Accurate non-stationary short-term traffic flow prediction method

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Abstract—Precise and timely traffic flow prediction plays a critical role in developing intelligent transportation systems and has attracted considerable attention in recent decades. Despite the significant progress in this area brought by deep learning, challenges remain. Traffic flows usually change dramatically in a short period, which prevents the current methods from accurately capturing the future trend and likely causes the over-fitting problem, leading to unsatisfied accuracy. To this end, this paper proposes a Long Short-Term Memory (LSTM) based method that can forecast the short-term traffic flow precisely and avoid local optimum problems during training. Specifically, instead of using the non-stationary raw traffic data directly, we first decompose them into sub-components, where each one is less noisy than the original input. Afterward, Sample Entropy (SE) is employed to merge similar components to reduce the computation cost. The merged features are fed into the LSTM, and we then introduce a spatiotemporal module to consider the neighboring relationships in the recomposed signals to avoid strong autocorrelation. During training, we utilize the Grey Wolf Algorithm (GWO) to optimize the parameters of LSTM, which overcome the overfitting issue. We conduct the experiments on a UK public highway traffic flow dataset, and the results show that the proposed method performs favorably against other state-of-the-art methods with better adaptation performance on extreme outliers, delay effects, and trend-changing responses.

Index Terms—Deep learning, Short-term traffic flow prediction, Intelligent transportation, Mode decomposition, Spatiotemporal features

I. INTRODUCTION

With the rapid growth of population and urbanization, traffic congestion has become increasingly severe, leading to social problems such as prolonged travel times and frequent traffic accidents. By leveraging cutting-edge technologies to circumvent traditional infrastructure enhancement constraints, Intelligent Transportation System (ITS) can effectively ameliorate the congestion and safety issue [1], [2]. As an essential element in the ITS deployment, traffic flow prediction has attracted significant attention in the research field. By seeing the traffic flow in advance, the government can better allocate traffic resources to reduce congestion, and individuals can make more efficient travel decisions [3].

Despite the tremendous potential benefits, predicting traffic flow accurately and timely is challenging. Traffic flow is usually influenced by various complicated factors such as weather, geography, and the time of day, which are highly nonlinear and volatile. Moreover, traffic forecasts must be capable of foreseeing the traffic in the upcoming future (typically 15 minutes-30 minutes) to be meaningful, and such a short-term trend is difficult to capture as traffic flow can change dramatically in a short period. Although recent advancement in deep learning has brought remarkable improvement in traffic flow prediction, most existing methods still cannot handle the challenges above well. They either have a slow response to the quick traffic flow change or tend to fall into local optimum during training due to overfitting, leading to unsatisfied accuracy.

This paper proposes an ensemble model to solve the short-term traffic flow prediction accuracy. We first use the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) [4] method to decompose the non-stationary signal, where the trend in sub-components is easier to be captured. Meanwhile, to reduce the computational cost, SE is introduced to discard the similar sub-components and only keep the ones with high entropy. The remained components are then fed into LSTM to consider the temporal information. The low-frequency components of the LSTM outputs will be further sent into a Spatiotemporal module to examine the neighboring relationships between them to reduce the autocorrelation. Eventually, the predictions from different components will be aggregated to obtain the final results. During training, we deploy the GWO to optimize the model parameters to avoid the over-fitting issue.

We conduct experiments on a UK public highway dataset to evaluate our approach and compare it with other state-of-the-art models. The results show that our model outperforms other methods both quantitatively and qualitatively.

The main contributions of the paper are as follows.

- We present a robust ensemble model for short-term traffic flow prediction, which can timely and accurately respond to the dramatic change in the traffic flow. Extensive experiments demonstrate that our model can perform better than other baseline methods.
- We propose a CEEMEAN-SE module to reduce the complexity of the raw traffic data by decomposing it into several sub-components and keeping the computation cost low.
- We develop a spatiotemporal module to reduce the autocorrelation of low-frequency traffic flow signals.
- We integrate the GWO optimization in our model, which solves the common over-fitting problem.

II. RELATED WORK

Traffic flow has a strong regularity and periodicity, which is the basis for accurate prediction. However, there is also noticeable uncertainty existing in the short-term traffic flow [5], which makes the prediction task challenging. Researchers have devoted themselves to this field in the past years, and
the approaches can be divided into parametric and non-parametric methods.

