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The effect of the dataset on evaluating urban traffic prediction

Yue Hou [a,*], Jiaxing Chen [a], Sheng Wen [b]

[a] *School of Electronics and Information Engineering, Lanzhou Jiaotong University, Lanzhou 730070, China*
[b] *MIEEE School of Software & Electrical Engineering, Swinburne University of Technology, VIC 3122, Australia*

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Abstract With the continuous development of economic strength and science and technology, the construction of Intelligent Transportation System(ITS) has become a new development direction in many cities. A complete and accurate traffic dataset can improve the accuracy of traffic prediction and promote the construction of ITS in cities. Most of the existing traffic datasets are collected on highways, and they are only one-way road data. There is little analysis of the impact of weather on traffic prediction, and more traffic auxiliary information is lacking at the same time. The use of such datasets for experiments can lead to inaccurate and unconvincing results, which is of little significance for the study of urban road prediction reference. In this paper, we are motivated to develop a new dataset for the evaluation of Metropolitan Traffic Prediction. Our dataset(XiAn Road Traffic) collected 308 urban road data and included two-way road data, weather data, driving angles, and congestion levels. XiAn Road Traffic can provide help for urban road state prediction and intelligent transportation city construction. We use the current more popular machine learning model for experiments. It is also proved by experiments that our dataset is more accurate and persuasive than the prediction results of other datasets.

1. Introduction

With the rapid growth of the global economy, private cars have become a must for many families. By the end of 2018, Xian had 3.2395 million motor vehicles, Net Assets of 371600 vehicles over 2017 [10]. In addition, the complex urban traffic network system makes the road traffic pressure increase, the urban road tends to be oversaturated, resulting in traffic congestion and reducing travel efficiency. At present, the more effective way to alleviate traffic congestion is to use intelligent transportation system (ITS) [70] based on computer technology, data communication technology, sensor technology and electronic control technology to realize traffic control and traffic guidance. Accurate traffic state prediction is the basis of traffic control and traffic guidance. However, the scale of the dataset and the quality of the model will directly affect the accuracy of traffic state prediction. ITS developed from the 1970s. Its data acquisition methods include ring coil detector, electromagnetic detector, ultrasonic detector and so on. and it

* Corresponding author at: School of Electronics and Information Engineering, Lanzhou Jiaotong University. Office: 88 Anning West Road, Anning District, Lanzhou City, Gansu Province, China.
E-mail address: houyue@lzjtu.edu.cn (Y. Hou).

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provides better transportation service [11–13] for drivers and passengers. At present, there are a few public datasets. For example, most widely used datasets are PeMS [3,6,7] and Beijing Ring Road data [1]. The traffic parameters contained in these datasets are only about the main information such as flow, density and speed, but the auxiliary information of traffic state is very important to reflect the characteristic analysis of traffic. Having an accurate and comprehensive traffic dataset has an important influence on the prediction results of the model.

Most of the current traffic state prediction models are based on neural networks. Chen [8] et al. proposed an adaptive rolling smoothing (ARS) method. The filtering parameters are adjusted dynamically by rolling level scheme for online application. Ibai Lana [63] et al. proposed a long-term estimation scheme based on automatic pattern discovery by using evolutionary peak neural network (ESNN). Jonathan Mackenzie [4] et al. used hierarchical time memory (HTM) model to improve traffic flow prediction and abnormal traffic flow detection. Jinjun Tang [9] et al. proposed evolutionary fuzzy neural network (EFNN) to improve learning ability. Kshitij Jerath [64] et al. proposed a method inspired by statistical mechanics, and a new end-to-end depth learning model (ST-3DNet) was proposed by introducing 3D convolution network to simulate traffic flow. Guo S [2] on micro scale by generalized Ising model. Used in traffic raster data prediction. Zhou [69] et al. proposed a trajectory-based collaborative vehicle network for reliable content distribution and D2D that fully considers the impact of correlations between vehicles on traffic state prediction, prove that any traffic information has a certain influence on the prediction of traffic state. After that, most of the studies used mixed models to predict traffic state. More research focuses on the quality of the analysis model, and the analysis of traffic data is rarely studied [65,68,70,71]. Two-way analysis [66] and noise research [67] are also applied to traffic state prediction.

Most of the datasets used in these papers are information collected on highways. It is only one-way road data, while there is little analysis of the impact of weather on traffic forecasting. More traffic Supporting information available datasets are rarely involved. These incomplete datasets lead to inaccurate and unconvincing experimental results, which is of little significance for the study of urban road prediction reference. At the same time, the prediction model is very dependent on the dataset, and an accurate and comprehensive traffic dataset plays an important role in the prediction results of the model. An incomplete, inaccurate dataset gathering results in inaccurate predictions. Therefore, it can not provide important reference for traffic management department to effectively direct traffic and alleviate road congestion. Then it is difficult to promote the construction of intelligent city.

There are two difficulties in the study of traffic forecasting. Regarding data acquisition: First, most of the datasets on traffic belong to the relevant departments, and many scholars have few traffic data. Second, there are many tools to collect road state information. The types of data obtained by different collectors are different, which makes the data processing work more complicated [14,15]. About the data content: First, more data collection points are located at highways, leading to more research leaning toward highway traffic conditions [16,17]. With the increasing congestion of urban traffic, more and more people are paying more attention to urban road traffic conditions. The state of the expressway is relatively simple compared to the state of the urban road. Therefore, the forecast model of expressway traffic does not apply to urban roads. Second, most datasets have a time interval of five minutes during data collection, even ten minutes. For the prediction results of the model, the shorter the data update time, the more accurately the prediction can be made. The long-time-interval of data collection will seriously affect the prediction effect of the model, resulting in inaccurate road state prediction. On the other hand, it cannot reflect the traffic state information in time. Third, In the traffic state prediction, many studies use data from past time periods for prediction, and there are many works that use future short-term or longer-term traffic data for prediction. Fourth, most studies use a single-attribute dataset to predict congestion, flow, speed, without considering other influencing factors, or considering only a single factor, which makes the predictions inaccurate.

To better deal with the above two issues, this study uses the obtained XiAn Road Traffic dataset (Section III will explain in detail) to predict traffic state, minimize the time interval of data collection, and apply multiple traffic data parameters to the data model for prediction, which greatly improves the accuracy of predictions. This study makes full use of the data to predict the traffic state, with congestion, flow and speed, etc. This dataset will be helpful for the subsequent work, with predicting future traffic state. Research results will obtain road traffic information accurately and timely, provide convenience for people to travel, and ease the work pressure of the transportation department.

This work has found that many factors should be considered for traffic state prediction. There should be a dataset containing multiple traffic parameters to analyze and predict traffic status. In this regard, the main contributions of this research work can be summarized as follows:

We collected a more complete and accurate dataset. We collected weather datasets and added them to the experiment. We use the current more popular traffic prediction algorithms for experimental analysis combined with own dataset.

The other parts of the paper are arranged as follows: Section II is about the related work, which introduces the traffic theory, traffic data, the concept and theory of traffic prediction. Section III introduces the dataset that is commonly used in traffic status prediction research. Section IV describes the dataset collected in this study, and the experimental results are obtained based on different models combined with different parameter analysis. Section V is the conclusion and the future research. .

2. Related work

2.1. Traffic state prediction theory

The actual traffic state data collected by the traffic state detector reflects the actual situation of traffic state on the road network and provides decision support for traffic managers to release accurate induced information to travelers. The traffic information will be continuously updated with the traffic state at each moment, the decision of each moment of traffic guidance information must adapt to the state of traffic state in the next moment. Traffic information is a multiple amount of information. The effect of these amounts of information on traffic state is different. The correlation between various traffic volumes and traffic state is a very necessary research topic. Traffic state prediction is a key point and focus in the research of solving traffic congestion problem, and it is the key to realize traffic control and induction system [55].

There are many methods to predict the traffic state [20–27], which can be divided into two categories: qualitative prediction and quantitative prediction. Qualitative forecasting refers to people and experts with rich experience and comprehensive analysis capabilities, relying on familiar business knowledge to make judgments about the future development of things [56]. The main implementation methods are the Delphi method, the scenario prediction method and the subjective probability method. The quantitative prediction method uses certain mathematical methods to predict. It is scientifically processed and collated according to relatively complete historical statistics to predict and speculate on future developments and changes, thus revealing the regular relationship between relevant variables. Having statistical prediction method [28–33], historical trend method, exponential smoothing method, auto-regression comprehensive moving average model (ARIMA), support vector regression [41–45], Kalman filtering model [46–54] and neural network model [34–40]. The more popular traffic state prediction models are LSTM (Long Short-Term Memory) [57–59], GRU (Gated Recurrent Unit) [60,61], SAE (The Stacked Autoencoder) [62], T-GCN (Temporal Graph Convolutional Network).

