Innovative approaches for short-term vehicular volume prediction in Intelligent Transportation System

by

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Abstract

Accurate and timely short-term traffic flow predictions can provide useful traffic volume information beforehand and help people make better route decisions, which plays a vital role in the Intelligent Transport System (ITS). Currently, mainly two problems are focused in this field. The first one is the spatiotemporal relations mining problem. With the road networking in ITS, the capture of spatiotemporal correlations is significant for conducting an accurate traffic flow prediction. However, most of the previous studies rely on the information collected from the single road point, which lost many useful road information. The second one is the model adaptability problem. In fact, simple road contexts such as suburban highways are preferred by previous researches due to simplex and easily captured features. However, with the progress of ITS, a great prediction model is supposed to fit into more complex road conditions. Therefore, how to make the designed models fit into more complicated prediction environments is necessary and critical.

Currently, mainly two sorts of approaches, statistic-based and machine learning (ML)-based are used for short-term traffic flow predictions, but both of them face challenges mentioned above. Statistic-based models generally have better model interpretability, but delicate interpretative formulas conversely limit the model structure flexibility. As for the ML-based models, although they have a more flexible model structure and stronger non-linear pattern capture ability, the high training cost is a remarkable drawback. In this thesis, these two categories of models are both optimized to achieve a more accurate prediction. Based on the Vector Autoregressive Moving Average model (VARMA), an innovative Delay-based Spatiotemporal ARIMA (DSTARMA) is proposed to improve the spatiotemporal features mining ability of statistic-based models. This model focus on the travel delay problem, which is represented by a weighting matrix to help describe the real spatiotemporal correlations. As for the improvement of the ML-based category, an innovative Selected Stacked Gated Recurrent Units model (SSGRU) is proposed, particularly which includes a linear regression data pre-processing system to analyzes spatiotemporal relations. Further, for enhancing the model adaptability, an optimized model Multivariable Delay-based GRU (MDGRU), based on SSGRU is designed. This model extends the prediction scenario to a more complex traffic condition with a more compact model structure, and also the travel delay is considered into the prediction process. The prediction results show it outperforms many other similar models.

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Publications Related to This Thesis

Yanjie Tao, Peng Sun, and Azzedine Boukerche, "A Delay-Based Deep Learning Approach for Urban Traffic Volume Prediction", IEEE ICC, 2020.

Yanjie Tao, Peng Sun, and Azzedine Boukerche, "A Novel Travel-Delay Aware Short-Term Vehicular Traffic Flow Prediction Scheme for VANET", IEEE Wireless Communications and Networking Conference (WCNC'19) – Track 4: Emerging Technologies, Architectures and Services, 2019.

Yanjie Tao, Peng Sun and Azzedine Boukerche."A Hybrid Stacked Traffic Volume Prediction Approach for a Sparse Road Network." In procedings of 2019 IEEE Symposium on Computers and Communications (ISCC).

Peng Sun, Azzedine Boukerche and Yanjie Tao."Theoretical Analysis of the Area Coverage in a UAV-based Wireless Sensor Network." 2017 13th International Conference on Distributed Computing in Sensor Systems (DCOSS) (2017): 117-120.

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Chapter 1

Introduction

As an essential part of the Intelligent Transportation System (ITS) [1], traffic flow prediction has attracted much attention. With the development of ITS, the higher requirements for reliable and timely road information are needed [2] [3] [4]. However, the high mobility of the vehicles results in more diverse and volatile traffic environments [5] [6], which is a difficulty to achieve highly reliable and accurate traffic flow predictions.

Based on the mentioned difficulty, there are mainly two sorts of approaches can be used to do short-term traffic flow predictions, the statistic-based models and ML-based models. In fact, statistic-based models such as Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA model (SARIMA) [7] are widely used in earlier ages. Generally, they have better model interpretability, but the rigid model structure is their main drawback. Recent years, with stronger feature mining ability, especially for non-linear parts, ML-based models are given more focuses.

Although many efforts have been made to improve the traffic flow prediction accuracy and reliability in previous researches [8] [9] [9], there are still some problems that have not been solved, which can significantly influence the prediction results. In this chapter, based on the current traffic flow prediction challenges and background, research motivations, and objectives are illustrated. Also, some contributions derived from this research will be listed, following by a brief introduction for overall arrangement in the end.

1.1 Motivation and Objectives

For previous researches corresponding to the short-term traffic flow predictions, as mentioned before, models from two categories are employed, statistic-based as well as ML-based. In fact, statistic-based models described by some delicate formulas have great performance in earlier years. The predictions based on this kind are usually set on the single points of road segments in suburban areas, where the traffic patterns are simple and easy to be captured. However, with the road networking and the complexity increase of transportation system, simple statistical-based models are not able to offer an accurate prediction. With more flexible model structures, ML-based models are leading a new trend. However, high computation cost caused by deep learning fashion and large dataset requirement are the main problems. Besides, when vehicles move from one place to the another, there is a time cost considered as the travel delay, which ignored by previous studies. In view of the above problems, three objectives are proposed in this thesis. The first one is taking the travel delay factor into the prediction process in an appropriately manner, and the second is to improve the spatiotemporal mining ability, expanding the model from single road point to an entire road network. The final one is to improve the model adaptability, extending the prediction contexts to more complicated situations, and also reduce the computation cost with a more compact model structure as well.

1.2 Contribution

In this thesis, the contributions are listed as followed.

- **Improved mining ability for spatiotemporal correlations**: For previous traffic flow predictions, most of them are based on a single road point, but in this thesis, all works are set on an intact road network, where spatiotemporal relations are captured, and this is more fit into the road situations in the real world. In addition, the travel delay problem is solved, which is represented by a weighting matrix, and the prediction accuracy gets significantly improved.
- **Improved model adaptability**: Extending the prediction scenario from simple traffic environment such as suburban areas to more complex road context, and the results show proposed models still have great performance.

1.3 Outline

The remainder of this thesis is organized as followed. Chapter 2 will give a general review of previous works with regard to the short-term traffic flow prediction, and following Chapter 3 will propose a delay-based statistical model, DSTARMA. This model is aimed at solving the travel delay problem in road networks. Besides the usage of statistic-based model, SSGRU model that belongs to ML-based kind is also came up with in Chapter 4. Specially, by adding a data-preprocessing system and in a stacked structure, SSGRU outperforms many other similar models. Considering the spatiotemporal relations in a road network as well as the travel delay, model MDGRU in Chapter 5 is more compact and cost-saving, and also it extends the prediction environment from an only suburban area to the urban by a separation method. Finally, future works and conclusion are discussed in Chapter 6.

Chapter 2

Related Work

For providing a full-scale understanding of short-term predictions, related literature will be reviewed and summarized in this chapter. Statistical methods, including Autoregressive (AR) family and Exponential Smoothing (ES) family as well as some basic concepts will be illustrated at the very beginning. Then, ML-based approaches are focused, in which Recurrent Neural Network (RNN), Support Vector Machine (SVM), etc., are explicitly discussed. In addition, some other helpful methods, e.g., Hidden Markov Machine (HMM) and Kalman Filter, are described in detail. Through analyzing several supportive cases, the general framework of short-term prediction for recent years is obtained.

2.1 Preliminary concepts of traffic flow prediction

The entire short-term traffic flow prediction procedure will be introduced in this section to help later introduction. For each step, some significant concepts are illustrated in detail since they are easily misunderstanding and promiscuous. As shown in Fig. 2.1, there are mainly four steps to design and evaluate a traffic flow prediction model, i.e., model selection, model training, prediction, and result evaluation.

2.1.1 Model Selection

Model selection is the start of design a short-term traffic flow prediction (see Fig. 2.1), which has a great impact on the subsequential steps. A good model leads to a good output

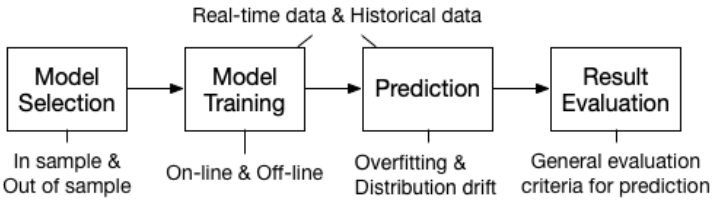


Figure 2.1: General procedure of short-term traffic flow prediction

and results in a great performance but with less cost. In-sample and out-of-sample [10, 11] are two commonly seen selection mechanisms in traffic flow prediction process.

2.1.1.1 In-sample and out-of-sample

The most remarkable diverse between statistic-based and ML-based approaches are the model building fashion. To be more precise, most statistical models are in-sample model selection, which means the same dataset is used in both model building and fitting stage. In-sample ways make the user model building firstly to determine parameters in the model. For instance, in the Autoregressive Integrated Moving Average (ARIMA) process, critical parameters p,d,q are determined by using the autocorrelation function (ACF) and the partial autocorrelation function (PACF) pictures from the very beginning. Further, relying on the adopted criterion, (e.g., Bayesian information criterion (BIC), Akaike information (AIC),) the optimal values are selected for the control parameters of the prediction model [12]. On the other hand, based on a given rule, out-of-sample divides the single dataset into two parts to implement the training and validation of the prediction model, respectively. Typically, ML-based approaches often rely on the out-of-sample.

2.1.2 Model Training

After the determination of the prediction model, the training begins. In this period, how to choose a suitable training fashion and the dataset are also big challenges. On-line and Off-line training are the two popular options for the training stage, and also whether using real-time or historical data source also needs to be considered. In fact, the training process is not easy, which needs to face some difficulties such as overfitting and distribution drift.

2.1.2.1 On-line and off-line training

The correlation of On-line and Off-line seems like the relationship between In-sample and Out-of-sample. On-line training means that the training process begins as the data comes in. Conversely, Off-line training is based on a static dataset. To be more precise, for On-line training the algorithm updates parameters after learning from one training instance. In contrast, in off-line training, the parameters are updated when all data has been learned. As mentioned in [13], these two training strategy are both widely used in many classic machine learning models, such as Convolutional Neural Network (CNN), and Support Vector Regression (SVM), etc. While, For reinforcement learning-based method, online training is more common.

2.1.2.2 Real-time data and historical data

The historical data is the data gathered from a specified period in the past. The advantage of historical data is that it can tell the past trend and help to analyze mistakes, but it may take more time and effort to make decisions. In the contrary, the real-time data is considered as a more-recent data [14], which can be strictly guaranteed to be time-sensitive by minimizing or even eliminating delays between data acquisition and data processing. For example, in [15], real-time traffic data is defined as data collected within 40 minutes, and the historical data is defined as the daily data. Particularly, in real-time data predictions, there is no need for the historical data analysis, and the acquisition of prediction results is more dependent on the intrinsic relationship between the recently acquired data.

2.1.2.3 Overfitting and distribution drift

Overfitting is the situation that focuses on the details overly, and hence over fit some quirks and random noise, which results in a complicated model. Generally, overfitting usually happens in regression data analysis stage, especially machine learning process [16]. To get rid of this, a proper learning rate to update weights is significant. Another unexpected case is the distribution drift, which is more found in statistical-based prediction models [17]. In fact, there is no need to use big data while applying a statistical-based model to predict since too many data can cause the covariate drift phenomenon and lead to lousy predict result [17].

2.1.3 Result Evaluation

After the completion of the model building, the model evaluation begins, which can level the quality of prediction models. Some criteria are introduced in this part from different perspectives, such as computation time as well as prediction accuracy.

2.1.3.1 Computation time

Computation time is a significant indicator, as a good prediction in transportation system requires that it is fast and timely. Generally, computation time in short-term traffic flow prediction is the lenghth of the whole prediction process, from model selection to prediction stage. Generally, pure statistical models have lower computation complexity than multi-layer machine learning based models. Hence, for the simple road structure, it is better to use statistical approaches, and for the more complex and more extensive dataset, which is more suitable to use machine learning based systems.

2.1.3.2 Accuracy

The accuracy of prediction can be influenced by many factors, including the prediction methods, experimental conditions, the reliability of data source, etc. Therefore, it is necessary to give a general standard to level the prediction quality. This indicator is the most critical one, which shows the quality of a prediction model directly. There are mainly four figures are adopted by previous studies [18, 19, 20].