A. Parametric methods

Autoregressive Integrated Moving Average is a standard parametric method for forecasting time series data, a statistical analysis model that uses time-series data to understand better the data set or predict future trends. Yu et al. [6] propose switching the ARIMA model and applying it to actual data obtained from UTC/SCOOT system. Kumar et al. [7] propose a Seasonal ARIMA model for short-term traffic flow prediction. Chen et al. [8] propose an Autoregressive Integrated Moving Average with Generalized Autoregressive Conditional Heteroscedasticity model for traffic flow forecasting.

Another standard parametric method for time series prediction is the Kalman filter technique. Kumar et al. [9] propose a traffic flow prediction model based on the Kalman filter technique. Guo et al. [10] propose an Adaptive Kalman filter approach to update the process variances for short-term traffic flow prediction. Although the parametric method has demonstrated effectiveness, it is limited by strong assumptions such as smoothness of the time series, which may lead to poor accuracy when the data varies irregularly in the temporal dimension. Therefore, the parametric approach has limited applicability in the transportation field.

B. Non-parametric methods

1) Traditional machine learning methods: Due to the constraints of parametric methods, non-parametric methods have become the first choice for traffic flow prediction nowadays. Yang et al. [11] propose a combined wavelet-SVM prediction model for short-term traffic flow prediction. Duan et al. [12] use a particle swarm optimization (PSO) algorithm to select the appropriate learning parameters to achieve the best PSO-SVM prediction model. Alam et al. [13] apply five regression models: linear regression, sequential minimum optimization (SMO) regression, multilayer perceptron, M5P-tree model, and random forest to predict the traffic flow in the city of Porto.

2) Deep learning methods: Recent advancement in deep learning has brought outstanding progress in many fields, such as autonomous driving [14]–[17], and intelligent transportation system [18]–[20]. Traffic flow prediction has also been advanced by deep learning. Zhang et al. [21] propose a short-term traffic flow prediction model based on a convolutional neural network (CNN). Zheng et al. [1] propose a traffic flow prediction model based on a Long Short-Term Memory (LSTM) network. Qu et al. [22] propose a new end-to-end hybrid deep learning network model, M-B-LSTM, for short-term traffic flow prediction. Ma et al. [23] use a particular convolutional neural network (CNN) to extract daytime and intra-day traffic flow patterns and feed the extracted features into the LSTM model. Zhao et al. [24] investigate temporal convolutional networks (TCN) for short-term traffic forecasting in the city. Although LSTM is widely used for time series predictions, it tends to be trapped in local optimum when the data is complex and noisy [25].

To further reduce noise and improve the prediction accuracy, Chen et al. [26] proposed an empirical mode decomposition (EMD) method. The method decomposes the original short-term traffic flow data into several intrinsic mode functions (IMFs) and uses them as inputs to the model. However, the IMFs decomposed by the EMD method suffer from mode mixing. Ensemble Empirical Mode Decomposition (EEMD) improves the mode mixing of EMD by adding Gaussian white noise to the original sequence. Liu et al. [27] use EEMD to decompose the traffic flow data into several intrinsic mode functions (IMFs) and a residue. CEEMDAN improves the processing of EEMD and achieves better decomposition results with higher computational efficiency. Lu et al. [28] used the CEEMDAN method to decompose the raw traffic flow data into multiple intrinsic mode function components and a residual component. These methods aim to pre-process the data in a better manner to decrease the data noise.

C. Traffic flow prediction with perception system

As traffic visual recognition is the prerequisite for traffic flow prediction, some researchers also involved perception systems in the field. The key to such system enhancement is whether each vehicle can be accurately recognized. The authors of [29] come up with an edge-computing framework that utilizes the real-time multi-object detection and tracking algorithms to provide the inputs to the traffic flow prediction. As cooperative perception system can largely enhance the perceiving range and help see through occlusions [30]–[32], the authors of [33] integrate cooperative perception concept with traffic prediction together to better estimate the traffic states. Similarly, the authors of [34] study how to boost the traffic state estimation accuracy by enhancing the perception performance under a partially connected vehicle environment.

III. METHODOLOGY

We propose a robust ensemble model that can effectively learn from non-stationary signals and utilizes spatiotemporal features to optimize the traffic prediction process, avoiding common problems including over-fitting, local optimum, and autocorrelation.