The existing models have their own advantages and disadvantages, and there is no recognized optimal method. Although some scholars have carried out in-depth research in the field of traffic state prediction and achieved some results, the problem of traffic state prediction has not yet formed a perfect theoretical system. What model should be selected for prediction and what algorithm to improve it is still a problem worthy of study. LSTM, GRU, ASE three models used in this paper are now more popular and effective models. Based on this model, it is more realistic and persuasive to analyze the effect of dataset on prediction results.

2.2. Traffic data

The content of traffic information is very extensive, including four categories: traffic flow information, vehicle operation information, traffic facilities operation information and emergency information [18]. In the process of collecting basic traffic information, speed and flow information are important traffic data to realize traffic control and traffic guidance. The automatic collection of these two kinds of traffic data is the basis of realizing the intelligence of traffic system.

In the road traffic system, the performance of the traffic detector determines whether the collected traffic data is accurate and effective. With the development of electronic technology and computer technology, the traffic detector has been developed from the beginning of the pneumatic sensor to the present toroidal coil, magnetic field sensor, microwave, ultrasonic, infrared and video detector. The development of the detector greatly improves the accuracy and richness of the traffic data.

With the rapid development of ITS, the contradiction between the demand of sensor layout and limited investment is becoming more and more serious [19]. In China, most of the detectors are currently distributed on the highway, which has great limitations on the data sources required for urban road traffic state prediction. At the same time, most of the data acquired by the detector are private in the traffic management, and the published dataset is small. The currently open datasets include PeMS [6], Beijing loop data [9], Q-traffic [1], and so on. These datasets contains less traffic parameters and less auxiliary information data, which are also applied to various prediction models.

The problems with the traffic dataset can be grouped into the following four aspects: First, most of the data on road traffic are privately owned by a certain department, and many scholars obtain very little traffic data. Second, because of the different working principle of all kinds of detection equipment, the data produces heterogeneity, which makes the complexity of data processing on the high side. Third, more data collection points focus on the highway, which leads to more research on the highway traffic state. As urban traffic congestion continues to increase, more and more people are paying more attention to urban road traffic conditions, which are relatively simple relative to urban road conditions, the prediction model of highway traffic is not suitable for urban roads. Fourth, the time interval between data collection of most data is 5 min, or even 10 min. For the prediction results of the model, the shorter the data update time, the more accurate the prediction can be. The longer the time interval will seriously affect the prediction effect of the model, resulting in inaccurate road state prediction.

To a large extent, the quality of the prediction model is determined by the advantages and disadvantages of the dataset. The state of traffic at every moment must be influenced by a variety of traffic information. The traffic state prediction results are greatly improved by using a rich and complete traffic dataset.

3. Dataset comparison

From the analysis of the prediction results, we can divide the dataset into three categories: predicting traffic flow, traffic speed, and traffic congestion. Most of the research on traffic state in recent years is also these three aspects.

Each research object for traffic prediction is different, and there is no relatively complete, universal dataset for researchers to study traffic conditions. Most datasets are collected from highways, and a data interval of 5 min or even longer. At the same time, there are only a single parameter, or fewer related factors are considered. These problems will make the prediction results difficult to achieve the expected results and cannot meet the needs of users. Therefore, it is very important to collect a complete dataset.

Liao [1] use the Q-traffic dataset to study traffic prediction based on deep sequence learning. Guo [2] use the TrafficBJ dataset to study traffic data forecasting based on deep spatial–temporal 3D convolutional neural networks. Oh [3] use the VDS dataset to study traffic state prediction based on KNN. Chu [5] to study real-time prediction using the NGSIM dataset. Yuan [23] to study real-time prediction using the Shangtang-Zhonghe Expressway dataset. MackenzieJ use the Mitchell Freeway dataset for traffic flow forecasting. Zhan [65] use the Arcadia dataset to sutdy traffic flow prediction. Tan [6] and Pietro [7] used the PeMS dataset to study short-term traffic prediction. Tang [9] use the 4th Ring Road dataset from Beijing for traffic speed prediction. Zang [68] use the Shanghai Expressway dataset for long-term traffic speed prediction.

Table 1 shows the comparison between different traffic state prediction datasets. It can be seen from the table that Xi'an Road Traffic dataset has many advantages compared with other datasets. The most popular traffic prediction dataset is the Caltrans Performance Measurement System(PeMS), but it only provides traffic flow information. The XiAn Road Traffic dataset provides more detailed road information that should improve traffic prediction research.

The dataset "XiAn Road Traffic" used in this paper is the Xi'an urban road traffic data captured from the Amap. We get a series of JSON formatted traffic data and weather data from the open platform of the Amap using the Python language and web crawler technology, and get the data every two minutes. The original JSON format data is then processed using regular expressions and saved as useful data. And the redundant and incomplete data of the data are pre-processed at the same time. Finally, a complete CSV file for the model recognition is generated.XiAn Road traffic dataset covers three types of roads in Xi'an: main roads, secondary roads and branch roads, including 308 road traffic data. The weather data are also divided into the weather conditions of each area in detail. So far, the dataset contains data from August 1 to September 30. The data acquisition time is 6:00–23:30, and the interval is 2 min.

Table 2 shows some street information collected by Xi'an Road Traffic dataset (308 road data collected), The attributes included are street name (name), traffic status (status), driving angle (angle), speed (speed), time (time). Table 3 shows the meteorological dataset of Xi'an City, The attributes included are city name(city), area(adcode), weather condition(weather), temperature(temperature), wind direction(wind direction), wind scale(wind power), humidity(humidity), time(time). The experiment used only the weather condition attribute, Other attributes have a certain impact on traffic, This makes further research more efficient and convenient. Table 4 is a summary of Xi'an road traffic dataset and weather dataset, Each con-

Table 1 Comparison of different datasets for traffic speed prediction.

name	Data time	Time Interval	Special Date	Scale	Highway	Two-way Lane	Available	Weather
Q-traffic	2017/04/01–2017/05/31	15 min	–	15073	×	×	√	×
TrafficBJ	2017/05/14 – 2017/12/05	6 min	–	904	√	×	×	×
VDS data	2013/01–2014/07	5 min	week days	1	√	×	×	×
the NGSIM Data	2005/6/15	15 min	–	1	√	×	×	×
Shangtang-Zhonghe Expressway	2015/06/11 – 2015/11/22	5 min	–	1	√	×	×	×
Mitchell Freeway in Perth	2012/01/01 – 2013/07/11	5 min	weekends	2	√	×	×	×
Arcadia, CA in 2015	2015	15 min	–	1	×	×	×	×
PeMS	2011/03/01 – 2011/05/29	5 min	weekends	164	√	×	√	×
4th ring road in Beijing	2014/11/01 – 2014/11/30	2 min	–	1	√	×	×	×
Shanghai data	2011	10 min	–	3	√	×	×	×
XiAn Road Traffic	2019/08/24 – 2019/10/24	2 min	weekends	308	×	√	√	√

Table 2 Samples of XiAn Road Traffic.

name	status	angle	speed	time
bei da jie	1	89	40	2019/9/27 6:00
nan da jie	1	94	40	2019/9/27 6:00
xi da jie	1	359	35	2019/9/27 6:00
dong da jie	1	1	35	2019/9/27 6:00
jie fang lu	1	90	40	2019/9/27 6:00
he ping lu	1	91	30	2019/9/27 6:00
nan guan zheng jie	1	88	40	2019/9/27 6:00
xi guan zheng jie	1	359	40	2019/9/27 6:00
dong guan zheng jie	1	0	35	2019/9/27 6:00
feng hao xi lu	1	358	40	2019/9/27 6:00
feng hao dong lu	1	1	40	2019/9/27 6:00
lao dong lu	1	89	35	2019/9/27 6:00
lan dong nan lu	1	89	35	2019/9/27 6:00
xing huo lu	1	90	56	2019/9/27 6:00
feng qing lu	1	356	40	2019/9/27 6:00

Table 3 Samples of XiAn Weather.

city	adcode	weather	temperature	wind direction	wind power	humidity	time
Shaanxi	610100	2	17	5	$\leqslant 3$	92	2019/9/27 6:00
Shaanxi	610102	2	17	5	$\leqslant 3$	92	2019/9/27 6:00
Shaanxi	610103	2	17	5	$\leqslant 3$	92	2019/9/27 6:00
Shaanxi	610104	2	17	5	$\leqslant 3$	92	2019/9/27 6:00
Shaanxi	610111	2	17	5	$\leqslant 3$	92	2019/9/27 6:00
Shaanxi	610112	2	17	5	$\leqslant 3$	92	2019/9/27 6:00
Shaanxi	610113	2	17	5	$\leqslant 3$	92	2019/9/27 6:00
Shaanxi	610114	1	16	6	$\leqslant 3$	78	2019/9/27 6:00
Shaanxi	610115	2	16	6	$\leqslant 3$	78	2019/9/27 6:00
Shaanxi	610116	1	16	6	$\leqslant 3$	82	2019/9/27 6:00

Table 4 Statistics of XiAn Road Traffic and XiAn Weather.