- Mean squared error (MSE)
  MSE shows the average squared difference between the observations and predictions. And it works based on the equation as follows.

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(X_t - \hat{X}_t\right)^2, \tag{2.1}$$

  in which, X_t is the observation value, $\hat{X}_t$ is the estimated value.

- Mean absolute percentage error (MAPE)
  MAPE is another basic index to evaluate the accuracy of an estimator. Different from the MSE, it is widely used in both statistics-based and machine learning based

models, which is defined as follows.

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{X_t - \hat{X}_t}{X_t} \right|. \tag{2.2}$$

- R-square (R^2)
  Typically, this metric is usually used to measure the consistency between the regression lines obtained by a given algorithm and the given dataset, i.e., the distance between the regression line and data points, which is derived as,

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 1 - \frac{\sum_t \left(X_t - \hat{X}_t\right)^2}{\sum_t \left(X_t - \bar{X}\right)^2}, \tag{2.3}$$

  where, the R^2 is a value between $0 \sim 1$, in particular, the closer to 1, the higher the prediction accuracy is. Conversely, the closer to 0, the lower the accuracy is.

- Root mean square error (RMSE)
  RMSE evaluate the performance of a prediction model from another perspective, i.e., it draws the standard deviation of the prediction errors (residuals), which is defined by,

$$RMSE = \sqrt{\overline{\left(\hat{X}_t - X_t\right)^2}}. \tag{2.4}$$

In addition to the criteria mentioned above for measuring timeliness and accuracy, other principles that used to evaluate the quality of a model are broad. For example, reliability is one of the significant aspects that widely considered by most researchers nowadays. Basically, the error evaluation criteria are supposed to be easily adapted in real situations and should be selected according to the actual needs of the method design. After giving the general idea of the whole prediction procedure, models commonly used in traffic flow prediction will be introduced explicitly in the following sections.

2.2 Statistic-based model

With benefits of comparatively lower computation complexity, good model analytical ability, and more well-rounded implementation experience [21], statistic-based models are

widely adopted for implementing short-term traffic flow prediction. There are many different models in this category, from the simplest Autoregressive (AR) [22], Moving Average (MA) [23] to more complex models, AutoRegressive Integrated Moving Average model (ARIMA) [24], Seasonal ARIMA (SARIMA) [25] and Vector ARIMA (VARIMA), etc. Besides, Exponential Smoothing series are also included.

For this sort of models, their features are listed and compared in Tab. 2.1, which gives a better view for them. In the rest part of this section, some of the existing prediction approaches designed based on these statistical models will be reviewed.

Table 2.1: Features of statistical-based models

Model	Interpretability	Seasonality	Stationary dataset	Ability for non-linear dataset	Multivariate	Effect for Long-term dataset	Effect for Short-term dataset
ARMA (AR/MA)	Simple	N	Y	N	N	Medium	Good
ARIMA	Simple	N	N	N	N	Medium	Good
SARIMA	Medium	Y	N	N	N	Good	Good
VARIMA	Medium	N	N	N	Y	Medium	Good
ES (SES, DES)	Simple	N	N	N	N	Bad	Good

2.2.1 ARIMA

ARIMA model is a classic and fundamental model widely used in prediction fields, such as stock forecasting [26], weather prediction [27], etc. In transportation system, ARIMA is also widely used, for its simplicity and easily understood nature. It not only singly combines the AR model [28] with MA indicator [29], but also handles data to be stationary before prediction, where p is the number of time lags of autoregressive and q is the moving average term. As for the d, it represents the number of differential times that makes the sequence stable. The essence of the ARIMA model is to perform AR and MA calculations simultaneously by ensuring that the time series is stationary. The corresponding prediction result is derived as,

$$\hat{y}_t = \mu + \phi_1 * y_{t-1} + \cdots + \phi_p * y_{t-p} + \theta * c_{t-1} + \cdots + \theta * c_{t-q}, \tag{2.5}$$

where, ϕ and θ are the related polynomials of AR and MA, and $\hat{y}_t$ is the predicted value. Moreover, p, q are the time lag for AR and MA process, respectively. A general structure of the ARIMA model is shown in Fig. 2.2.

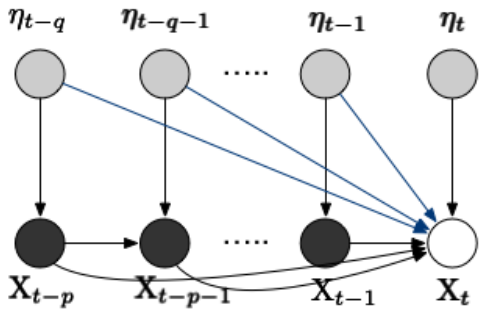


Figure 2.2: ARIMA model

ARIMA model exploits the data feature by conducting four-stage procedures, i.e., data acquisition, model fitting, validation, and prediction. And, there are some exclusive models designed based on ARIMA. For instance, random walk model, first-order autoregressive model, differenced first-order autoregressive model are the frequently used simple models that are derived from the ARIMA model but with different p, d, q values. Typically, for ARIMA-based short-term traffic flow prediction methods, historical dataset is preferred, since the offline parameter selection procedure is essential for implementing ARIMA.

As a classic time series analysis model, the advantages and disadvantages of ARIMA are also apparent. First, the model is straightforward, requiring only endogenous variables without resorting to other exogenous variables. On the other hand, as for is shortcomings, it requires that the time-series data be stable or differentiated to be stable. Also, it essentially captures linear relationship, but cannot capture the nonlinear relationship.

ARIMA shows its high adaptability and feasibility to be an essential method that widely used in early traffic flow prediction field. However, because ARIMA lacks the ability to extract the inherent nonlinear characteristics of vehicular traffic flow information, solely used ARIMA may not derive the sufficiently accurate prediction results. Therefore, when using ARIMA in practice, some data preprocessing methods are usually used to remove the trend in the data, such as, wavelet analysis, Kalman filter, even some other more complicated algorithms.

In [30], a prediction system was proposed based on the wavelet analysis. In this system, through a wavelet analysis system, the original time series $V(k)$ was firstly decomposed into two sequence, i.e., the N-level approximate coefficients $V^N(k)$ and j-level interference

factor $W^j(k)$. Further, an image reconstruction system is employed to reconstruct these decomposed signals, to enable ARIMA conducting a 5-min traffic flow prediction. In this study, only db2, db4, and db5 wavelet were compared, and 4-level decomposition was used. The highlight of this hybrid approach is that nonlinear parts of time series are decomposed firstly by wavelet analysis into different signals that carry details of traffic condition, and then the ARIMA models properly tuned by ACF and PACF analysis handle this series of signals. Different from the conventional ARIMA, it introduces the wavelet analysis-based data preprocessing stage, which greatly improves the prediction accuracy. As for its shortcoming, the decomposition reduces the error rate remarkably, but the time cost also increases.

For better solving the volatile traffic problem in prediction, the authors in [31] built different ARIMA models with appropriate parameters to fit into different pattern states within a day, namely switching ARIMA through introducing a variable duration concept. This model has stronger ability to overcome the challenge of volatile road situations. Also, the authors defined the traffic flow waveform by two pairs of patterns (M=4), i.e., ascending and descending patterns, bottom and peak patterns. Better than previous simple switching ARIMA, it built a duration state transition probability $p = (S_{t+1} = j \mid S_t = i)$, in which S_t is under the state l_i to smooth the link between two different state ARIMA models and further improved the prediction accuracy as well. For this study, model switching is its main advantage. However, there are still some disadvantages. The most obvious one is that high time cost for model selecting. Precisely, it needs more time to do pattern analysis, and if encounter diverse traffic situation that includes more complicated traffic states, this cost will be dramatically increased. Also, considering of this problem and the similarities in traffic flow pattern in the specified period within a day, for simple traffic context, time division first and then modeling is a good choice but for a complex road network, the benefit of this approach maybe dramatically falling. Similar work can be seen in [32], where Dong et al. used a time-oriented dataset, in which, data is dealt with separately on the basis of different periods.

The combination is becoming a new trend in short-term traffic flow prediction in recent years, enhancing the model adaptability of conventional ARIMA model. A model named ARIMA-GARCH is introduced in [33], which combines the ARIMA with the Generalized autoregressive conditional heteroscedasticity (GARCH) analysis. In this hybrid model, ARIMA is for analyzing the linear part of input traffic flow data, and GARCH is for the nonlinear part. For the nonlinear part in series, GARCH captured the sequential

dependence based on the observations, and it depicted the conditional variance of prediction error ϵ_t. Moreover, GARCH (1,1) was used in this study. The benefit of using GARCH is that it only needs several lags to estimate the randomness instead of all lags, which greatly improves efficiency. A similar hybrid model was proposed in [34], combing an initial classifier, Kohonen self-organizing map, and ARIMA model to make short-term traffic flow prediction.

To sum up, ARIMA is a simple model, which has good performance under simple traffic scenarios, and when using this model, a stable and linear dataset is required.

2.2.2 ARIMA derivatives for traffic flow prediction

To better fit the complex traffic system in the real world, many prediction algorithms derived from ARIMA have been introduced. Here, I discuss two most widely used models, i.e., SARIMA and VARIMA.

2.2.2.1 SARIMA

SARIMA is a model evolved from the ARIMA, which adds more attention to the periodicity and seasonality of data source to enable a better prediction result. Apart from the three parameters represented in the ARIMA model, there are another three new parameters, P, D, and Q. These three parameters are added to SARIMA as the factors to revealing the seasonality, indicated as $SARIMA\left(p,d,q\right)\times\left(P,D,Q\right)_s$. To give a better view of its nature, Eq. (2.6) is used for describing and showing the inner relationship of this model,

$$\psi\left(B\right)\phi\left(B^S\right)\left(1-B\right)^d\left(1-B^S\right)^D X_t=\omega\left(B\right)W\left(B^S\right)\eta_t. \tag{2.6}$$

As showing in equation above, the capital letters decouple the seasonal part according to this expression, and each parameters meaning listed as follows: B is the back-shift (lag), the same as the one in ARIMA model; $\psi\left(B\right)$ and $\phi\left(B^S\right)$ are the polynomials from AR and seasonal AR individually. Difference frequency and seasonal difference frequency are represented as d and D. As for the MA processing, $\omega\left(B\right)$ and W are adapted to be related coefficient.

To enhance the accuracy of the 15-min traffic flow prediction, the SARIMA + GARCH method was proposed by Guo et al. [35]. More precisely, by adopting the specific SARIMA(1,0,1)

(0,1,1) plus GARCH(1,1) structure, the short-term vibrations within input traffic flow data is eliminated to a certain extent, which in turn improve the ability of the model facing the traffic volatility. Moreover, this model made a seasonal exponential smoothing operator and two state-space models. And then the introduced Adaptive Kalman recursion solved these two state-space models. Apart from the combination of GARCH, another highlight of this one is the replacement from the Ljung-Box test to Adaptive Kalman filter. Compared with the ARIMA-GARCH structure, this one is more powerful and stable.

Further, for better illustrating the spatial relationships, a hybrid improved SARIMA (ISARIMA) model was proposed by [36]. In this model, A sliding-window function $S_{\triangle}$ was added in a simple SARIMA to update the training set. The proposed ISARIMA is mainly responsible for the prediction task. Different from previous studies, this one is based on the road network, which means it needs to consider the spatial correlations. The high correlated road with aim road was selected by the genetic algorithm (GA) to form a matrix to feed into prediction process. The experimental results showed this model is time-saving and accurate. Another similar work can be found in [37]. Compared with ARIMA, SARIMA is able to deal with more complex flow data and usually achieve higher accuracy.

Generally, SARIMA has better performance than ARIMA, due to its ability to handle seasonality in dataset. While, since SARIMA is still not separated from ARIMA in essence, it still can only deal with the stable and linear data.

2.2.2.2 VARIMA

Arising from the needs of multivariate forecasting, the VARIMA model is proposed. As an advanced model deriving from ARIMA, the nature of VARIMA is also the statistical process, which can be defined as follows,

$$A\left(L\right)X_t = M\left(L\right)\eta_t, \tag{2.7}$$

where X_t and L denote the aim feature at time t and the lag operator, respectively. In particular, polynomial A and M are both metrics.