We first adopt the theory of CEEMDAN [35] to decompose the original non-stationary traffic flow signals into several IMF sub-signals with different frequencies. We then utilize SE (sample entropy) to measure the nonlinear complexity of the IMF subsequence to merge similar sub-signals for computation reduction. For the prediction model, we deploy the LSTM model with GWO optimization to improve the prediction accuracy and decrease the training duration. Finally, we will extract the spatiotemporal features from the output of LSTM to avoid the autocorrelation problem. The pipeline of our approach is demonstrated in Fig. 1.
A. CEEMDAN-SE

1) CEEMDAN: EMD (Empirical Mode Decomposition) is a classic adaptive method for solving non-stationary signal problems [36]. This method utilizes the signal extreme point information to decompose the signal into several IMFs (Intrinsic Mode Functions). However, the modal aliasing problem of EMD will cause severe sawtooth lines in the time-frequency distribution and makes certain eigenmode functions lose their physical meaning, which leads to the degradation of the performance of EMD.

Based on EMD, we develop the CEEMDAN (Complete Ensemble Empirical Mode Decomposition with Adaptive Noise) algorithm, which applies the EEMD (Ensemble Empirical Mode Decomposition) method to add Gaussian noise to the original signal. The mode mixing problem is solved by stacking and averaging multiple operations to cancel the influence of noise to gain better mode decomposition results. The process of the CEEMDAN algorithm is shown in Fig. 2.

2) Sample Entropy Theory: N sub-sequences will be generated after the CEEMDAN decomposition. Directly using them as the input data of the prediction model GWO-LSTM will cause a large computational cost. Therefore, we employ SE (sample entropy) [37], an approximate entropy (ApEn) [4] method that evaluates time series complexities by measuring the probability of the new generated patterns, to classify and reconstruct the traffic flow temporal data for reducing the complexity of the sub-sequences. SE is defined as the negative natural logarithm of the conditional probability, where self-matches are not included:

$$\text{SampEn}(m, r) = \lim_{N \to \infty} \left\{ -\ln \left[ \frac{A_m(r)}{B_m(r)} \right] \right\}$$

(1)

$B_m(r)$ in Eq. (1) is the probability of the two sequences matching $m$ points under the similarity tolerance $r$, and $A_m(r)$ is the probability of the two sequences matching $m + 1$ points. The calculation formulas are Eq. (2) and Eq. (3), respectively.

$$A_i(r) = \frac{1}{N - m - 1} A_i$$

(2)

$$B_i(r) = \frac{1}{N - m - 1} B_i$$

(3)

$$A_m(r) = \frac{1}{N - m} \sum_{i=1}^{N-m} A_i^m(r)$$

(4)

$$B_m(r) = \frac{1}{N - m} \sum_{i=1}^{N-m} B_i^m(r)$$

(5)

$A_i$ and $B_i$ are the number of the maximum distance, not greater than $r$, between the vector sequences $X_m(i)$ and $X_m(j)$ of the dimension $m$ composed of time series data when the dimension is $m + 1$ and $m$ respectively. Specifically, $X_m(i) = \{ x(i), x(i+1), \ldots, x(i+m-1) \}$, $1 \leq i \leq N - m + 1$, represents $m$ consecutive values of $x$ starting from the $i$th point.

The amount of data is usually limited in specific applications. Thus, Eq. (1) evolved into Eq. (6).

$$\text{SampEn}(m, r, N) = -\ln \left[ \frac{A_m(r)}{B_m(r)} \right]$$

(6)
B. GWO-LSTM

LSTM [38] is first presented to solve complex artificial long-time-lag tasks. As the GWO algorithm [39] mimics the leadership hierarchy and hunting mechanism of grey wolves in nature, it could be used to optimize the LSTM model. Our model has a significant optimization effect compared to the state-of-the-art LSTM neural networks and BP neural networks. Thus, we use the GWO-LSTM method to complete the post-processing of CEEMDAN-SE. The general process of the GWO-LSTM framework part is shown in Fig. 1.

1) LSTM: Recurrent neural network (RNN) [40] cannot solve the long-term dependence problem in which the output is related to a long sequence of preceding segments. Thus, LSTM is designed to solve this problem. Compared to RNN, LSTM has three more gates - forgetting gate, input gate, and output gate - enabling it to achieve better results in traffic flow prediction.

Since the output is a linear combination of the inputs, the nonlinearity of LSTM needs to be enhanced. The enhancement will be done through the use of the activation function as it exacerbates the nonlinearity of the network model. Common activation functions for LSTM are tanh(-1, 1), sigmod (0, 1), and relu(0, 1). Following experimental verification, tanh(-1, 1) presents better results to our problem and is selected as our activation function.