Dataset XiAn	Traffic	XiAn Weather
Location	XiAn	XiAn
Road segments	308	-
Time interval	2 min	2 min
Time	August 24,2019 October 24,2019	August 24,2019 October 24, 2019
Total records	1244400	311100

Table 5 Examples of geographical attributes of XiAn Road Traffic.

Field	Description
name	road segment id
status	Road congestion level. 0: Unknown; 1: Unblocked; 2: Slow; 3: Congested; 4: Severe congestion
expedite	Percentage of unblocked
congested	Percentage of slowing
blocked	Percentage of congestion
direction	Direction of travel. 0:from start node to end node; 1: from end node to start node
angle	Driving angle
speed	Driving speed
lcodes	The segment id in the road
polyline	Road coordinates

tains 1244400 and 311100 data. Tables 5 and 6 show the detailed meaning of the parameters in both datasets.

The advantage of comparing Xi'an Road Traffic dataset with other datasets is that the time interval is shortened to 2 min; it contains more auxiliary information (weather, congestion degree, driving angle, etc.), and it is the traffic data of urban roads, which is different from highway data and has more research significance. (Download Link: https://github.com/FIGHTINGithub/Xi-an-Road-Traffic-Data)

4. Experiments

In this section, we will use the three models mentioned in the second section (LSTM, GRU, SAE), combined with the datasets we collected to analyze traffic state predictions and discuss the differences in predictions at different input scales.

4.1. Experimental details

This experiment is used to predict average road speed. The time interval between the data is 2 min, and the total duration is from 6 am to 11 pm, so the amount of data put in is 510 in the single-scale model each time, and the amount of data put in is 510*n at multiple scales each time (n is the scale of the model). Each neural network contains 64 neurons while performing 600 rounds of training. Through the preliminary analysis of the data and some studies, and there are significant differences in traffic conditions between workdays and weekends. The experiment conducts separate predictive analysis on workdays and weekends. At the same time, the effects of two excitation functions (Sigmoid, ReLU) on the experimental results are analyzed. GRU is LSTM improved algorithm, Its input and output data form is similar. resulting in its parameter setting being similar. LSTM first layer of the GRU model is the input layer, An input format is a three-dimensional

Table 6 Examples of geographical attributes of XiAn Weather.

Field	Description
city	city name
adcode	Area code
weather	Weather phenomenon. 1:Sunny, 2:cloudy, 3: overcast, 4:foggy, 5:light rain,
temperature	Real-time temperature
wind direction	Wind direction description. 1:East, 2:West, 3:South, 4:North, 5:Southeast, 6:Northeast, 7:Southwest, 8: Northwest
wind power	Wind level
humidity	Air humidity

(batch_size, lag, 1), batch_size = None represents the value of this dimension to be specified. lag = 12 is a time span, represents the value of predicting the next time span with data per 12 time spans. The input data is passed into the first LSTM (GRU) layer (input: (None, 12, 1); output: (None, 12, 64)), then passed into the second LSTM (GRU) layer (input: (None, 12, 64); output: (None, 64)). And then through Dropout layers, Random loss of a certain proportion of parameters. It can effectively prevent overfitting during training. And finally the full connection layer, the output latitude of the fully connected layer is 1. Because it's twelve data prediction, here the number of output neurons is set to 1. The result of training or prediction (input: (None, 64); output: (None, 1)). SAE model is a full-connection layer that takes the dimension of the input data from (None, 12) adjusted to (None, 400), Then through two groups of fully connected and activated layers, Increase the depth of the training network, Improve the accuracy of prediction. passing data into the Dropout layer

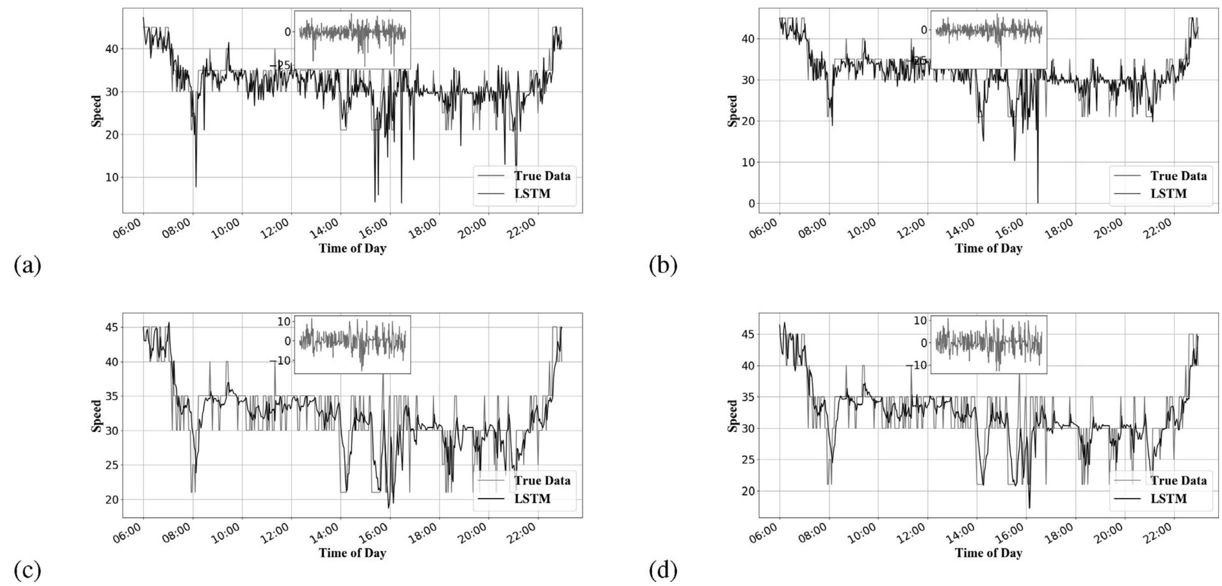

Fig. 1 The experiment under the LSTM model (21 workdays in September). (a) single-scale (speed) experiment; (b) multiscale (weather + speed) experiment; (c) multiscale (status + speed) experiment; (d) multiscale(weather + status + speed) experiment (Based on ReLU).