The traffic flow data has two intrinsic features, i.e., spatial-correlation and temporal-correlation. However, in most of ARIMA- and SARIMA-based models, the spatial-correlation of traffic flow data is ignored due to the dimension of these models is only one. Therefore,

besides considering the temporal correlation, more and more studies begin to focus on the spatial-correlation existing in the transportation system, especially when conducting a traffic flow prediction. For this reason, Space-Time ARIMA (STARIMA) model was proposed based on VARIMA. Data in two dimensions, i.e., time domain and space domain, are included in this model. A weighted matrix is introduced to formulate the spatial-temporal correlation of the traffic flow information, which is the highlight of this algorithm. Eq. (2.8) is the general definition of STARIMA,

$$X_t = \sum_{l=1}^{p} \sum_{k_l=0}^{k_l} \phi_{lk_l} W^{(k_l)} X_{t-l} - \sum_{l=1}^{q} \sum_{k_l=0}^{m_l} \theta_{lk_l} W^{(k_l)} \eta_{t-l} + \eta_t, \tag{2.8}$$

in which, n is the number of roads; X_t is a $n \times 1$ vector at time t; $W^{(k_l)}$ is $n \times n$ matrix with k_lth order. While, ϕ_{lk_l} and θ_{lkl} are the related parameters for spatial-temporal AR (STAR) and spatial-temporal MA (STMA) respectively. Owing to its high adaptability for the transportation system, STARIMA performs well and widely used in traffic flow prediction. Most of the cases that using STARIMA is based on the road network, which is more accord with the real traffic scenario.

In [38], a model named Multi-variate STARMA (MSTARMA) was proposed to improve the prediction efficiency. It defines the traffic flow as y_{jtr}, which includes two parts, i.e., the time-space-dependent mean value μ_{jtr}, and the deviation of the mean x_{jtr}. For the first one, MSTARMA(6,0) was employed to illustrate μ_{jtr}, in which speed variate gave a general idea of which regime the volume belongs to. As ordinary STARIMA, a square matrix S was built to describe the spatial relationships between multiple traffic flows. The advantage of this model is not only predicted the speed but also using the predicted speed to conduct a better traffic flow prediction.

By coupling with a basis function, the authors [39] also proposed an improved spatiotemporal random effects model (STRE), which is on the texture of the urban road network. By using this basis function, they significantly reduced the computational complexity. This study also tested this new model through forecasting traffic flow with intervals of 5 min, 25 min, 75 min, and 300 min in two areas. Compared with conventional ARIMA, STARMA, and Artificial Neural Network (ANN), they demonstrated that STRE is the best one under the proposed experimental circumstance. The superior thing of VARIMA than ARIMA and SARIMA is that it can consider the whole road network, and this feature dramatically enhances the prediction accuracy, especially for urban roads.

Similar work can also be found in [40], Pavlyuk et al. conducted a 5-min traffic flow prediction by using STARIMA and other models such as ARIMA, VARIMA, etc. The derived prediction results also showed the superior of STARIMA. In addition to the short-term traffic flow prediction, this algorithm is also pretty helpful to solve some transportation issues. For instance, a study regarding how to solve the missing counting problem in bicycle traffic system was introduced in [41], in which STARIMA was adopted to address this issue. By utilizing data from nearby road segments, the missing accounting number is estimated. The spatial relationship plays an essential role in this case and dramatically improves the estimation accuracy as well.

2.2.3 Exponential Smoothing

Another simple but useful statistical model that usually applied in short-term traffic flow prediction is the Exponential smoothing (ES). The basic logic behind this method is that the time series is stable and can be smoothed by using the exponential window function [42]. In fact, ES belongs to the MA category. The basic idea of ES is going through items in time series one by one and then calculating the sequential averages of them. Therefore, ES distinguishes itself by a series of weights for past observations. ES is divided into simple exponential smoothing, double exponential smoothing as well as triple exponential smoothing under the differencing times. The predicted value is the weighted sum of previous observations, and generally, new data is given a larger weight, and the old data is given a smaller weight. In nature, simple ES (SES) is a kind of weighted moving average, which adds decrease weights into past data, so it can also be summarised in a more simple fashion shown below.

$$\hat{Y}_{t+1} = \alpha Y_t + (1 - \alpha)\, \hat{Y}_t, \tag{2.9}$$

where $\hat{Y}_t$ and Y_t represents the predicted value and the actual value at time t, respectively. The smoothing factor is denoted by α. SES has a smoothing effect on the historical time-series sequence. The smaller the weighting coefficient (α), the more significant the smoothing effect.

As mentioned above, SES has a smoothing effect on the time series, and smoothing effect increases with weighting coefficient (or smoothing coefficient) becoming smaller. However, the volatility of the actual data is small in practical [43, 44], the double exponential smoothing (DES) is proposed. Unlike the methods in AR/MA family discussed previously, due to the simple structure, the model belonging to the ES family lacks the ability for facing

the traffic flow violations. Alternatively, the ES family is comparatively fundamental and easy understanding, so it is a unique algorithm to help do traffic flow prediction. Another advantage of ES is the great adaptability, which means that predictive models can adjust automatically with changes in traffic flow data patterns. In practice, only one parameter α needs to be selected for prediction, and that is simple and easy to implement. Combining with other methods to improve the prediction reliability is a new trend for this family.

In [45], simple ES was combined with a neural network (NN) structure, and also a Taguchi Method was adopted in this innovative model. In detail, simple ES was used to filter the noises in the raw dataset at first, and then these preprocessed data were imported into the Taguchi system and after that a extreme learning was used on them to do a prediction. The mechanism of Taguchi system is to use an orthogonal array to realize the effects of variates, which can greatly reduces the computation cost compared with the traditional trial-and-error method.

Briefly, based on the traffic flow information in a given road network, the proposed method can prune the input network according to the effect of the traffic flow of each road segment within the road network on the change of traffic volume of the target section, and only retain the valid road segments (i.e., high-impact roads). Relying on the simplified road network, the system further determines the hyper-parameter for the NN. Through this procedure, unnecessary traffic data are removed, which further facilitates pattern mining and to make a more accurate short-term traffic flow prediction.

For avoiding the overfitting problem, the approach presented in [46] enrolled a simple ES. Precisely, the simple ES was used to eliminate the lumpy characteristics of raw data, which relies on the irregular variation on raw dataset. Also, smoothing constant α controlled the filtering speed, for which the larger the α is, the faster the change of filtered traffic flow data $\theta'(l)$ is. To further improve the prediction accuracy, through minimizing the mean absolute relative error e_{MARE}, Levenberg-Marquardt algorithm replaced Back-Propagation (BP) method to train NN, which had better performance. They compared their approach with other parallel models such as Bayesian NN, Exponential LSTM, etc. The derived results showed this EXP-LM model had best performance among them. Similar work, in which ES is used to be preprocess tool,can be also found in [47].

However, the lack of identification ability for the turning point of data and lower accuracy for long-term traffic flow prediction is the primary shortages of the ES-based method. Therefore, this sort of method more is more suitably used in the single road of suburban areas.

Table 2.2: Comparision of some existing statistial prediction models

Category	Model	Prediction period	Road structure	Prediction area	Combination or Single Use	Highlight
ARIMA	ARIMA-GARCH [33] (2011)	3, 5, 10, 15-min	Single road	Suburban highway	Combination	Generalized autoregressive conditional heteroscedasticity (GARCH) analysis
	WARIMA [30] (2010)	5-min	Single road	Suburban (railway)	Combination	Wavelet analysis for non-linear noises
	ARIMA [32] (2009)	5, 10-min	Single road	Urban	Single	Multi-period data training
SARIMA	ISARIMA [36] (2018)	15-min	Road network	Suburban highway	Combination	Consideration of spatio-temporal relationship & Genetic algorithm (GA) optimization
	SARIMA [37] (2016)	15-min	Single road	Suburban highway	Sinlge	Comparision with most of curent popular models
	SARIMA+ GARCH [35] (2014)	15-min	Single road	Suburban & Urban highway	Combination	Adaptive Kalman filter and GARCH
VARIMA	VARIMA [40] (2017)	5-min	Single road	Urban	Single	Consideration of spatio-temporal relationship in urban area
	STRE [39] (2016)	5-min	Road network	Urban	Combination	Reduced computational complexity by a basis function
	MSTARMA [38] (2011)	5-min∼1h (5-min interval)	Road network	Urban highway	Combination	Real-time prediction
ES	E-ELM [45] (2019)	1h∼3h (15-min interval)	Road network	Suburban highway	Combination	Introduction of Taguchi method
	EXP-LM [46] (2012)	1-min	Single road	Suburban highway	Combination	Combination with NN
	EXP-NN [47] (2011)	1-min	Single road	Suburban highway	Combination	ES as a data pre-process tool, combined with NN

Here, I summarize the characteristics of some recent researches designed based on the aforementioned statistical models in Tab. 2.2.

To sum up, statistic-based models generally have good model interpretability, which means they can be described more clearly and explicitly by some delicate formulas. However, rigid and straightforward model structure leads to bad model adaptability, which is a big challenge for design a practical traffic flow prediction method, especially under complex traffic conditions. Also, how to properly capture the spatiotemporal correlations in road networks is another challenge for this sort of models, which is widely ignored by previous studies.

2.3 Machine learning-based prediction approaches

As mentioned previously, ML-based models, that have a deep connection with various fields, such as pattern recognition, statistical learning, data mining, computer vision, speech recognition, and natural language processing, etc., have caught considerable attention in recent years. Multi-disciplined nature makes these methods have better adaptability for different contexts. Accordingly, how to design a practical ML-based approach for supporting the Intelligent Transportation System (ITS) [48] [49] has become a hot research topic [50]. Recent years, as a supportive component of ITS, ML-based models are widely adopted as the popular short-term traffic flow prediction methods due to their high accuracy and strong non-linear capture ability for big data [51]. In general, machine learning goes to three types, supervised learning, unsupervised learning, and reinforced learning. In fact, supervised learning is more widely used than another two categories in short-term traffic flow prediction owing to the learning mechanism. Accordingly, in this section, I will focus on prediction models designed relying on supervised learning, and introduce the related algorithms in detail based on the core principles of these prediction methods, i.e., classification-based method, regression models, and recurrent neural network. While, for the unsupervised learning as well as reinforced learning, I will give some simple introduction only. Moreover, a general taxonomy of the ML-based prediction method is shown in Fig. 2.3.

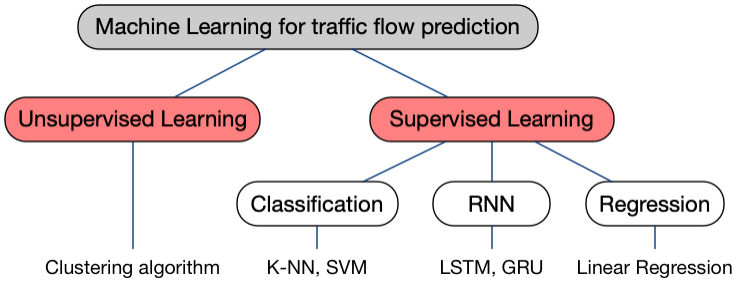


Figure 2.3: Machine learning for traffic flow prediction

2.3.1 Supervised learning-based approaches

Supervised learning separates the dataset into two sets, one for training and one for validation. Classification and regression are two typical categories in this learning fashion. For the classification category, the K-nearest neighbors algorithm (KNN) [52] and decision tree classification [53] are the most commonly seen algorithms. It is worth to pint out that when applying recurrent neural network (RNN) to the field of traffic forecasting, I usually classify it as supervised learning, in which, long-short term memory (LSTM) and the gated recurrent unit (GRU) are two most widely adopted models. Therefore, this part will begin from the K-NN algorithm, and then linear regression as well as Support vector machine (SVM), and RNN is illustrated at the end. Here, in Tab. 2.3, I summarize some features of these supervised ML-based prediction models.

