded LSTM	11.533	13.862	16.488	19.320	21.382	22.787
Cascaded GRU	11.148	13.593	15.774	18.514	20.298	22.174
AutoEncoder	11.113	13.526	15.487	17.638	20.004	21.761
Neural Networks	10.924	12.951	14.981	16.333	18.781	21.656
AutoEncoder-RBF	10.898	12.582	14.260	16.317	18.707	20.957
AI-TFP Model	10.528	12.117	13.347	15.446	17.886	20.205
SMOBGRU-TP	9.523	10.755	12.655	15.123	16.341	17.820

Tab. 4 and Fig. 9 portrays the predictive output produced by SMOBGRU-TP model and other recent models under distinct time durations. The experimental results exhibit that the proposed SMOBGRU-TP model accomplished a minimal MSE under all-time durations. For instance, with a time duration of 5 mins, the proposed SMOBGRU-TP model provided a low MSE of 142.265, while RNN-LSTM, RNN-GRU, cascaded LSTM, cascaded GRU, AE, NN, AE-RBF, and AI-TFP methodologies reached high MSE values such as 188.626, 182.593, 175.741, 175.382, 165.035, 164.913, 162.353, and 157.846 respectively. Likewise, at 30 mins duration, SMOBGRU-TP system provided the least MSE of 235.966, but RNN-LSTM, RNN-GRU, cascaded LSTM, cascaded GRU, AE, NN, AE-RBF, and AI-TFP techniques reached high MSE values such as 452.353, 449.797, 441.446, 428.327, 414.809, 398.998, 372.006, and 289.229 correspondingly.

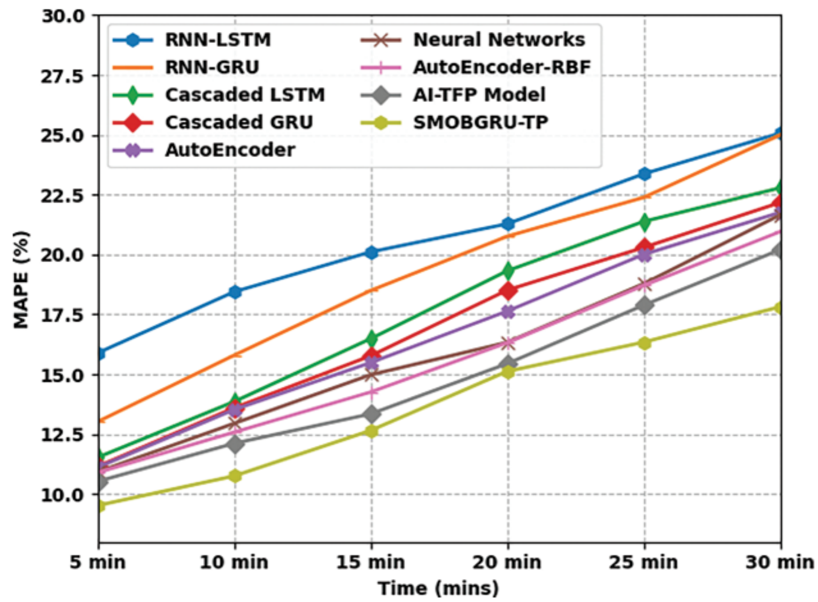

Figure 8: MAPE analysis results of SMOBGRU-TP technique under distinct time durations

Table 4: MSE analysis results of SMOBGRU-TP technique and other recent algorithms under distinct time durations

Mean Squared Error						
Algorithms	Time (min)					
	5	10	15	20	25	30
RNN-LSTM	188.626	251.810	299.685	373.490	411.059	452.353
RNN-GRU	182.593	221.044	294.174	349.806	399.869	449.797
Cascaded LSTM	175.741	218.048	285.264	340.920	381.915	441.446
Cascaded GRU	175.382	216.170	276.808	336.721	381.524	428.327
AutoEncoder	165.035	215.751	259.057	323.966	381.500	414.809
Neural Networks	164.913	211.089	258.491	320.641	363.263	398.998
AutoEncoder-RBF	162.353	210.627	252.652	281.474	338.353	372.006
AI-TFP Model	157.846	178.504	195.675	218.776	238.698	289.229
SMOBGRU-TP	142.265	157.254	176.923	199.115	213.294	235.966

Tab. 5 and Fig. 10 showcases the predictive results attained by the proposed SMOBGRU-TP model and other recent models under distinct time durations. The experimental results demonstrate that the proposed SMOBGRU-TP model accomplished the least RMSE at all-time durations. For example, for 5 mins time duration, SMOBGRU-TP system provided the least RMSE of 11.927, while RNN-LSTM, RNN-GRU, cascaded LSTM, cascaded GRU, AE, NN, AE-RBF, and AI-TFP techniques reached high RMSE values such as 13.734, 13.513, 13.257, 13.243, 12.847, 12.842, 12.742, and 12.564 correspondingly. In addition, with a time duration of 30 mins, the proposed SMOBGRU-TP approach reached a low RMSE of 15.361, whereas RNN-LSTM, RNN-GRU, cascaded LSTM, cascaded GRU, AE, NN, AE-RBF, and AI-TFP techniques reached high RMSE values such as 21.269, 21.208, 21.011, 20.453, 19.870, 19.209, 18.493, and 17.007 correspondingly. Based on the comprehensive comparative analyses and the simulation results, the proposed SMOBGRU-TP model proved its superiority to other models, in terms of performance.