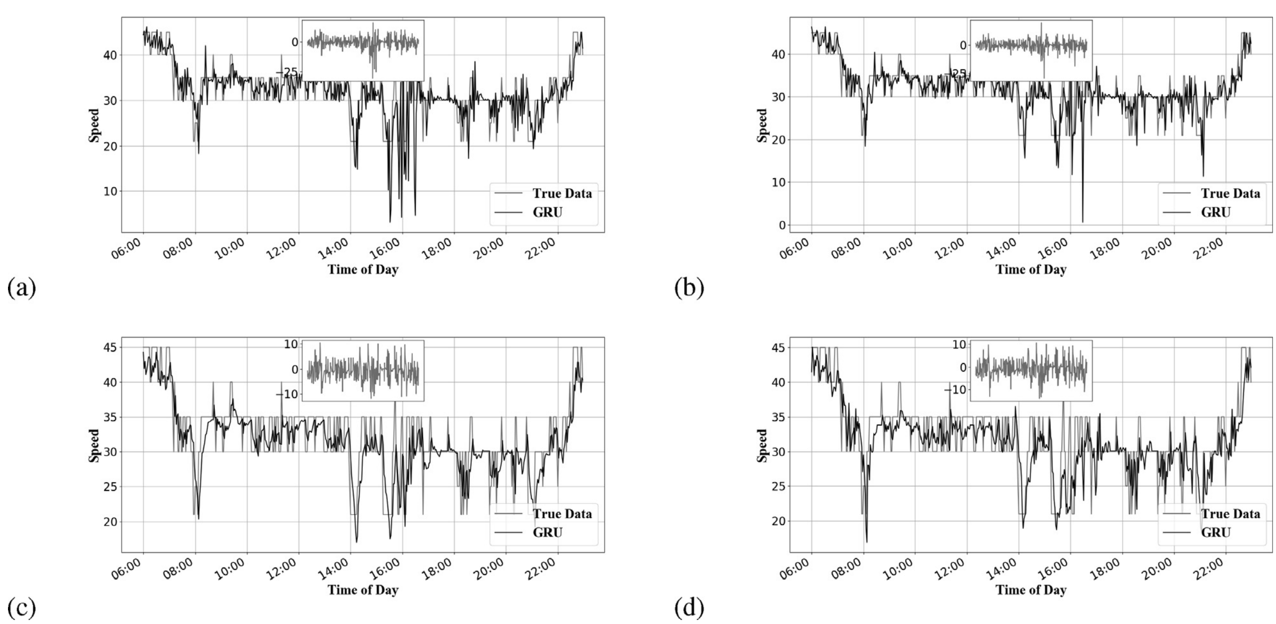

Fig. 2 The experiment under the GRU model (21 workdays in September). (a) single-scale (speed) experiment; (b) multiscale (weather + speed) experiment; (c) multiscale (status + speed) experiment; (d) multiscale(weather + status + speed) experiment (Based on ReLU).

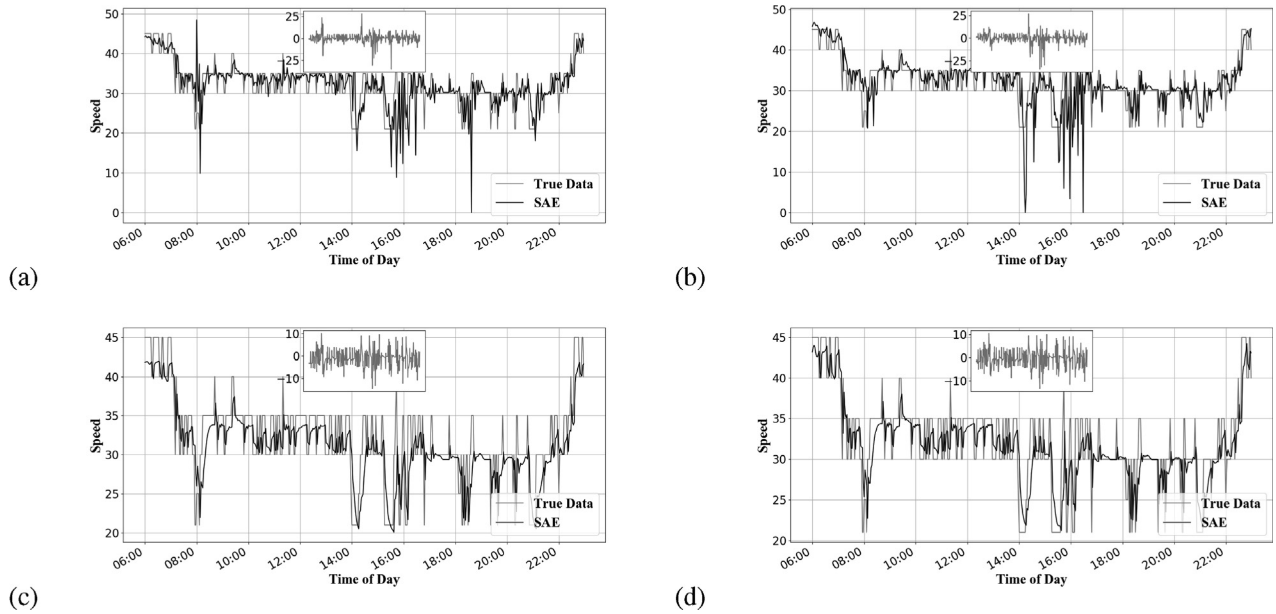

Fig. 3 The experiment under the SAE model (21 workdays in September). (a) single-scale (speed) experiment; (b) multiscale (weather + speed) experiment; (c) multiscale (status + speed) experiment; (d) multiscale(weather + status + speed) experiment (Based on ReLU).

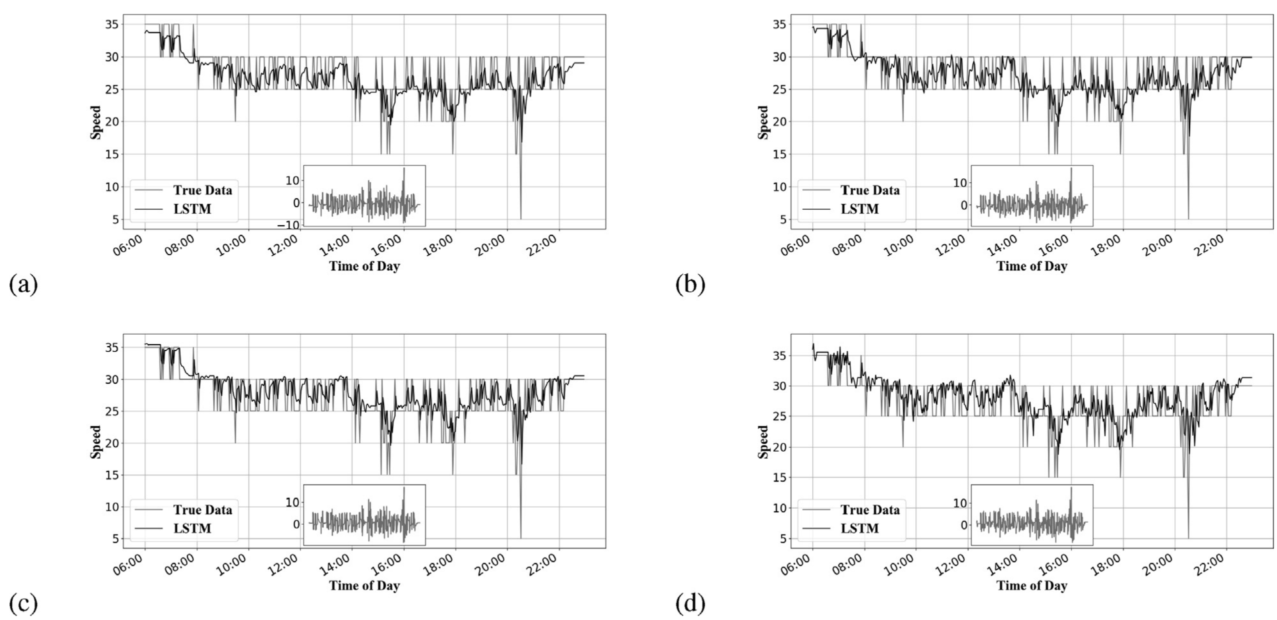

Fig. 4 The experiment under the LSTM model (8 weekends in September). (a) single-scale (speed) experiment; (b) multiscale (weather + speed) experiment; (c) multiscale (status + speed) experiment; (d) multiscale(weather + status + speed) experiment (Based on ReLU).

through the last activation layer, Random loss of a certain proportion of parameters, To prevent overfitting, And finally into the full connection layer, get trained or predicted results (input: (None, 400); output: (None, 1)).

Based on LSTM, GRU and SAE models, experiments were conducted on weekend data (weekend data is significantly different from workday data, and separate experiments can help to analyze data in more detail), respectively, through single-scale attribute speed (average speed of the vehicle 2 min) Experimental analysis was performed on multi-scale attributes (weather + speed, status + Speed, Weather + status + Speed) data. The experimental results are shown in Figs. 5–12, where the gray curve represents the real value and the black curve represents the predicted value under different models. An internal inline diagram shows the distance between the predicted value and the actual value, the abscissa represents the time (6:00–23:30), and the ordinate represents the velocity (in km/h).