Table 2.3: Features of supervised ML-based models

Model	Interpretability	Ability for non-linear dataset	Ability for non-normalized dataset	Memory requirement	Effect for Long-term dataset	Effect for Short-term dataset
K-NN	Simple	Y	Y	Large	Medium	Good
Linear regression	Simple	N	Y	Large	Medium	Good
SVM	Medium	Y	N	Large	Bad	Good
LSTM	Complex	Y	Y	Large	Good	Good
GRU	Medium	Y	Y	Large	Good	Good

2.3.1.1 K-NN algorithm

K-NN algorithm is one of the most straightforward classifications, which is a simple but high efficient model that can be easily applied in short-term traffic flow prediction. In short, the essence of K-NN is that, based on the classification result derived by learning

the training dataset, the K-NN model classifies the newly sampled data and put them into fitted categories. It is also a non-parametric, lazy learning algorithm which mainly contains five steps. First, it determines the value of K (i.e., the number of nearest neighbours), and then calculates the distance between the query-instance and all training samples. After that, these distances are sorted to determine the nearest neighbours. By gathering the category Y of nearest neighbours, the aim feature is finally assigned to the group which owes the closest distance with the aim.

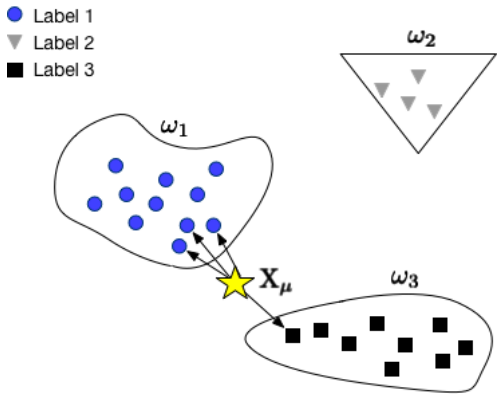


Figure 2.4: K-NN algorithm

For instance, Fig. 2.4 shows the K-NN algorithm for $k = 4$, where there are three groups, labeled as ω_1, ω_2 and ω_3 respectively. It can be found that there are three out of four points belong to the blue group, only one belongs to the black group, so it can conclude that the unknown point X_μ belongs to the blue group. The aim feature X_μ is classified into group ω_1 based on the corresponding Euclidean distance d between itself and a labeled feature $X_h = \{x_{h,t-1}, x_{h,t-2}, \cdots, x_{h,t-n}\}$, which is given by,

$$d = \sqrt{(x_{t-1} - x_{h,t-1})^2 + \cdots + (x_{t-n} - x_{h,t-n})^2}. \tag{2.10}$$

K-NN is adopted by many researchers in short-term traffic flow prediction field since it can be easily adapted into the real traffic situation, especially when the flow data is noisy and large.

In [57], it adopted a dataset recorded in 5-min interval to make a short-term traffic flow prediction. Different from the previous data preprocessing, it made a data selection standard to first roughly clean the input dataset by removing the unnecessary data. For example, it only kept the volume between 0 and $m_c \times CAP \times T/60$. After the preprocessing, the standardized data were imported into K-NN system to do prediction, and this process

Table 2.4: Comparison of recent works in K-NN

Model	Distance metric	Number of k	Method for data pre-processing	Method for spatial correlation	Improvement
[54] (2016)	Euclidean distance	$k = 4$	N	Divide road networks into upstream, downstream to construct KNN	Multi-step prediction
[55] (2015)	Normalized Euclidean distances	$k = 5, 10$	N	N	Sequential-search strategy
[56] (2014)	Euclidean distance	$k = 10$	Single-factor analysis of variance (ANOVA)	N	Improved model ability for special event context

was based on the distance q_i between the actual data and k nearest neighbors. In this work, $k \in [5, 30]$. To further improve the prediction accuracy, K-NN was weighted by parameter a_i, which is the highlight of this method. After calculating the MAD and MAPE, the derived results showed that this weighted K-NN had better performance than non-weighted K-NN, with the accuracy higher up to over 90%.

In [56], a basic K-NN was used to do the 1-hour traffic flow prediction under some typical circumstances. For reducing the bad influence originated from the special events on prediction results, the authors used a NN to do a prediction analysis, in which Twitter and traffic features were both fed into the prediction system, and extracted by four components. Then the optimal features were determined to further build a model. In this work, the adopted dataset is large, which is aggregated from the different social media platforms. If using statistical methods such as ARIMA, SARIMA, it will be a great challenge and need to consume large memory requirement. Conversely, for K-NN, it can fast category these data and accurately capture their patterns.

Another example that put K-NN into data preprocess can be found in [58], in which traffic flow prediction is to do pattern recognition. Precisely, through digging and identifying different traffic flow patterns of the raw dataset, the authors optimized the original K-NN algorithm. They conducted a series experiments with prediction horizon varying from 30-min to one-hour to evaluate their new enhanced K-NN model, and demonstrated its great ability for traffic prediction.

To conclusion, K-NN is a suitable method for short-term traffic flow prediction, which has a good model interpretability and lower computation cost. When using this mehtod

to do a short-term traffic flow prediction, raw historical traffic flow with time can be used directly. From the Tab. 2.3, I can find that K-NN has the ability to handle both the non-linear and non-normalized datasets, which means it can be directly used without any data pre-processing stages. This feature is important since for most of the traffic system the flow patterns usually non-linear and statistical-based models cannot handle them directly. On the other hand, there are still some shortages of the conventional K-NN-based approach. The computation for the distance that determines the final lable needs to comsume large memory space, especially when the historical dataset is large, and may hence have higher requirement for the memory space. For example, when calculating the distance, K-NN cannot figure out which method is the best under the existing circumstance, i.e., whether to use all attributes or only specific attributes to do the classification. This shortcoming reduces the prediction accuracy to some extent. Therefore, to overcome this shortage, many optimized K-NN approaches are designed. For example, there is a sequential research of K-NN popping out, which is worth to give some briefly introduce. In [55], the proposed work used a method of disaggregating the cluster to reduce the computational complexity, thereby improving the accuracy and efficiency of the prediction. In the past traffic flow prediction, there are usually two feature vectors, one to reflect the speed and the other to indicate the acceleration. These two feature vectors are considered together when clustering. However, in the normalization process, it brings a difficulty to predictor due to their different units. In this model, the authors separated the two feature vectors for clustering, which dramatically simplifies the problem of cumbersome normalization. By splitting the complex non-uniform variables into two sets of sequences, the K-NN processing is performed separately. Accordingly, in the normalization process, the inconvenient unit unification can be avoided. Consequently, the computational complexity of the proposed work is reduced. Meanwhile, the prediction accuracy is also improved to some extent.

2.3.1.2 Linear regression algorithm

Linear regression algorithm is a type of regression method, which belongs to the supervised learning. In essence, the purpose of regression is to predict continuous value. There are several standard algorithms included in the regression algorithm, i.e., simple linear regression, polynomial regression, decision tree regression, etc. As the simplest one, simple linear regression is more commonly used in short-term traffic flow prediction. There are two compelling reasons why linear regression is more accessible in short-term traffic flow prediction field: the first one is its simplicity, and the second one is that it can reduce the

risk of over-fitting by regularization.

The main objective of Linear Regression is to find the most fitted line to describe the characteristics of the input dataset. Typically, linear regression process is done by using the well-known least squares method.

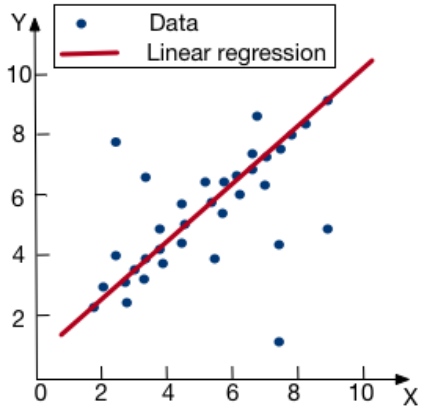


Figure 2.5: Simple linear regression algorithm

As shown in Fig. 2.5, the points are the training data, and the line is the predicted line fitting training data. The following formula can represent this fitted line,

$$Y = aX + b \tag{2.11}$$

Accordingly, training and building a linear regression model can be considered a process of seeking appropriate coefficients a, b, finally to find the best fit line Y. Apparently, if variables in the dataset have a linear relationship, they fit well. Moreover, the regression algorithm expects to use a hyperplane to fit the non-linear data.

In [59], a local linear regression model was proposed. Different from non-parametric models used before, this one has a higher minimum efficiency, and greater ability to deal with the distributed dataset. In this study, traffic flow data was described as a multivariate covariate X_i, and by using a cross-validation approach to determine the the dimension d of the covariate vector and the bandwidth h, the useful data were selected to build a regression model $\hat{m}_{h,i}$, and finally the predicted value $\hat{y}$ was obtained. Moreover, both single-step and multi-step predictions are adopted in this research.

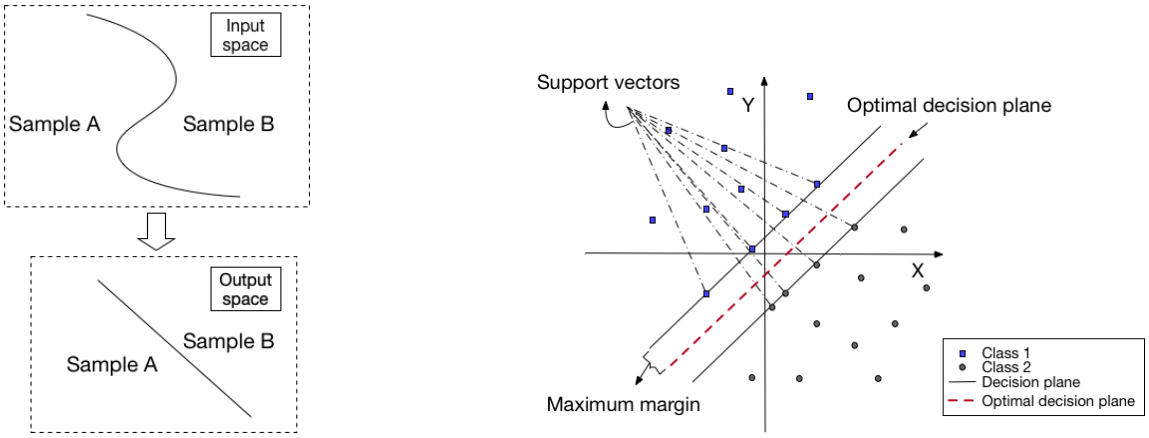
To sum up, linear regression algorithm has two distinct disadvantages. First, it has poor performance when variables are non-linear. In fact, real traffic flows are high oscillatory, expecially in suburban areas, which means that most of the flow sources are the non-

linear, and linear regression alogorithm is not able to used directly on raw dataset. The computation cost will increase due to the employment of extra stationary process. Besides, it is not flexible enough to capture more complex patterns due to its machanism. The single fitted straight line can only cover fundamental features but usually ignores some critical details that are not on the line, so the more complex traffic conditions, the more details are lost, leading worse results accordingly. But the fact is that with the development of ITS, the flow patterns are becoming more and more complicated, but the standard input data for this method is non-linear and simple, so it is difficult for this algorithm to fit into modern traffic systems. However, instead of using as a core model, linear regression methods are often used in conjunction with other algorithms to support a short-term traffic flow prediction, which is also its new trend in future works. Generally, there are pretty limited simple case studies learned in early researchers, even though linear regression have some unique advatages, such as its high efficiency for simple structural road.

2.3.1.3 Support vector machine (SVM)

Another classic ML model widely used for traffic flow prediction is the support vector machine (SVM), which also can be extended to the nonlinear classification problem by using a technique called kernel function. Briefly, this function essentially calculates the distance between two observation data, hence called support vectors [60]. SVM aims to find the decision boundary, which can maximize the border using the sample interval. Therefore, SVM is also known as a large space classifier, an enhancement of the logistic regression algorithm. The most significant advantage of SVM is the use of nonlinear kernel function, which is introduced to figure out the model nonlinear decision boundary. In a simple context, the nonlinear problem can be effectively transformed into a linear problem, as shown in Fig. 2.6(a). In this picture, the straight line separating sample A and sample B is a normal SVM that makes two divided samples A and B become linearly separable. From the Fig. 2.6(b), three steps are included in SVM: the first step is to find an optimal decision plane for two linearly separable classes, and then make the minimum distances between each class and optimal decision plane are maximized to minimize the decision error. In the last step, only the data points that lie in the boundary of the optimal decision plane are chosen as support vectors.