2) GWO: We first divide the traffic flow prediction into four layers and enter them into the GWO model to complete the initialization, with the first three layers being of greater significance. We define $\alpha$ as the optimum solution. During the hunt, the behavior of grey wolves rounding up their prey is defined as Eq. (7) and Eq. (8), where $t$ is the current iterative generation, $A$ and $C$ are the coefficient vectors, $X_p$ and $X$ are the prey position vector and the grey wolf position vector, respectively.

$$D = \left| C X_p(t) - X(t) \right|$$

$$X(t + 1) = X_p(t) - AD$$

The calculation equations of $A$ and $C$ are shown in Eq. (9) and Eq. (10), where $\alpha$ is the convergence factor. As the number of iterations decreases linearly from 2 to 0, the norms of $r_1$ and $r_2$ are random numbers between [0, 1].

$$A = 2\alpha r_1 - \alpha$$

$$C = 2r_2$$

In the GWO model, the upper layer leads the lower layer to the set of update equations shown in Eq. (11), and after completing the update, the GWO model outputs $X(t + 1)$ to the LSTM model according to Eq. (12). Subsequently, the model calculates the loss function and adjusts the learning rate of the GWO model according to the vector $X$.

$$\begin{align*}
D_\alpha &= |C_t X_\alpha - X|, \\
D_\beta &= |C_t X_\beta - X|, \\
D_\delta &= |C_t X_\delta - X|
\end{align*}$$

$$X(t + 1) = \frac{(X_\alpha - A_1 D_\alpha) + (X_\beta - A_2 D_\beta) + (X_\delta - A_3 D_\delta)}{3}$$

3) Combining GWO with LSTM: We reference the data on the LSTM model to derive a prediction of the baseline model. Subsequently, We incorporate the LSTM prediction results into the GWO model to obtain the new four strata. Once the four strata are obtained, GWO will calculate the coefficient matrices $A$ and $C$ according to Eq. (9) and Eq. (10). Then it will calculate the ratios of each stratum in the four strata using $A$ and $C$, inputting them into the LSTM model for automated parameter tuning, and continue to train the LSTM model. The above process will then repeat until a user-specified number of iterations is reached.

Machine learning training aims to update the parameters and optimize the objective function. In this paper, the GWO is set as an optimizer to perform a local estimation ($|A|$ shown as Eq. (9)) based on the results of each LSTM iteration to minimize the loss function. We use 1024 as the initial batch size and 0.01 as the initial learning rate. GWO decides to update or not update (eliminate or not eliminate) the population of grey wolves based on the results of each LSTM iteration and, thus, dynamically adjusts the learning rate of the LSTM each time. In addition, our GWO network is optimized for four layers.

C. Spatiotemporal optimization for low frequencies IMFs

Due to the obvious daily cycle characteristics of traffic flow, training with a small amount of data can easily cause autocorrelation problems, resulting in low instantaneous accuracy. Directly training undecomposed instability short-term traffic flow data will lead to the problems mentioned above, and at the same time, the decomposed traffic flow has the problem of data scale difference. Accurate predictions on low frequency components often determine the overall performance of the model. Therefore, we propose to consider spatial characteristic factors in the low-frequency synthetic component (larger value, representing macroscopic changes). Taking the traffic flow of neighboring stations at the previous moment as input can increase the feature dimension and avoid the autocorrelation problem. The algorithm details are shown in Algorithm [1].

Finally, we construct an integrated model for short-term traffic flow prediction based on unsteady signal decomposition and optimization of spatiotemporal features, which can better adapt to instantaneous traffic changes, overcome delayed response, and avoid overfitting caused by small data samples, etc.

IV. EXPERIMENT

A. Dataset

We conduct experiments on the British Highways dataset [41], which is published and maintained by the
Algorithm 1 Spatiotemporal spare optimization

1: Given \( \{S_i\} \leftarrow \text{Target site and its adjacent traffic flow} \)
2: Initialization: Extract low frequency components \( \{Y_i\} \) of each \( \{S_i\} \), \( n \leftarrow 0 \)
3: Pre-training Spatiotemporal-LSTM with \( \{Y_i\} \)
4: repeat
5: \( n \leftarrow n + 1 \)
6: Update \( \hat{y}_i^1 \) based on GWO-LSTM
7: Update \( \hat{y}_i^2 \) based on Spatiotemporal-LSTM
8: \( \text{error}_{t-1} = \min ||\text{error}_{t-1}||_2 \)
9: Update \( \hat{y}_i^t \) based on \( \text{error}_{t-1} \)
10: until End of sub-sequence

Output: Low frequency signal predicted value \( \hat{Y}_i \)

British Highways Agency. This dataset contains the majority of highways in British, and the collection frequency of traffic flow at each highway station is 15 minutes. As the traffic flows near the airports are usually challenging for traffic estimation methods, we majorly compare different approaches on the M25 motorway near Heathrow Airport (a subset of the British Highways dataset). The chosen subset covers detailed information for the traffic states, including Day Type (working day or special day), Vehicle Flows (the number of different length vehicles detected on any lane within the 15-minute time slice), Speed (the average speed in km/h over the 15-minute period), and Quality Index (the number of valid one minute reported and used to generate the Total Traffic Flow and speed). The data volume became 2880 at each site ensuing the interpolation method, which is applied to fill in the missing values of the time series and remove the outliers. The ratio between the samples of training and testing set is 8:2.