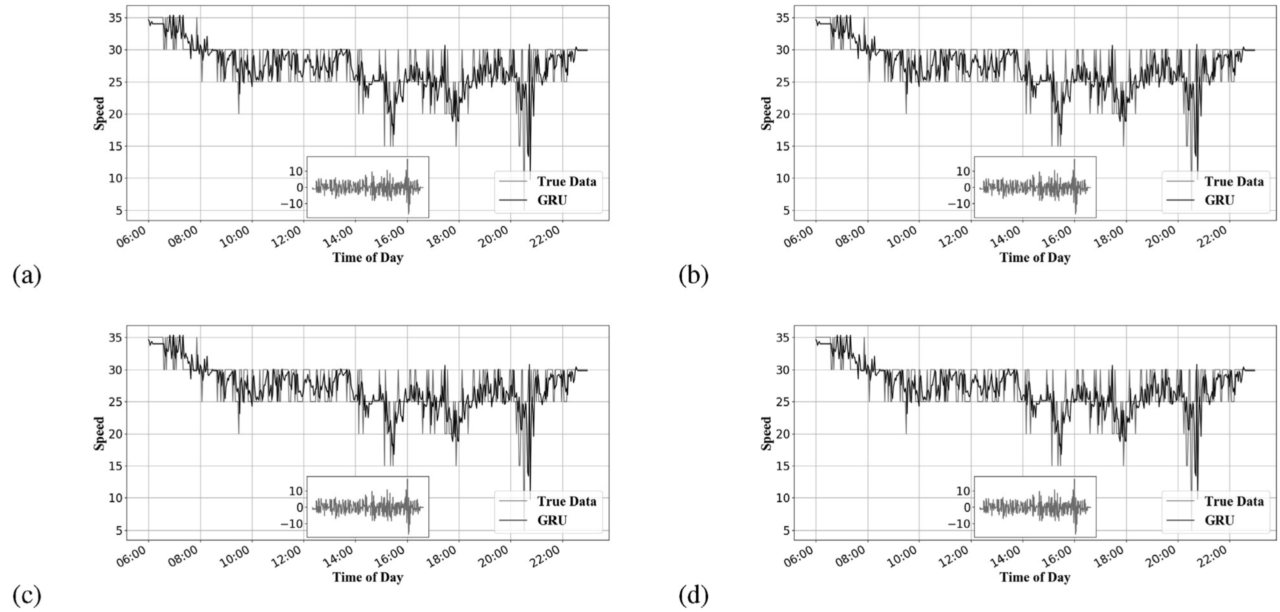

Fig. 5 The experiment under the GRU model (8 weekends in September). (a) single-scale (speed) experiment; (b) multiscale (weather + speed) experiment; (c) multiscale (status + speed) experiment; (d) multiscale(weather + status + speed) experiment (Based on ReLU).

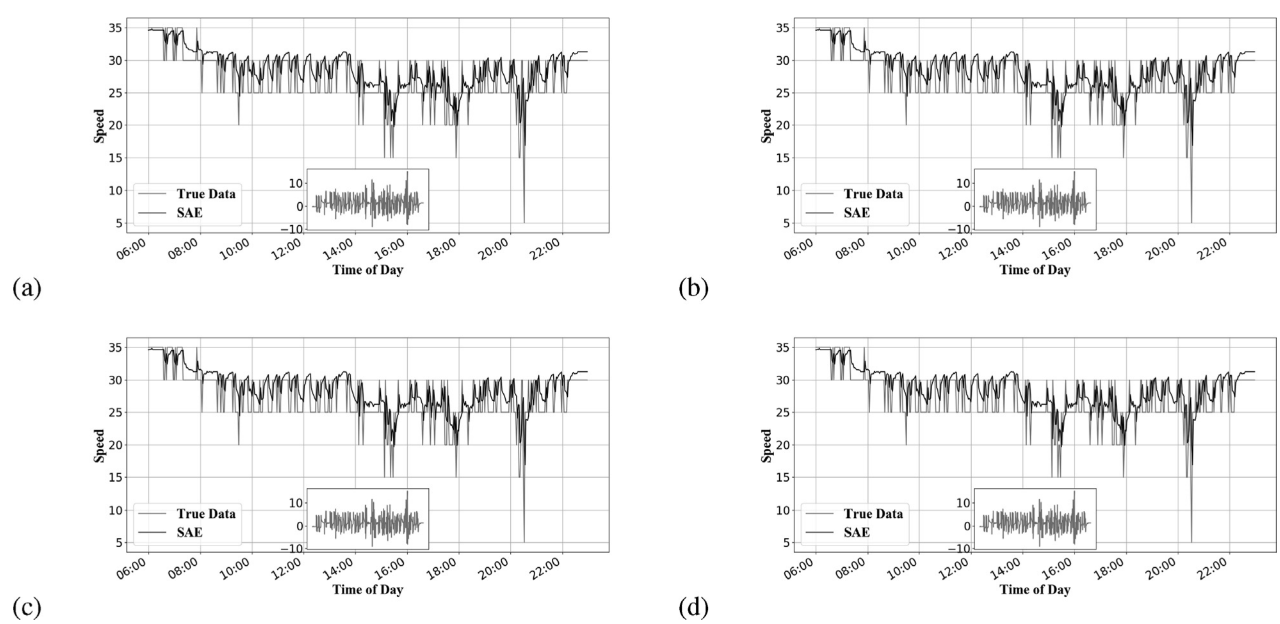

Fig. 6 The experiment under the SAE model (8 weekends in September). (a) single-scale (speed) experiment; (b) multiscale (weather + speed) experiment; (c) multiscale (status + speed) experiment; (d) multiscale(weather + status + speed) experiment (Based on ReLU).

Figs. 1–3 is the result of the simulation experiment using the LSTM, GRU, SAE model, which uses the ReLU function as the data processed is the data of the workday. (a) graph is a prediction result that contains only velocity data; (b) graph is the prediction result containing velocity and weather data; (c) graph is the prediction result that contains velocity and congestion state data; (d) graph is the prediction result that contains data on speed, weather, and congestion status(The four graphs in Figs. 4–12 have the same meaning). Figs. 4–6 is the result of the simulation experiment using the LSTM, GRU, SAE model, which uses the ReLU function as the data processed is the data of the weekend.

Figs. 7–9 is the result of the simulation experiment using the LSTM, GRU, SAE model, which uses the Sigmoid function as the data processed is the data of the workday. Figs. 10–12 is the result of the simulation experiment using the LSTM,

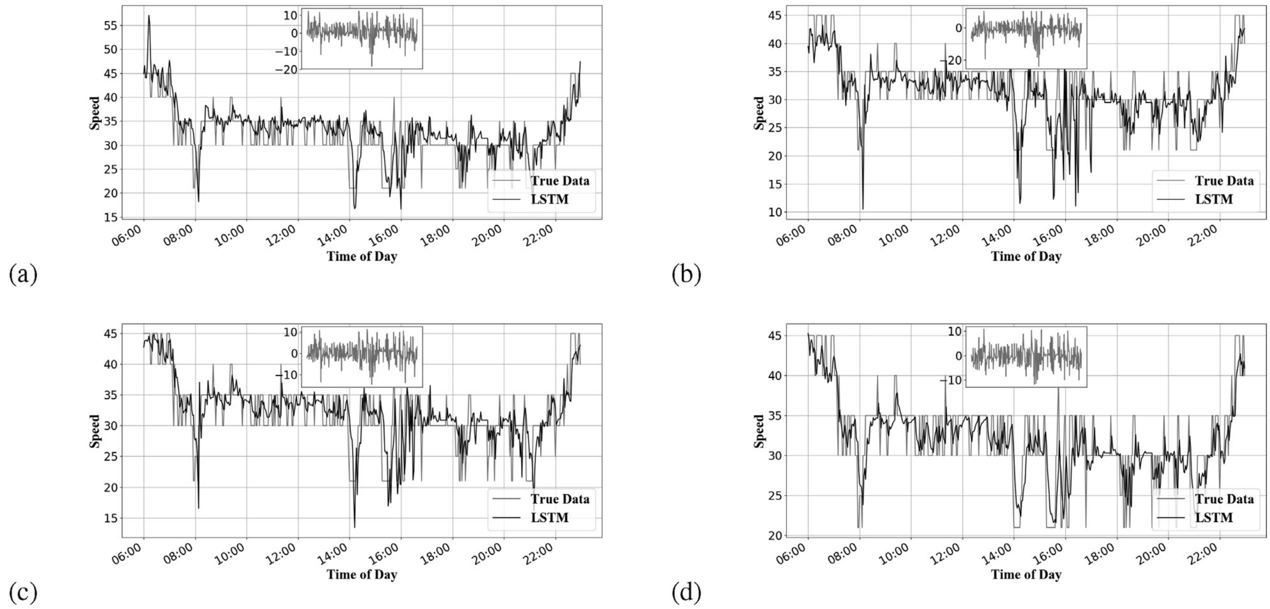

Fig. 7 The experiment under the LSTM model (21 workdays in September). (a) single-scale (speed) experiment; (b) multiscale (weather + speed) experiment; (c) multiscale (status + speed) experiment; (d) multiscale(weather + status + speed) experiment (Based on Sigmoid).