As an outstanding short-term traffic flow prediction method, SVM can model nonlinear decision boundaries and has many alternative forms of kernel functions, which is superior to



(a) Mechnism of SVM

(b) Details of SVM

Figure 2.6: An illustration of SVM

simple linear regression. However, it also faces considerable over-fitting robustness, which is especially prominent in high-dimensional space. Moreover, since it is vital to choose the correct kernel, SVM is challenging to tune and cannot be extended to more massive datasets, and as a result, it is a memory-intensive algorithm. This feature makes SVM more suitable for short-term traffic flow prediction rather than the long-term. Besides, SVM is a unique algorithm that not only can maintain computational efficiency but also get outstanding classification results. Considering all the characteristics of SVM, it is suitable for short-term traffic flow prediction.

In [61], the authors proposed an improved SVM-based method, namely ISVR, to improve the model capability with the increase of traffic structural complexity, which is based on the least square support vector machine. The ISVR was completed when matrix A_l^{-1} can be obtained from the A_{l+k}^{-1} without any repeatly calculation, in which the matrix A_l and A_{l+k} were both the kernel correlation matrix of learning set S. Different from previous cases, this study aimes for a road network, in which input data were in matrices fashion fed into ISVR model. Besides, this hybrid model combines with the incremental learning strategy to dynamically update the forecasts to achieve a higher pattern mining ability for this road structure. Compared with BPNN regarding six error indicators, such as MAPE, RMSER, this model showed its stronger prediction ability.

Another innovative hybrid model can found in [62], in which, according to the incorporation of ARIMA and SVM, the noise of raw dataset is eliminated and further fast the prediction speed with higher accuracy. More precisely, the time series was treated as a signal sequence S_t, containing the white noises. After Wavelet analysis, this time series

was regarded as a nonlinear sequence y_t that contains two part, linear autocorrelation L_t as well as nonlinear autocorrelation N_t. ARIMA was firstly used to predict y_t , and the SVM was used to predict the error ϵ_t, and final prediction result was the combination of these two forecasting values. The benefit of using wavelet analysis and hybrid model shows in the reduced E_{MAPE} and increased r^2. The minimal sequential optimization was also introduced by [63], which was combined with the SVM algorithm to improve the prediction accuracy for short-term traffic flow. In this study, SVM was employed to make a 10-min traffic flow prediction under the urban intersection circumstance, and their experiment results proved the SVM is a reliable approach in short-term traffic flow prediction field.

In Tab. 2.5, I summarize the features of the SVM-based traffic flow prediction methods discussed above. To conclusion, for the SVM model, it has great effect on the predictions for short-term traffic flow, and compared with Linear regression, it is more suitable in volatile traffic environmnets. Although it performes well in short-term traffic flow predictions, there are two distinct shortcomings of this algorithm, and the first one is intensive memory. To be more precise, the training fashion for SVM is memory-intensive, and prediction nature is the linear combination of all support vectors. Therefore, if the number of support vectors are large, a big store space is recquired, and this is a big challenge for some low-memory devices. Another challenge for SVM is the kernel selection, as the function of kernel is to take data as input and transform it into the required form, and therefore, different kernel leads to different SVM effect. Among most of the kernels, the RBF kernel and Gaussian kernel are the most popular two, because they can be used when there is no prior knowledge about the data, and have higher prediction accuracy than others proved by many previous studies, which is more fit in the supervised learning process in traffic flow predictions. Conversely, inappropriate kernels will reduce the prediction accuracy and load more computation cost as well. In addition the multi-kernel SVM is also brought forward to overcome the strong stochastic and non-linear characteristics in city ITS.

2.3.1.4 Recurrent neural network (RNN)

Most used machine learning models nowadays can be supervised or unsupervised fashion, which depends on the specific requirements. However, in traffic flow prediction, most of the researches related to RNN are supervised [68], so it is included in this part. In the traditional neural network model, from the input layer to the hidden layer and then to the output layer, the layers are fully connected, and the nodes between each layer

Table 2.5: Comparison of recent works in SVM

Model	Kernel function	Method for selecting control parameters	Method for obtaining spatial-temporal correlations	Improvement
[64] (2018)	RBF + polynomial kernel function	Chaotic Cloud Particle Swarm Optimization	Analysing the periodicy and change tendency of nearby points in the same Point of Interest (POI) to capture spatial correlations, and these data are gathered through roadside units (RSU).	Decomposing the road network into several POIs, to obtain the spatial-temporal correlations and also by introducing the real-time information to further enhance the model adaptability, especially in rush hour.
[65] (2018)	RBF kernel	Predeterminate parameters: $C = 100$, $\gamma = 0.01$, $\epsilon = 0.1$	N	Combined with ARIMA model, SVM is used for residuals prediction, and ARIMA is for the linear part prediction.
[62] (2009)	Mercer kernel function	Determined by Libsvm package [66]	N	Employing Wavelet Denoising firstly to reduce the noise in raw dataset for prediction accuracy improvement.
[61] (2007)	Gauss kernel	Implemented based on LS-SVM algorithm [67]	N	Using the real-time data to update the prediction function, which is more fit in volatile traffic conditions.
[63] (2005)	Gauss kernel	Based on Sequential Minimal Optimization (SMO), Predeterminate parameters: $C = 5$, $\sigma^2 = 0.5$, $\epsilon = 0.05$	N	By introducing SMO, the prediction accuracy and speed are increased.

are disconnected. Due to this connection feature, the global neural network is weak for many problems, especially time-series problems. However, the traffic flow patterns change with time, so traditional neural network with the global connection structure such as a convolutional neural network (CNN), is unsuitable for short-term traffic flow prediction problem. For better solving the time-series-based problems, RNN was proposed. The core principle of RNN is using classifiers repeatedly, and precisely, only one classifier is used to summarize the state, and other classifiers receive training for the corresponding time and then pass the state, which avoids the need for a large number of historical classifiers, and is more effective for time-series problems.

RNN is an appropriate approach for handling traffic flow data, as its purpose is to process sequential data. What is more, RNN is called a recurrent neural network because the current output of a sequence is related to the previous output, which is shown in Fig. 2.7. This network can memorize information stored in previous nodes, and then applied to the current output process. In other words, hidden layers are connected, unlike the traditional neural network, which is no correlations between any hidden layers. Considering the above factors, RNN is more suitable than CNN in short-term traffic flow prediction process.

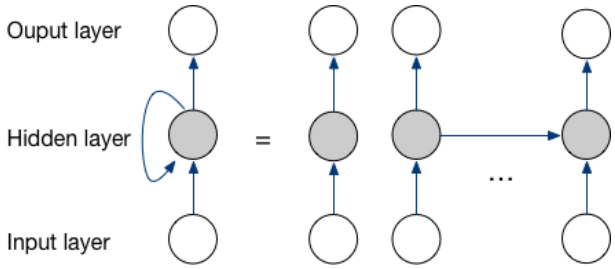


Figure 2.7: RNN structure

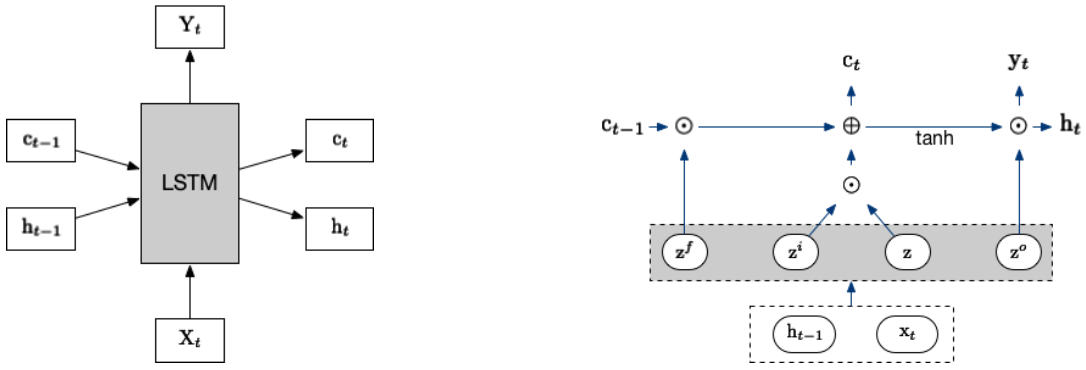
In RNN family, there are two well-known models, Long short-term memory, and Gate recurrent unit. These two are the most popular learning units used in short-term traffic flow prediction nowadays.

Long short-term memory (LSTM): In essence, LSTM is a special RNN unit with the ability to overcome the gradient disappearance and gradient explosion problems in long sequence training [74]. Simply put, LSTM can perform better in longer sequences than normal RNN. Compared to naive RNN, which has only one transfer state h_t, LSTM has two transfer states, i.e., the cell state c_t and the hidden state h_t. A general structure of LSTM is illustrated by Fig. 2.8.

There are three inputs into current LSTM unit, current input X_t, last cell state c_{t-1},

Table 2.6: Comparison of recent works in RNN

	Model	Method for obtaining spatiotemporal correlations	Features
LSTM	[69] (2018)	Using a traffic graph convolution operator to capture the spatiotemporal correlations.	Two different Norms (L1-Norms and L2-Norms) are added in loss function as two regularization terms to upgrade the training weight stability.
	[70] (2017)	Using Convolutional Neural Network (CNN) and LSTM together to capture spatiotemporal relations, and this module is named Conv-LSTM.	Conv-LSTM is for spatio relations capture and Bi-LSTM is used for the traffic flow prediction.
	[71] (2017)	Describing the spatiotemporal relations among road networks by the origin destination correlation (ODC) matrix.	Combined with ODC matrix in a 2-D cascade connecting LSTM network.
GRU	[72] (2018)	CNN is used to mine road spatio correlations.	The employment of attention model in stacked GRU, which works based on a attention weight matrix, to select high-impact roads and further help spatiotemporal mining.
	[73] (2018)		Constructing a multi-level residual architecture, which adds some residual learning layers in stacked GRU.



(a) Genertal structure of LSTM (b) Working mechanism of LSTM

Figure 2.8: An illustration of LSTM

and last hidden state h_{t-1}. The first step of LSTM is to use the LSTM's current input X_t and the h^{t-1} stitching passed from the previous state to get four states z, z^i, z^o and z^f. While, z^f, z^i, z^o are multiplied by the splicing vector and then converted to a value between 0 and 1 by a sigmoid activation function as a gating state. Moreover, z is the result of converting the result to a value between -1 and 1 through a tanh activation function. Having these states, the mechanism of LSTM can be introduced in detail.

There are mainly three states in LSTM, the forget stage, selected memory stage as well as output stage. The forget stage, which is mainly to forget the input from the previous node selectively. Simply put, it only keeps the necessary information and deletes secondary information/the redundancy. The corresponding functionality is achieved by,

$$z^f = \sigma\left(x_t U^f + h_{t-1} W^f\right), \tag{2.12}$$

in which, x_t is the current input; h_{t-1} is the last node's hidden state; U^f works as a bridge for the connection of inputs and current hidden layer. By the link generated by W^f, the last hidden layer and the current hidden layer is connected. The main aim of selective memory stage is to electively memorize the inputs. It records more significant information and keeps less about not very important parts. The corresponding process can be formulated by Eq. (2.13) and Eq. (2.14), respectively.

$$z = tanh\left(x_t U^c + h_{t-1} W^c\right), \tag{2.13}$$

$$z^i = \sigma\left(x_t U^i + h_{t-1} W^i\right). \tag{2.14}$$

Particularly, superscript c represents the current cell state, and z^i is regarded as selected gating signal. As for the output stage, this phase will determine which outputs will be treated as current states and mainly controlled by z^o, which is given by,

$$z^o = \sigma\left(x_t U^o + h_{t-1} W^o\right). \tag{2.15}$$

Controlling the state of transmission through gated state, remembering that it takes a long time to remember, forgetting unimportant information; unlike ordinary RNNs, there is only one way to superimpose memory. It is especially useful for many tasks that require long-term memory.