B. Evaluation Metrics

The total duration of the selected dataset is one month, and the data in the last week in this month belongs to the test set. We predict the traffic flow every 15 minutes to assess whether the model can capture the traffic changes timely. To quantitatively evaluate the performance of the models, six commonly evaluation metrics are utilized in this paper: Sum of squares error (SSE), Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R-Squared (\( R^2 \)). The smaller number on these metrics represent better model performance. We compare our methods with Back Propagation neural network (BP), the vanilla LSTM, GWO-LSTM without signal input signal preprocessing, and CEEMDEAN-SE-GWO-LSTM that does not consider spatiotemporal correction.

C. Implementation Details

Before feeding the data into the model, we first decompose the original non-stationarity one-dimensional traffic flow signal into 12 IMF sub-signals as shown in Fig. 3. In the process of empirical mode decomposition, we set the standard deviation of the noise as 2000, the number of realization to 500, and the maximum number of sifting iterations to 2000. In order to reduce the computational cost, some of the IMF components are merged. For example, IMF1, IMF2, and IMF3 have similar complexities (as shown in Fig. 4), and thus they are combined into a single component. The details of the recombination results are shown in Table II, and the new subsequence after reconstruction is shown in Fig. 5. We take the above processed data as the input to the GWO-LSTM model, with a batch size of 1024, an initial learning rate of 0.01, and a time window size of 3. All models are trained with 200 iterations on a Quadro P1000.
In this paper, we propose a robust model for short-term traffic flow prediction. By utilizing the signal decomposition, GWO optimization, LSTM model and spatiotemporal feature optimization, our method can better handle the non-stationary characteristics of short-term traffic flow, solve the over-fitting and local optimal problems, and avoid the strong autocorrelation issue. We compare our model with several state-of-the-art baselines and demonstrate the superiority of our model.

V. CONCLUSION

In this paper, we propose a robust model for short-term traffic flow prediction. By utilizing the signal decomposition, GWO optimization, LSTM model and spatiotemporal feature optimization, our method can better handle the non-stationary characteristics of short-term traffic flow, solve the over-fitting and local optimal problems, and avoid the strong autocorrelation issue. We compare our model with several state-of-the-art baselines and demonstrate the superiority of our model.

D. Quantitative Results

Table I shows the quantitative results of different models, and it can be seen that our proposed approach method outperform all others. Our proposed model is 90.8%, 65.3%, 90.8%, 69.7%, and 42% lower in SSE, MAE, MSE, RMSE, and MAPE evaluation compared to the BP model, and 7.2% higher in the $R^2$. Similarly, compared to LSTM, these numbers are 89.4%, 59.4%, 89.4%, 67.5%, 37.4% and 6% respectively; and those values for GWO-LSTM are 71.1%, 25.2%, 71.1%, 46.2%, 15.6% and 1.6% while for CEEMDAN-SE-GWO-LSTM they are 17.2%, 13%, 17.2%, 9%, 10.7% and 0.1% respectively.

E. Qualitative Analysis

Fig. 6 depicts the qualitative results of different models on part of the test set. BP network obviously suffers from outliers caused by traffic congestion. LSTM handles the traffic congestion prediction better, but it fails to capture the trend change timely. Although GWO-LSTM demonstrates good numeric performance, it has obvious fluctuations at certain times, which is caused by the non-stationary signals. Other hand, by involving the CEEMDAN decomposition and SE reconstruction, our model’s predictions can be well aligned with the observed traffic flow.

Fig. 7 shows the predictions of each component reconstructed from SE, and these results are merged together to obtain the final outcome. It is obvious that the low-frequency part NEW4 has a large error due to the autocorrelation issue, which will result in an increase in the cumulative error along with the temporal dimension. This indicates the importance of spatiotemporal sparse optimization in our model to vanish such autocorrelation.
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Fig. 6. Comparison of different models.

Fig. 7. The results of the Subsequences.