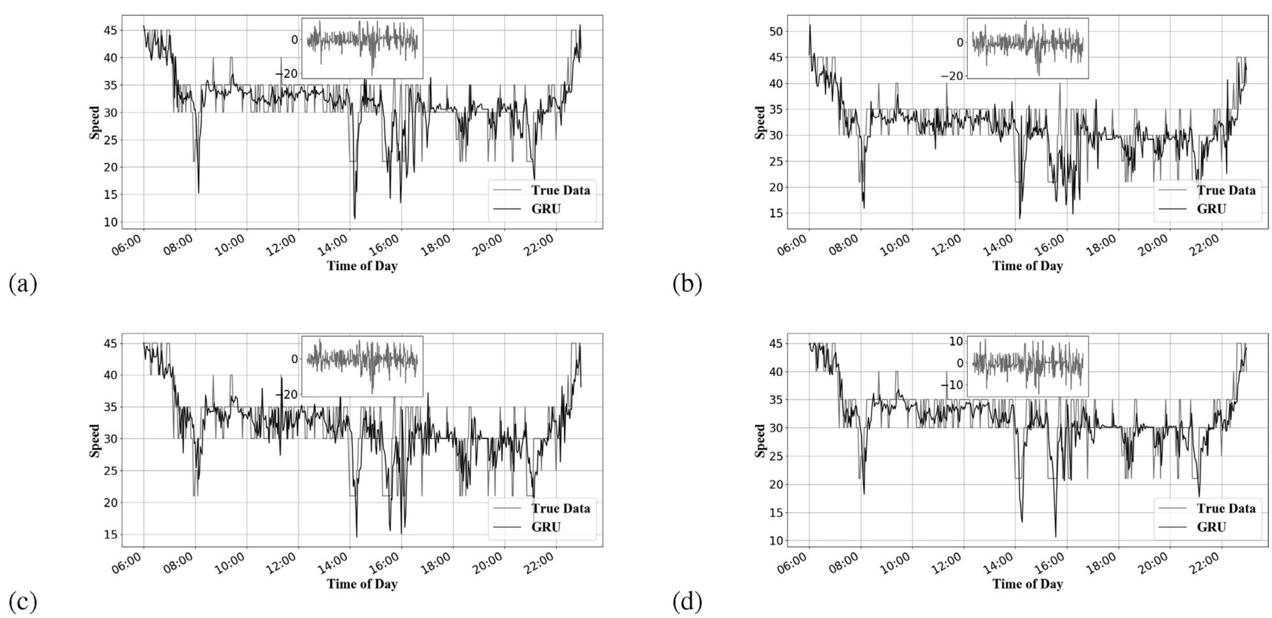

Fig. 8 The experiment under the GRU model (21 workdays in September). (a) single-scale (speed) experiment; (b) multiscale (weather + speed) experiment; (c) multiscale (status + speed) experiment; (d) multiscale(weather + status + speed) experiment (Based on Sigmoid).

GRU, SAE model, which uses the Sigmoid function as the data processed is the data of the weekend.

4.2. Evaluation metrics

There are five commonly used regression evaluation metrics: Mean Absolute Percentage Error(MAPE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-Squared(r2r2). A MAPE of 0% indicates a perfect model, and a MAPE greater than 100% indicates a poor model. The smaller the values of MSE, RMSE and MAE, the better the model is established, and the predicted result is closer to the true value. R-Squared has a value range of 0–1: the result is 0, indicating that the model fits poorly; if the result is 1, the model has no errors.

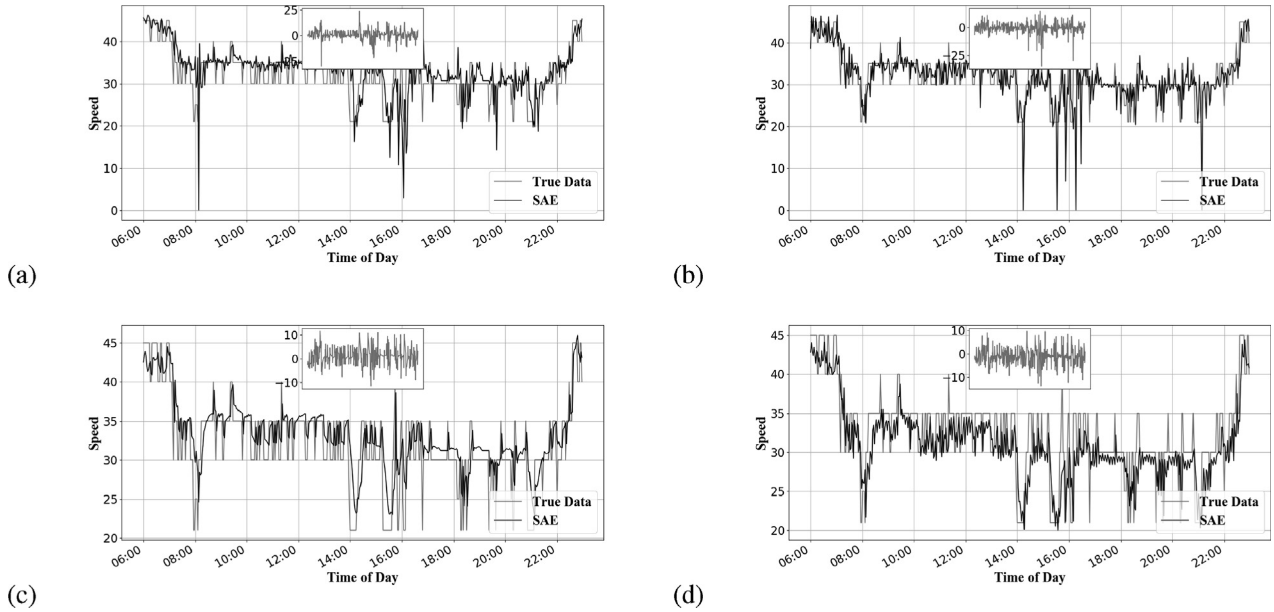

Fig. 9 The experiment under the SAE model (21 workdays in September). (a) single-scale (speed) experiment; (b) multiscale (weather + speed) experiment; (c) multiscale (status + speed) experiment; (d) multiscale(weather + status + speed) experiment (Based on Sigmoid).