Accordingly, in recent years, many LSTM-based prediction models have been proposed for addressing traffic flow predicting. For example, a 15-min interval traffic flow prediction

was conducted by [75]. In this study, they proved the superiority of simple LSTM, through comparing it with other similar methods such as SAE, SVM, and FFNN, etc. Currently, there two new trends for LSTM in short-term traffic flow prediction. The first one is the combination model structure, and the other is the concern about Spatial-temporal relationship.

In [69], a physical network topology, TCG-LSTM model was built to capture the spatial correlations within the traffic flow information. By introducing a localized spectral graph convolution, which works according to a $N \times N$ adjacency matrix A. A link counting function $d(v_i, v_j)$ further defined the spatial correlations by using the adjacency matrix. Creative thing of this model is that the input is the graph convolution features, which is a vector. This structure greatly interpreted the spatial relationship by convolution weights. Based on LSTM, this model showed a great performance on both suburban and urban road networks.

Similarly, for better decribing the road spatial correlations, the authors in [70] introduced a hybrid model, in which the traffic flow data was represented by a one-dimension vector. Conv-LSTM and Bi-LSTM were both used to learning the traffic patterns. For the Conv-LSTM, it aimed for the spatial relationship features. While, Bi-LSTM was for the periodicity feature mining. Combining these two types of LSTM together, a 30-second traffic flow prediction was conducted for both suburban and urban roads. The derived MSE value significantly decreased compared with the many other approaches, such as pure LSTM, ARIMA, SAE, etc. Particularly, it also replaced the Conv-LSTM with CNN-LSTM, but the performance was not become better, which further showed that the combination of Conv and LSTM was the optimal in this context.

Moreover, based on the conventional LSTM, a deep learning LSTM was proposed by [71], in which two-dimensional LSTM was built for digging the spatial-temporal relationships of the traffic flow. They validated their model by comparing it with other commonly seen models. For further digging out the spatial correlation, two variables, traffic speed and occupancy were both adopted by [76], and the authors also adopted K-NN to help improve the prediction accuracy.

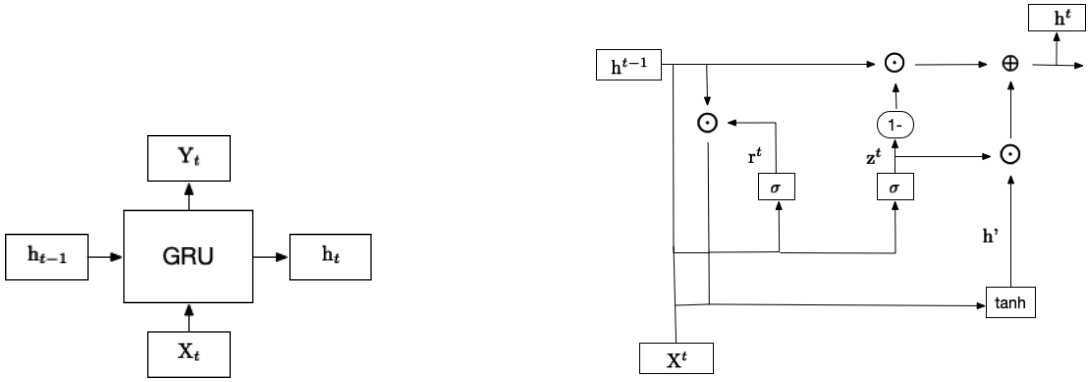
Gate Recurrent Unit (GRU): Similar to LSTM, GRU is also considered a upgraded RNN-based method that is proposed for dealing with the gradient-missing problem in the training for long-term sequences. Compared to LSTM, the use of GRU can achieve comparable results, and it is easier to train in comparison, which can greatly improve training efficiency, so short-term traffic flow predictions are more inclined to use GRU in

recent years. Different from the multi-gate framework in LSTM, GRU has less control gates, which can be seen in Fig. 2.9, and that is why it has a lower computational cost than LSTM in general. Only two control gates in GRU, the reset gate r and update gate z (see Fig. 2.9(b)). These two gates can be calculated by Eq. (2.16) and Eq. (2.17),

$$r_t = \sigma\left(x_t U^z + h_{t-1} W^z\right), \tag{2.16}$$

$$z_t = \sigma\left(x_t U^r + h_{t-1} W^r\right), \tag{2.17}$$

where σ denotes the sigmoid function. x_t is the current input, and h_{t-1} is the state passing from the last node. Similar to the LSTM, here, the W, U are also the weight matrices acting as the critical link between the last hidden layer and current hidden layer, and the connection of inputs and current hidden layer, respectively.



(a) Genertal structure of GRU

(b) Working mechanism of GRU

Figure 2.9: An illustration of GRU

After getting the gating signal, GRU firstly use the reset gate to get the reseted data. And this process is described in following equation.

$$h_{t-1}' = h_{t-1} \odot r, \tag{2.18}$$

where $\odot$ is the Hadamard Product, and that is to say, the corresponding elements in the operation matrix are multiplied, so the two multiplication matrices are required to be homo-typed. And then, the memory task is achieved by combining these processed data and current input x_t, which is,

$$h' = tanh\left(x_t U^h + \left(r_t \odot h_{t-1}\right) W^h\right). \tag{2.19}$$

Notably, in this formula, the effect of function $tanh$ is to range the data between -1 and 1. Similar to the selected memory phase in LSTM, h' mainly contains the data of current input x_t.

The last but not least stage is the update memory phase. At this stage, it has two functions, i.e., forgetting and remembering, implemented at the same time. It uses the previously acquired update gate z_t to figure out h_t, which is given by,

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot h'. \tag{2.20}$$

Particularly, the gate signal z_t ranges from 0 to 1. The closer the gating signal is to 1, the more data is remembered; the closer to 0, the more data is forgotten. The smartest thing of GRU is that it greatly reduces the number of control gates, using the same gate z to finish the memory and forgetting purposes, which is described in Fig. 2.9(b).

Compared with LSTM, the GRU has fewer gates inside, and accordingly, the parameters are less than LSTM, and even better thing is that it can also achieve the same function as LSTM. By considering the computing power and time cost of the hardware, GRU is a better option than LSTM for implementing short-term traffic flow prediction. Accordingly, there are many studies based on GRU in recent years.

In [77], authors conducted a 5-min traffic flow prediction by using the naive GRU, LSTM as well as ARIMA. In this paper, the traffic flow is predicted in 5-min interval relying on the traffic flow information recorded within the last 30-min. The derived prediction results showed that the deep-learning approach such as LSTM and GRU are better than the general statistical methods like ARIMA. Moreover, GRU even a little better than LSTM with reduced 5% MAE value.

For further enhancing the adaptability of prediction models, the combination GRU with other methods are commonly seen in recent years. For example, a hybrid GRU-based method was proposed by [72], in which three convolution layers were applied to extract spatial correlations and a stacked structure with two layers of GRU was adopted to dig out the temporal patterns. Compared with conventional GRU or CNN models, this proposed model owns a higher ability to handle the spatial-temporal relationships existing in the transportation system, and this sort of link has a significant influence in the forecasting process.

Similar work can be also found in [**?**], where an innovative model named STGCN came up with. Different from the previous one, the authors creatively put the spatial correlations

Table 2.7: Comparison of recent works in Machine Learning category

Category	Model	Prediction period	Road structure	Prediction area	Combination or Single Use	Highlight
K-NN	[54] (2016)	5-min	Road network	Urban	Single	Consideration of Spatial-temporal relationship in urban area
	[55] (2015)	5-min	Single road	Suburban highway	Single	Separation of two feature vectors for clustering
	[56] (2014)	1-h	Single road	Urban	Single	Social media dataset
Linear regression	[59] (2003)	5-min	Single road	Suburban freeway	Single	As one type of local weighted regression models, it can used in non-linear time-series prediction under certain mixing conditions
SVM	ISVR [64] (2018)	5-min	Road network	Suburban	Single	multi-kernel use to handle the temporal-spatial correlations
	[65] (2018)	5-min	Single road	Urban road	Combination	Combined with ARIMA to improve model adaptability
LSTM	ARIMA+ SVM [62] (2009)	1h	Single road	Suburban highway	Combination	Wavelet transform is employed to eliminate the noise of original traffic data as well as the combination with ARIMA
	TGC-LSTM [69] (2018)	5-min	Road network	Suburban & Urban	Combination	Spatial-temporal relationships are considered; Consideration of both urban and suburban areas
	[71] (2017)	5-min	Road network	Urban	Single	Consideration of spatial-temporal correlations in urban area
	[76] (2017)	5-min	Single road	Suburban (highway)	Single	Take advantage of traffic speed/occupancy as well as spatial relationships to help prediction
	Conv+Bi-LSTM [70] (2017)	5-min	Single road	Suburban and Urban	Combination	Conv-LSTM for spatial-temporal relationships,Bi-LSTM for prediction
GRU	DNN-BTF [72] (2018)	5-min	Single road	Suburban highway	Combination	GRU is used to mine temporal correlations
	HMDLF [78] (2018)	15-min	Single road	Suburban highway	Combination	Innovative CNN-GRU-Attention modules for spatial-temporal correlation features learning

on a graph, according to that, building the model. In their structure, GRU was adopted for extracting temporal features, and Graph CNN was for the spatial patterns mining. Other hybrid frameworks designed based on GRU can be found in [79, 80, 69, 78].

To sum up, RNNs that contain LSTM and GRU as basic units generally outperform many other traditional models such as ARIMA, K-NN, CNN etc., owing to their recurrent mechanism, which gives the neural network stronger memory ability for time sequences. When I predict the traffic volume, the input is a historical volumes vector covers a specific time period. If using previous ML-based algorithms, for example, CNN, some critical information may get lost with the learning process, which lowers down the final accuracy. Moreover, LSTM and GRU can further deal with the greadiant vanishing problem in RNN, and particularly, with less control gates and nearly same prediction ability, GRU is given more attention in recent years. As for the disadvantages of LSTM and GRU, the bad model interpretability is the main concern, and apart from that, some deep learning structure may over mining the details so that reduce the prediction accuracy while computation cost significantly soars up.

In conclusion, the supervised learning approaches (e.g., K-NN, SVM, Linear regression, etc.) are adopted by many researchers in last several years. They have significant contributions to the traffic flow prediction field. Due to road networking and highly non-linear nature of traffic flow, conventional statistics-based algorithms are not able to extract these complicated flow features. As for the machine learning approach, such as CNN, KNN, etc., is weak when it encounters the time-series problems. So, designing the RNN-based method, e.g., LSTM and GRU, etc., is a new trend to make short-term traffic flow prediction nowadays by exploiting its great memory for sequential data over time. In addition, combining multiple algorithms into one hybrid model is also a trend in traffic prediction. Generally, the commonly seen building fashion in most of the hybrid models is combing two sub-modules, i.e., one for capture the temporal correlation within the traffic information, and the other one is for the spatial part. For better illustration, the comparison of some existing supervised learning series methods are summarized in Tab. 2.7.

2.3.2 Unsupervised learning-based methods

Another machine learning category is unsupervised learning, which has no corresponding output for input. Having many commons with K-NN algorithm, the clustering algorithm is one of widespread unsupervised learning in traffic flow prediction field.

Based on the derived distances between samples (similar to Eq. (2.10)), the clustering algorithm is able to make those samples into the most proper groups. Different from the training data containing labels, the trained model can predict the label of other unknown data, the unsupervised algorithm represented by the clustering algorithm is not labeled, and the purpose of the algorithm through training infers the label of these data. Also, different from classification, classification is to classify a thing into a specified category. Ideally, a classifier will learn from the training set to have the ability to classify unknown data.

Many researchers have used the clustering algorithm in short-term traffic flow predictions for a long time. For instance, the authors in [81] designed a model to support the Intelligent vehicle-highway systems, where the dynamic clustering algorithm was introduced. They tested their model under the 15-min traffic interval, and the result showed that this model had better performance than general neural networks. An improved clustering algorithm was included in a hybrid short-term traffic flow prediction model in [82]. Instead of putting all task together, like the traditional clustering way in traffic flow predictions, the authors used a weight clustering approach to find correlated tasks. To better identify the traffic patterns in short-term traffic flow, the approach introduced in [83] employed a clustering algorithm to group similar traffic behaviors. In [84], subtractive clustering algorithm was adopted to help traffic flow prediction. In this method, subtractive clustering was enrolled into a data-driven NN model, for improving the accuracy of traffic flow predictions in high volatile situations. After compared with some of the similar models such as BP, FNN, and sub-FNN, etc., the authors showed the superiority of their model. Other publications related to the clustering algorithm in short-term traffic flow predictions also can be found in [85, 86, 87].