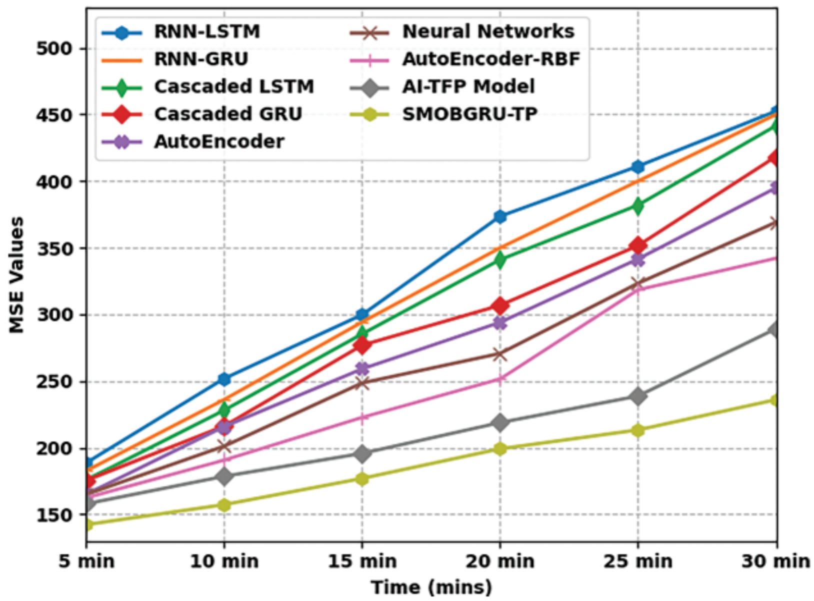

Figure 9: MSE analysis results of SMOBGRU-TP technique under distinct time durations

Table 5: RMSE analysis results of SMOBGRU-TP technique and other recent algorithms under distinct time durations

Root Mean Square Error						
Algorithms	Time (min)					
	5	10	15	20	25	30
RNN-LSTM	13.734	15.869	17.311	19.326	20.275	21.269
RNN-GRU	13.513	15.364	17.152	18.703	19.997	21.208
Cascaded LSTM	13.257	15.101	16.890	18.464	19.543	21.011
Cascaded GRU	13.243	14.703	16.638	17.513	18.749	20.453
AutoEncoder	12.847	14.688	16.095	17.145	18.480	19.870
Neural Networks	12.842	14.181	15.764	16.451	17.980	19.209
AutoEncoder-RBF	12.742	13.807	14.922	15.858	17.842	18.493
AI-TFP Model	12.564	13.361	13.988	14.791	15.450	17.007
SMOBGRU-TP	11.927	12.540	13.301	14.111	14.605	15.361

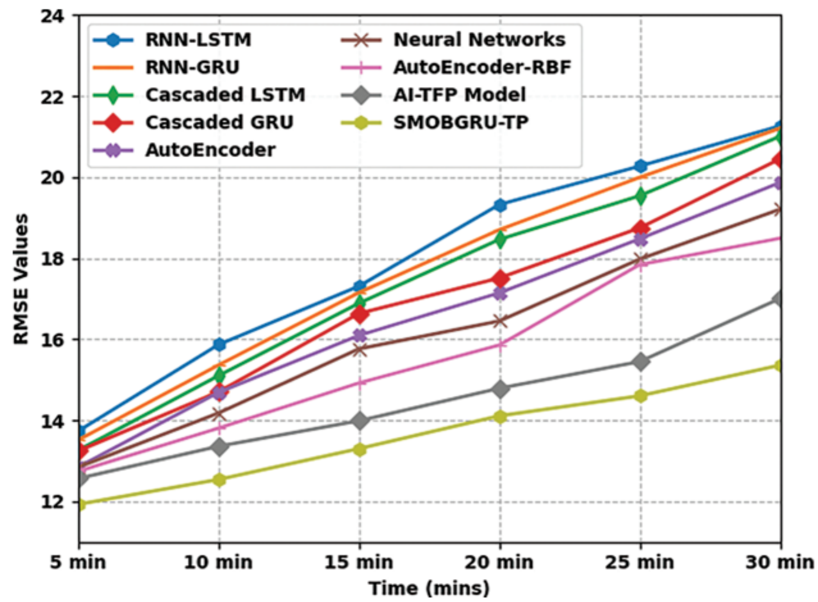

Figure 10: RMSE analysis results of SMOBGRU-TP technique under distinct time durations

5 Conclusion

In current study, a new SMOBGRU-TP model has been proposed to forecast the flow of traffic in smart city environment. In the initial stage of SMOBGRU-TP model, data pre-processing is performed to normalize the input data within a range of [0,1] using min-max normalization approach. BiGRU model is employed for effective forecasting of the traffic in smart cities. At last, SMO algorithm is utilized to fine tune the hyperparameters involved in BiGRU approach. In order to experimentally validate the superiority of the proposed SMOBGRU-TP models in terms of prediction performance, different analyses were conducted. The simulation outcome confirmed the superior results achieved by SMOBGRU-TP model than the existing techniques. In future, the efficiency of SMOBGRU-TP methodology can be improved with the help of hybrid DL models.

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