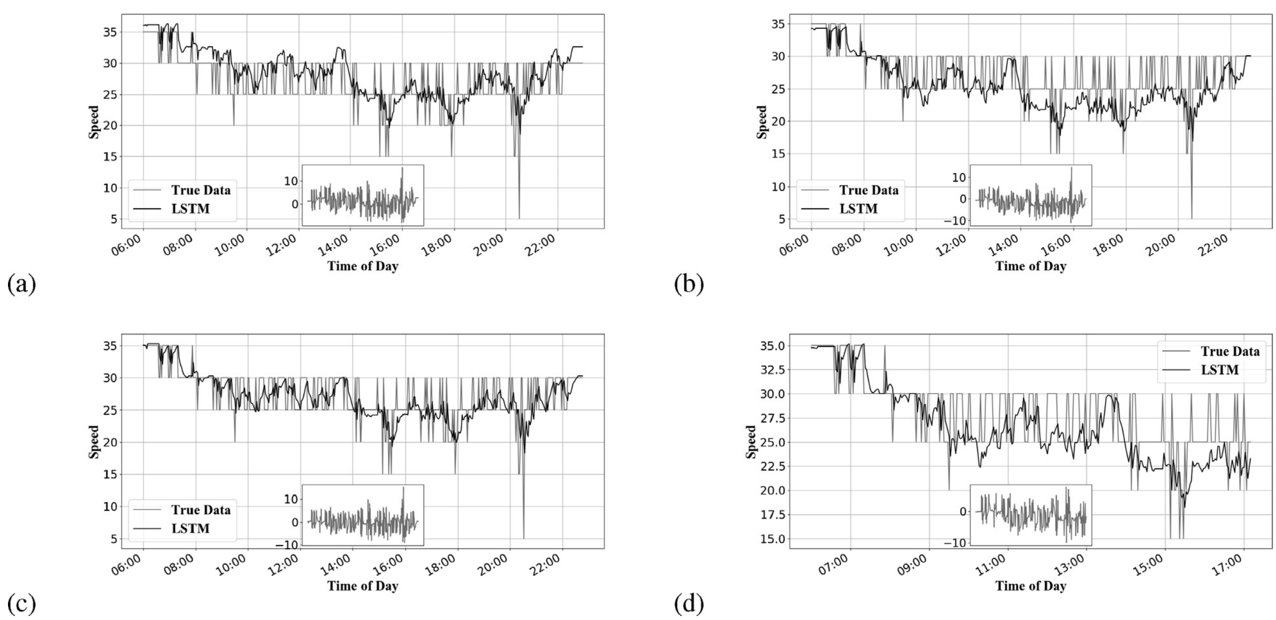

Fig. 10 The experiment under the LSTM model (8 weekends in September). (a) single-scale (speed) experiment; (b) multiscale (weather + speed) experiment; (c) multiscale (status + speed) experiment; (d) multiscale(weather + status + speed) experiment (Based on Sigmoid).

4.3. Results and discussion

The prediction analysis results shown in Tables 7–10 are based on the data of workdays of ReLU activation function. In the LSTM experiment of adding traffic congestion state and weather parameters, the mape value is 11.7637%, the mae value is 2.7781, the mse value is 14.2994, the rmse value is 3.7814, and the r2 value is 0.6924. The experimental results are better than the other three experimental results of LSTM models in Tables 7–9. GRU, SAE based experiments can also be seen through the table that the experimental prediction results of adding parameters are better than those without adding auxiliary information. Tables 15–18 shows the workday prediction results based on the Sigmod activation function.

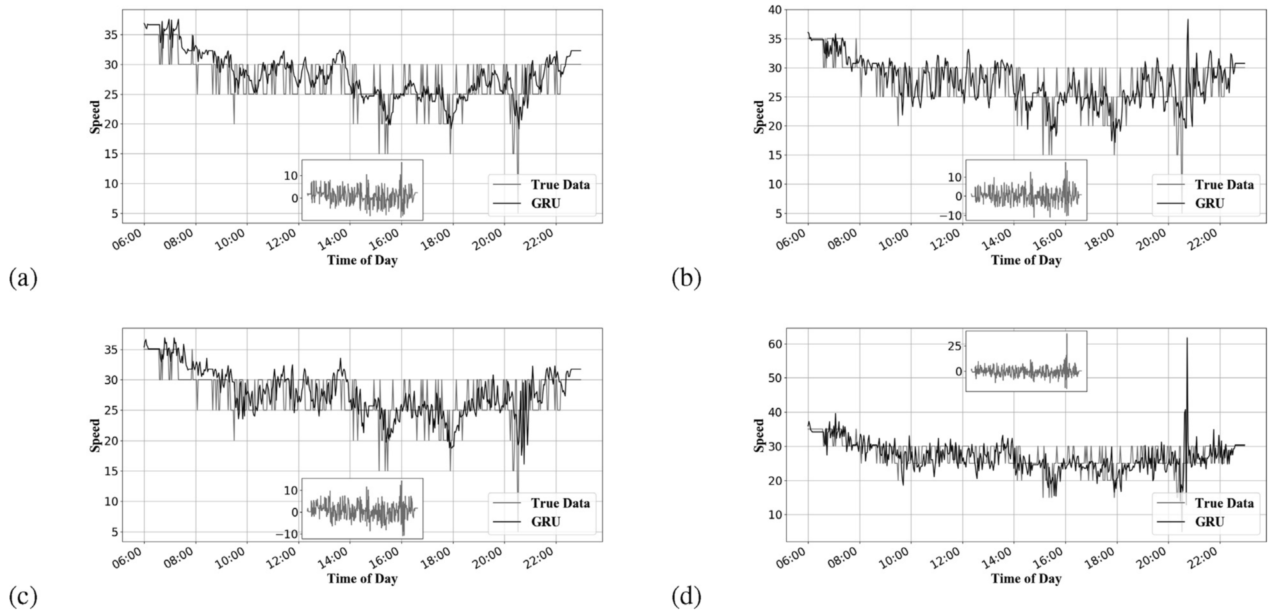

Fig. 11 The experiment under the GRU model (8 weekends in September). (a) single-scale (speed) experiment; (b) multiscale (weather + speed) experiment; (c) multiscale (status + speed) experiment; (d) multiscale(weather + status + speed) experiment (Based on Sigmoid).

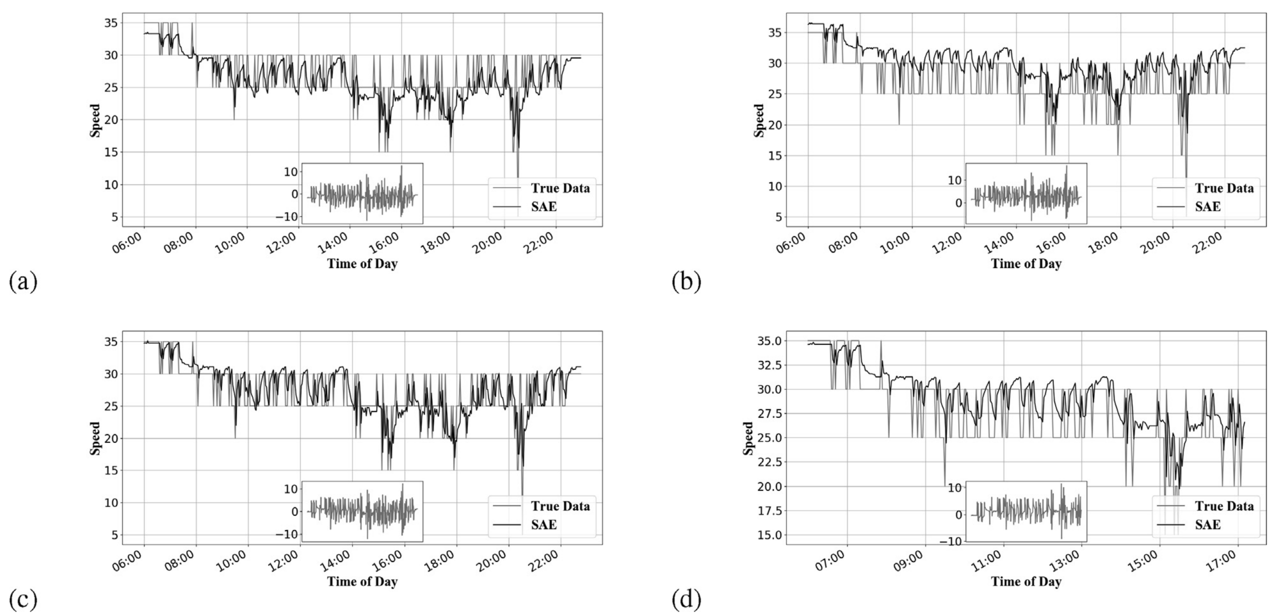

Fig. 12 The experiment under the SAE model (8 weekends in September). (a) single-scale (speed) experiment; (b) multiscale (weather + speed) experiment; (c) multiscale (status + speed) experiment; (d) multiscale(weather + status + speed) experiment (Based on Sigmoid).

The experimental results of adding auxiliary information can be obtained by analysis, which is superior to those without auxiliary information. Comparing the data in Tables 7 and 15, we can get that the model of Sigmod as activation function is better than that of ReLU as activation function. At the same time, the SAE experimental prediction results can be obtained is the most accurate by table analysis and comparison. Tables 11–14, 19–22 is the analysis and prediction of the weekend traffic speed experimental results, from the experimental results can be seen that the weekend and workday traffic speed is obviously different, but the overall distribution of the data is still similar. And the experimental results are the same as the conclusions of the workday analysis.

Through the analysis of the experimental data, we can be concluded that the multi-scale experimental results are compared with the single-scale: the value of R2 becomes larger;

Table 7 Evaluation metrics of experimental results of LSTM, GRU and SAE models under single-scale (speed).