Apart from the prevalent clustering algorithm, there are many other unsupervised learning algorithms, for example, Dimension reduction algorithm [88], Recommended algorithm [89], and so on. However, these are not very commonly considered by researchers when they prepare to forecast short-term traffic volumes. In this chapter, just some basic concepts of these two are introduced to give a new view of future work. For the Dimension reduction model, which is to reduce the data from high dimension to low dimension. By reducing the dimensionality, redundant information can be removed, and therefore reducing the data from high dimension to low dimension, which not only benefits the expression but also accelerates the calculation. For the second one, the recommended algorithm is a very straightforward and standard algorithm used in the business world for a long time.

In short, the main feature of the recommendation algorithm is that it can automatically recommend to the user what they are most interested in and help to make better decisions efficiently. There are two main types of recommendation algorithms; one is recommendation based on the content of items; the other is recommendation based on user similarity. These two are also potential good methods for short-term prediction but is less focused nowadays.

To sum up, ML-based models are more used in recent years due to their better model flexibility, higher model adaptability and stronger non-linear features mining ability. Although they have many advantages, some challenges still obstruct future researches and reduce model accuracy.

2.4 Other prediction algorithms

Apart from the statistic-based models and ML-based approaches discussed above, there are some other helpful algorithms, such as Kalman filter and Hidden Markov chain that benefit the short-term traffic flow prediction. These methods are helpful but few mentioned in past studies, so it is vital to put them together to introduce in this section.

2.4.1 Kalman Filter-based methods

Kalman filter is a linear system using the state equation, input, and output through the system observation data, which is also a system state optimal estimation algorithm [90]. Because the observed data includes the influence coming from the noise and interference in the system, and hence, the optimal estimation can also be regarded as the filtering process. Also, since it is convenient to update and process the real-time data collected in different fields and easy to be implemented, Kalman filter is the most widely used filtering method, and has been widely applied in many fields, such as communication, navigation, guidance, and control [91], etc. In recent years, Kalman filter combines other basic forecasting methods, which has been a new trend in short-term traffic flow prediction. For a system

$X(t)$, the simplest Kalman filter process is described as below.

$$X(t \mid t-1) = AX(t-1 \mid t-1) + BU(t), \tag{2.21}$$

$$P(t \mid t-1) = AP(t-1 \mid t-1) A' + Q, \tag{2.22}$$

$$Y(t) = X(t \mid t-1) + Kg(t)(Z(t) - HX(t \mid t-1)), \tag{2.23}$$

where $X(t \mid t-1)$ is the result of the previous state prediction, $X(t-1 \mid t-1)$ is the optimal result of the previous state. As for $U(t)$, it is the control quantity of the current state, and if there is no control Quantity, it can be 0. In addition, $P(t \mid t-1)$ is a covariance corresponding to $X(t \mid t-1)$, $P(t-1 \mid t-1)$ is a covariance corresponding to $X(t-1 \mid t-1)$, and A' represents the transposed matrix of A , and Q is the covariance of the system process. $Kg(t)$ is the Kalman gain, and $Z(t)$ is the measurement at time t.

Considered as a meaningful method, Kalman filter is used in many time series analysis to track past values, filter current values, and estimate future values [92, 93]. Accordingly, in traffic flow prediction field, there is a new trend for Kalman filter, that is to mix the Kalman filter with time series analysis approaches such as ARMA, ARIMA, etc. This sort of combination is effective and efficient, so it has caught lots of attention and is worthy of some introduction.

When combining the Kalman filter algorithm with the ARIMA model, the Kalman filter algorithm recursively updates the information of the state variables (predictors) as a new data point. In other words, the correction function improves the prediction accuracy of the ARIMA model to a certain extent. For Kalman filter part, it can be described by a state space model, in which state is related to the measurement, to remove the measurement error from the data, and Fig. 2.10 shows this process.

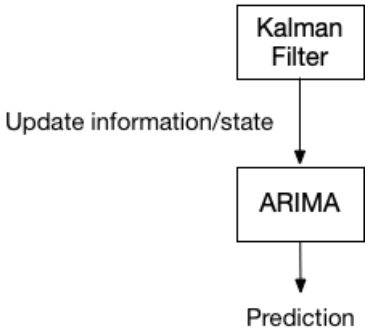


Figure 2.10: Working process of Kalman filter with ARIMA

Generally, the fitting results obtained by the ARIMA+Kalman filter algorithm are

smoother, which shows that the noise filtering effect is better after the Kalman filter adjustment. Therefore, the Kalman filter considered an effective method had been applied for facilitating the traffic flow prediction.

In [94], data preprocessing mechanism was used to reduce the corruption of local noises. In this model, traffic flow data was firstly denoised by using the discrete wavelet decomposition analysis, and maximum three-level decomposition was conducted based on the function $f(t)$, which was linearly composed of two parts, scaling $\varphi_{j,k}(t)$ as well as wavelet $\Psi_{j,k}(t)$. Traffic flow was treated as k-th time interval signal $vol(k)$, processed by the Kalman filter model. Especially, the transition matrix $F_{k,k-1}$ used in Kalman filter model was regarded as a smooth process, so the it was simplified as an identity matrix with $n \times n$ dimension, which reduced the computational cost and improve the efficiency. Finally, the derived MAPE and RMSE values also demonstrated the superior of this model.

Two Kalman filter-based models are given by [95], where the proposed models achieved a better trade-off between accuracy and computation cost in a short-term interval. For the first one, the average historical flow was used as an evaluation tool for current flow noises. However, the excessive dependence on historical data is its distinct shortage. The pseudo-observations was introduced for reducing the computation burden, which was able to catch some simple noises in traffic flow. When combined with an Adaptive Kalman filter, where Kalman filter was used to obtain the mean and variance and also the noises estimation. Although easy on-line implementation is its big advantage, the lack of the comparison with other models under different road context is its main shortcoming.

Another work, a new Kalman filter-based scheme, i.e., KFT [96], broke through from the preceding limitations including large dataset, reliable backup from the software, etc. By making less input convert to PCUs, they predicted the one-day traffic flow values and acquired a higher prediction accuracy. The Kalman filter is more than that, but due to its comparatively complex mathematical background, it is not easy to be creatively included in a model, which is also its weakness.

2.4.2 Hidden Markov Machine (HMM)

Hidden Markov Machine is based on the Markov chain, which is another supportive method used by many researchers to implement short-term traffic flow prediction. As for the Markov chain, supposing there is a process that consists of a sequence of states, this state sequence is called the state space. Furthermore, supposing the state at a precise moment is

a function of its state at the previous moment, and that is to say, it shows that this sequence has Markov character. Generally speaking, the state at that moment is only related to the state of its previous moment, and then the sequence has Markov property [97, 98]. Accordingly, only the current state is considered to predict the next state.

Markov process is aiming for the continuous-time scenario while Markov chain is related to the discrete state. The benefit to category these two classes is that it can easily use the matrix (one-step transfer probability matrix) to portray the transfer state (transition diagram). Accordingly, I can translate the problem abstracted from the random process into a linear algebra problem. The state transition matrix is a crucial factor in the Markov chain. It expresses the change of state when it is transferred from m to $m+n$. The transition probability can be expressed as the following equation,

$$P_{i,j}\left(m, m+n\right) = P\left\{X_{m+n} = a_j \mid X_m = a_i\right\}, \tag{2.24}$$

where, X_t represents the state at time t. The transition state matrix is a set of transition probabilities that can be expressed as,

$$\sum_{j=1}^{\infty} P_{i,j}\left(m, m+n\right) = 1, i = 1, 2, \cdots. \tag{2.25}$$

The above equation shows a state transition matrix of n steps, where n is a given value, and the number of rows and columns are denoted by i and j, respectively. Also, in this matrix, the sum of each individual row is 1. Moreover, $P_{i,j}$ represents the transfer probability of the n-step transfer probability matrix from a_i to a_j. There is a special case where the value of $P_{i,j}\left(m, m+n\right)$ is only related to n, and I have,

$$P_{i,j}\left(m, m+n\right) = P_{i,j}\left(n\right). \tag{2.26}$$

Accordingly, I can consider $P_{i,j}\left(n\right)$ as a time-independent constant. Meanwhile, the chain is deemed as homogeneous. Markov chain is also regarded as a Markov process that can be merged into many prediction structures.

As defined in [99], HMM is a special statistical model used to describe the Markov process of implicit unknown states. In fact, for the HMM, it is fairly easy to simulate the probability of transition between all implicit states and the output probability of all implicit states to all visible states in advance. However, when applying the HMM model,

it is often missing a part of the information. To be more precisely, supposing that there is a sequence $X_t = \{X_1, X_2, \cdots, X_n\}$, which represents the sequence of implicit variables. $Z_t = \{Z_1, Z_2, \cdots, Z_n\}$ is another sequence that represents the observations with time. The transitions between them are connected through the state transition matrix, and Fig. 2.11 depicts this mechanism.

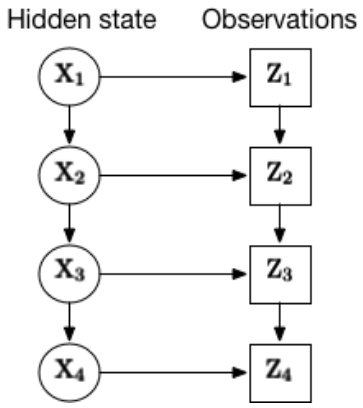


Figure 2.11: HMM model

Markov chain is a basic method to make short-term traffic flow predictions and has attracted considerable attention for a long time. Similar to Kalman filter, in recent years, HMM usually is employed to help the prediction process, rather than plays as the central role. For earlier researches, HMM is widely used for predicting short-term traffic flow due to its simplicity and high efficiency. However, with the increase of traffic complexity, this simple method is unable to meet the prediction accuracy requirement. So it turns to be an auxiliary method, to capture some specific features, such as spatial correlations or temporal relationships.

In [100], a novel model based on Markov chain was proposed, and playing as a role for obtaining the transition probability. Meanwhile, the Gaussian Mixture Model and Expectation Maximum algorithm were also included in this work. Traffic flow was treated as a high order Markov chain, and it assumed that the state transition obeyed the conditional probability. In this Markov process, the transition probability density function $p(Y \mid X)$ was learned based on the Gaussian Mixture Model. Even though this model has great prediction accuracy, it lacks the ability to be applied to road networks scenario.

For dealing with the flaw data, the authos in [101] proposed a model, named Sampling Markov Chain. The unique thing of this model is using the Monte Carlo integration to approximate the flaw data. With the basic idea of Monte Carlo integration that us-

ing random numbers to numerical integration, the prediction $\hat{Y}$ converted into the form $E(Y \mid X_{ti}) = 1/n \sum_{i=1}^{n} E(Y \mid X_{ti})$, which greatly overcome the missing data problem. For better proving the high performance of this model, the authors compared it with two similar models, Historical Average Markov Chain method and Joint Distribution Recalculating method.

Apart from the flow prediction, HMM also can be found in traffic state prediction. In [102], HMM was employed to make a short-term freeway traffic state and speed prediction, in which the traffic states are upgraded from one dimension to a higher dimension. Different from the previous studies using traffic volume to implement prediction, this work is by using the speed information to conduct a peak-hour traffic state prediction. Notably, the time series was imported into two-dimensional space to facilitate the HMM process.

To summarize, HMM is a simple and easily understood approach that suitable for short-term traffic flow prediction. However, for better dealing with the more and more complicated road structure and volatile transportation system, combining HMM with other prediction methods is becoming a new trend today.