		LSTM	GRU	SAE
speed	mape	13.3953%	12.4676%	16.7353%
	mae	3.3002	3.118716	3.7461
	mse	22.2846	20.4886	31.5873
	rmse	4.7206	4.5264	5.6203
	r2	0.4943	0.5350	0.3113

Table 8 Evaluation metrics of experimental results of LSTM, GRU and SAE models under single-scale (status + speed).

		LSTM	GRU	SAE
status + speed	mape	14.1808%	13.6654%	13.1513%
	mae	3.1038	3.1255	3.0922
	mse	16.7945	17.2872	17.2118
	rmse	4.0981	4.1578	4.1487
	r2	0.6338	0.6231	0.6247

Table 9 Evaluation metrics of experimental results of LSTM, GRU and SAE models under single-scale (weather + speed).

		LSTM	GRU	SAE
weather + speed	mape	12.1659%	12.6087%	13.8571%
	mae	3.0355	3.1032	3.3171
	mse	18.8178	19.2762	24.7322
	rmse	4.3379	4.3904	4.9731
	r2	0.5729	0.5625	0.4680

Table 10 Evaluation metrics of experimental results of LSTM, GRU and SAE models under single-scale (status + weather + speed).

		LSTM	GRU	SAE
status + weather + speed	mape	11.7637%	12.4691%	**10.7449%**
	mae	2.7781	2.9785	**2.6162**
	mse	14.2994	16.1946	**13.5203**
	rmse	3.7814	4.0242	**3.6770**
	r2	0.6924	0.6516	**0.7092**

Table 11 Evaluation metrics of experimental results of LSTM, GRU and SAE models under single-scale (speed).

		LSTM	GRU	SAE
speed	mape	9.5869%	10.2694%	10.0692%
	mae	2.5533	2.62732	2.5607
	mse	13.2704	17.0434	13.4255
	rmse	3.6428	4.1283	3.6640
	r2	0.1955	0.1805	0.1908

Table 12 Evaluation metrics of experimental results of LSTM, GRU and SAE models under single-scale (status + speed).

		LSTM	GRU	SAE
status + speed	mape	51.2336%	67.4375%	36.1347%
	mae	1.6585	8.5347	1.6443
	mse	7.5568	11.7374	7.9626
	rmse	2.7489	3.4259	2.8218
	r2	0.3657	0.2851	0.3639

Table 13 Evaluation metrics of experimental results of LSTM, GRU and SAE models under single-scale (weather + speed).

		LSTM	GRU	SAE
weather + speed	mape	16.8387%	27.2268%	31.2065%
	mae	1.5170	6.9827	1.8705
	mse	7.5994	74.9278	8.2260
	rmse	2.7567	8.6560	2.8681
	r2	0.3626	0.3314	0.3595

Table 14 Evaluation metrics of experimental results of LSTM, GRU and SAE models under single-scale (status + weather + speed).

		LSTM	GRU	SAE
status + weather + speed	mape	37.5815%	62.3702%	**38.2511%**
	mae	1.3541	9.4214	**1.4595**
	mse	5.4402	11.5569	**5.6536**
	rmse	2.3324	3.3995	**2.3777**
	r2	0.4705	0.3573	**0.4693**

Table 15 Evaluation metrics of experimental results of LSTM, GRU and SAE models under single-scale (speed).

		LSTM	GRU	SAE
speed	mape	15.5519%	15.7720%	15.1334%
	mae	3.3443	3.4019	3.5791
	mse	19.6131	20.3890	25.9194
	rmse	4.4286	4.5154	5.0911
	r2	0.5723	0.5554	0.4425

Table 16 Evaluation metrics of experimental results of LSTM, GRU and SAE models under single-scale (status + speed).

		LSTM	GRU	SAE
status + speed	mape	12.6091%	12.4178%	12.9521%
	mae	2.9456	3.0022	2.9539
	mse	15.9720	16.8418	15.1242
	rmse	3.9965	4.1038	3.8889
	r2	0.6564	0.6377	0.6747

Table 17 Evaluation metrics of experimental results of LSTM, GRU and SAE models under single-scale (weather + speed).

		LSTM	GRU	SAE
weather + speed	mape	12.8801%	13.1380%	11.6831%
	mae	3.1796	3.2061	2.9696
	mse	18.4959	18.6305	18.3203
	rmse	4.3006	4.3163	4.2802
	r2	0.6021	0.5992	0.5842

Table 18 Evaluation metrics of experimental results of LSTM, GRU and SAE models under single-scale (status + weather + speed).

		LSTM	GRU	SAE
status + weather + speed	mape	11.3788%	11.9664%	**9.9636%**
	mae	2.7286	2.8548	**2.6694**
	mse	13.8464	15.3530	**12.7082**
	rmse	3.7210	3.9182	**3.5648**
	r2	0.7121	0.6697	**0.7115**

Table 19 Evaluation metrics of experimental results of LSTM, GRU and SAE models under single-scale (speed).

		LSTM	GRU	SAE
speed	mape	10.7173%	16.9600%	8.4963%
	mae	2.7654	3.4660	2.1633
	mse	12.9604	28.3831	9.3822
	rmse	3.6001	5.3275	3.0630
	r2	0.1510	0.2643	0.3854

Table 20 Evaluation metrics of experimental results of LSTM, GRU and SAE models under single-scale (status + speed).

		LSTM	GRU	SAE
status + speed	mape	8.6758%	21.2333%	8.8244%
	mae	2.1244	3.1381	2.1583
	mse	8.5027	24.4501	8.2334
	rmse	2.9159	4.9447	2.8693
	r2	0.4430	0.3478	0.4199

Table 21 Evaluation metrics of experimental results of LSTM, GRU and SAE models under single-scale (weather + speed).

		LSTM	GRU	SAE
weather + speed	mape	8.7901%	16.4271%	13.3955%
	mae	2.3919	3.0466	3.2092
	mse	9.8789	23.4851	15.5574
	rmse	3.1430	4.8461	3.9442
	r2	0.3039	0.3679	0. 3501

Table 22 Evaluation metrics of experimental results of LSTM, GRU and SAE models under single-scale (status + weather + speed).

		LSTM	GRU	SAE
status + weather + speed	mape	10.6564%	10.6502%	**9.7822%**
	mae	2.7259	2.7317	**2.6990**
	mse	14.7965	16.0773	**14.4253**
	rmse	3.8466	4.0096	**3.7980**
	r2	0.5490	0.5100	**0.5603**

the values of MAPE, MSE, RMSE, and MAE also become smaller. It shows that the fitting effect is better than the single scale, the accuracy is greatly improved (Bold fonts represent the best compared to other results). This not only shows that multi-scale can influence the prediction results, but also shows that the more relevant attributes have a greater impact on the experimental results. Moreover, using sigmoid as an activation function is better than ReLU through the analysis of tabular data. The experimental results show that the auxiliary information can improve the accuracy of urban traffic speed prediction. It is very necessary to use a positive dataset for traffic state prediction.

Because of the different road structure and economic development of each city, the dataset of different urban roads reflects different contents, so it is not possible to illustrate the better problem of that dataset by comparing the experimental results under different datasets. However, the datasets of the same road can be compared vertically to show that the datasets containing more auxiliary information can predict the road traffic state more accurately. Then a dataset containing more auxiliary information is better than a dataset with single parameter. Most of these datasets (Table 1) mentioned in the paper have only one traffic parameter, and most of them are not available. The dataset provided in this paper contains multiple parameters of traffic state and weather data. More importantly, the dataset is accessible. From the above analysis, it can be concluded that the XiAn Road Traffic dataset is better than other datasets, and provides a better data base for traffic state researchers.

5. Conclusion

At present, most datasets contain one or two dimensions, and lack does not contain more traffic information (driving direction, congestion percentage, driving angle, weather condition), which can lead to inaccurate or overfitting of experimental results. Traffic state will be affected by various traffic information, and can not only use a single traffic information to analyze and predict. This paper emphasizes the influence of multi-scale on prediction results. The experimental results show that the prediction effect of multi-scale model is much better than that of single-scale prediction, and fully reflects the data set adding auxiliary information is more research significance. We did not analyze the correlation between attributes in our experiments, and many attributes we have not been used yet. The datasets XiAn Road Traffic and XiAn Weather provide great convenience for further study of traffic conditions in the future.

Declaration of Competing Interest

None.

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