2.5 Conclusion

This chapter gives a general review of the researches on the short-term traffic flow prediction field. Beginning from some fundamental concepts in the forecasting process, such as on-sample/out-of-sample, on-line/off-line, etc., which gives a basic idea of what it is the prediction. And then, two main prediction categories are introduced, i.e., the statistical models and machine learning-based ones. For the class of statistical models, it consists of different models such as AR/MA family (e.g., ARMA, ARIMA, SARIMA, and VARIMA, etc.) and ES series. For the machine learning category, both supervised methods and unsupervised learning methods are introduced. In supervised learning subclass, several popular algorithms are given, including K-NN, Linear regression, SVM, and RNN, etc. Notably, RNN including LSTM, GRU as a significant approach is adopted by more and more researchers nowadays in short-term traffic flow prediction area. Based on the previous works and also considering of the advantages as well disadvantages of them, some studies are conducted at the following chapters.

Chapter 3

DSTARMA: A travel-delay aware short-term vehicular traffic flow prediction scheme for VANET

In this chapter, an innovative hybrid prediction method, Delay-based Spatial-Temporal Autoregressive Moving Average model (DSTARMA) is proposed to enhance the patterns mining ability of statistic-based models. In fact, the high mobility of the vehicles makes the topology of Vehicular ad-hoc network (VANET) unstable [103] [104], and real-time road information is generally limited [105] [106] [107]. Considering these shortcomings, it is helpful to use the accurate traffic prediction to assist the topology control in the VANET [108] [109]. Particularly, this model also focuses on dealing with the travel delay problem in short-term traffic flow prediction, and by handling it in the form of spatial-temporal weighted matrices to help capture non-linear features in spatiotemporal relations. In addition, this method has been accpted and published in [110].

3.1 Problem statement

As we all know, the traffic volume generated by different roads may be able to interact with each other, which means the traffic volume at one road may be influenced by its nearby road segments directly or indirectly in the same certain area. For better illustrating the spatial correlations of these road segments, Seven probers located in different connected road segments were chosen, namely Location n ($n = 1, 2, 3...7$). So there are seven locations

in my tree-type road network shown in Fig. 3.1. In this road structure, It assumes that the traffic flow is one-way from top to bottom, and location 1 ($L1$), location 2 ($L2$), location 3 ($L3$) and location 4 ($L4$) are the level I, and location 5 ($L5$) as well as location 6 ($L6$) are the level II, following the location 7 ($L7$), the level III. It also assumes the traffic flow from a higher level has an effect on itself as well as the traffic volume at a lower level. For example, the impact of their own in level I is called the zeroth-order impact. Similarly, the influence from level I to level II is called first-order impact, and to level III is called second-order impact. So, these locations can be divided to k th order, $k = 0, 1, 2...$, on the impact degree basis. In the traditional equal weight STARMA model (EW-STARMA), the influence weight of locations at the same level is average. For example, the impact on $L5$ is shared evenly by $L1$ and $L2$. Likely to $L5$, for $L7$, six locations can have an impact on it, so each location contributes $1/6$ influence to $L7$. However, this allocation approach is too simple to capture the spatial-temporal characteristics entirely. In other words, the travel time of vehicles from one location to another location, namely travel delay, is ignored by this EW-STARMA model. So, how to properly take advantage of this travel delay for improving the accuracy of short-term traffic flow prediction is my goal in this chapter.

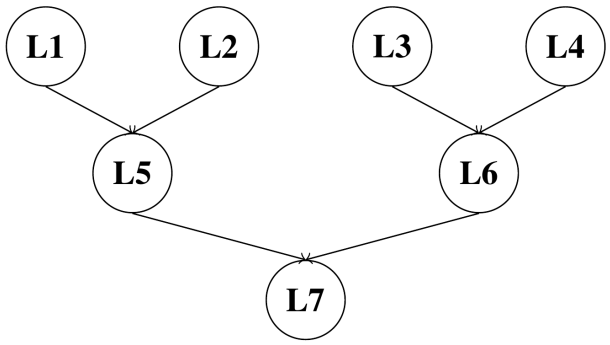


Figure 3.1: An example of a three-level road network

3.2 Proposed method

In consideration of the hypothesis stated before that the spatial-temporal relationship can make an impact on prediction result, DSTARMA is illustrated specifically in this section in a progressive manner. From the very beginning, some very fundamental theories and formulas will be explained briefly, such as VARMA and STARMA. After having a basic view of these models, my DSTARMA will be introduced precisely.

3.2.1 VARMA/ STARMA

Different from ARMA and ARIMA, the nature of VARMA is a multivariate process [111], in which, multivariate data and their patterns can be identified, and the mutual impact of them is shown at the same time. Especially, variables exist in the form of matrices in VARMA model. Similar to the ARMA and ARIMA, VARMA can be defined by a statistical formula, shown as follows.

$$\mathbf{A}\left(L\right)X_t = \mathbf{M}\left(L\right)\eta_t \tag{3.1}$$

In this equation, X_t is the aim variable at time t that needs to be predicted, and L is the lag operator like the function of B in ARMA [28].

$$\mathbf{A}\left(z\right) = \mathbf{A}_0 + \mathbf{A}_1 z + \mathbf{A}_2 z^2 + \cdots + \mathbf{A}_p z^p \tag{3.2}$$

$$\mathbf{M}\left(z\right) = \mathbf{M}_0 + \mathbf{M}_1 z + \mathbf{M}_2 z^2 + \cdots + \mathbf{M}_q z^q \tag{3.3}$$

In two above equations, coefficients $\mathbf{A}_0, \mathbf{A}_1, \cdots, \mathbf{A}_p$ and $\mathbf{M}_0, \mathbf{M}_1, \cdots, \mathbf{M}_q$ are both matrices with order $n \times n$.

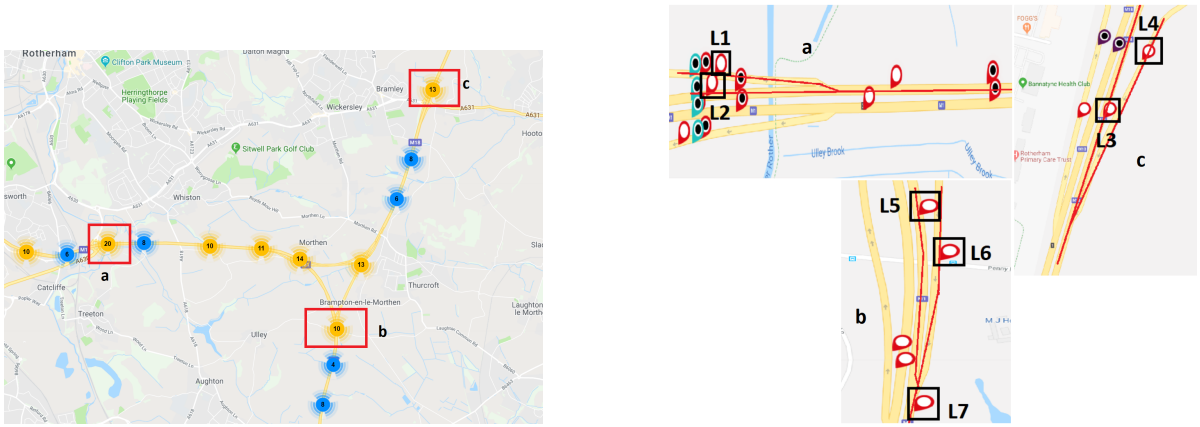
STARMA is derived from VARMA, and it distinguishes itself with weighted matrices. There are mainly two variables in STARMA, space and time. By using a weighted matrix to emphasize the spatial relationship is the main advantage of this model. The general definition is expressed as follows.

$$\mathbf{X}_t = \sum_{l=1}^{p}\sum_{k_l=0}^{k_l}\phi_{lk_l}\mathbf{W}^{(k_l)}\mathbf{X}_{t-l} - \sum_{l=1}^{q}\sum_{k_l=0}^{m_l}\theta_{lk_l}\mathbf{W}^{(k_l)}\eta_{t-l} + \boldsymbol{\eta}_t \tag{3.4}$$

in which, n is the number of locations, and $\mathbf{X}_t$ is a $n \times 1$ vector at time t. $\mathbf{W}^{(k_l)}$ is the k_lth order $n \times n$ matrix. ϕ_{lk_l}, θ_{lk_l} are parameters terms of spatial-temporal AR (STAR) and spatial-temporal MA (STMA) respectively, and η_{t-l} is a $n \times 1$ vector at time $t - l$. According to the second stage of Box-Jenkins models, modeling is split into three stages, model identification, parameter estimation and model checking [112]. As for parameter estimation process, different from ordinary STARMA, using Yule-Walker equation and Maximum Likelihood [113] as estimators to get ϕ and θ, in this study, Kalman fliter is adopted to be estimator due to its high efficiency and accuracy.

Particularly, two dominant parts STAR, STMA can be observed in Eq.(3.4). For the first polynomial, it conducts the autoregressive process for all spatial kth order from time lag1 to time lag p. Moving average is completed through handling residuals with the time lag l and space lag k_l simultaneously. $\mathbf{W}^{(k_l)}$ is the weighted matrices for digging and showing potential space correlations of all road segments, based on the geographical characteristic among areas. Generally, the simplest way to determine each element w_{ij} in $\mathbf{W}^{(k_l)}$ is equal-weight allocation, which is called EW-STARMA. In the case of tree-type structure road network in Fig. 3.1, for the level I locations, $L1$ and $L2$ both have the equal half contribution to $L5$ ($w_{15} = w_{25} = 0.5$), and the same allocation can be seen among $L3$ and $L4$ to $L6$. Moreover, all weight distributions are supposed to obey the followed rules in Eq.(3.5).

$$w_{ij}^{(s)} \geq 0,\ w_{ii}^{(s)} = 0,\ \sum w_{ij}^{(s)} = 1\,(j \in J_s) \tag{3.5}$$



(a) general road structure

(b) location details

Figure 3.2: Road Network Structure

3.2.2 DSTARMA

Weight matrices play a significant role in the whole prediction model, which can directly influence the accuracy of the prediction result. Obviously, simple equal weight allocation cannot meet the needs of the intelligent transportation system (ITS) which has complex road relationships. The travel delay is a serious issue that ignored by all STARMA-based processes. However, in my DSTARMA model, it takes a more reasonable calculation way to give weight value. It assumes downstream location k is the one that needs to be predicted,

and there are only two locations (Li, Lj) with directly connected, like the relationship of $L1$, $L2$ and $L5$ in Fig. 3.1. The distance between i, k and j, k are d_{ik}, d_{jk} respectively, and the travel delay is calculated with formulas in Eq.(3.6).

$$\tau_{ik} = \frac{d_{ik}}{\overline{\nu}_{ik}}, \tau_{jk} = \frac{d_{jk}}{\overline{\nu}_{jk}} \tag{3.6}$$

and the final weight of Li to Lk at time t is defined in Eq.(3.7).

$$w_{ik} = \frac{V_i\left(t-\tau_{ik}\right)}{V_k\left(t\right)} = \frac{V_i\left(t-\tau_{ik}\right)}{V_i\left(t-\tau_{ik}\right)+V_j\left(t-\tau_{jk}\right)} \tag{3.7}$$

In Eq.(3.7), $V_i\left(t\right)$ represents the traffic volume generated by upstream loation Li at time t. This equation describes a fact that traffic flow data acquired at the moment t for downstream location Lk is the sum of traffic volumes for upper stream location Li and Lj at the time $(t-\tau_{ik})$ and $(t-\tau_{jk})$. The travel delay τ_{ik},τ_{jk} in Eq.(3.6) are the time that vehicles travel from Li to Lk, Lj to Lk. In this way, travel delay becomes a factor in spatial weighted matrices when evaluating spatial relationship. Taking Fig. 3.1 for example, when $k_l = 0$, the weighted matrix for spatial lag 0 is an Identity matrix $\mathbf{W}^{(0)} = \mathbf{I}_{7\times 7}$, and for spatial lag $k_l = 1$:

$$\mathbf{W}^{(1)} = \begin{pmatrix} 0 & 0 & 0 & 0 & w_{15} & 0 & 0 \\ 0 & 0 & 0 & 0 & w_{25} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & w_{36} & 0 \\ 0 & 0 & 0 & 0 & 0 & w_{46} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & w_{57} \\ 0 & 0 & 0 & 0 & 0 & 0 & w_{67} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \tag{3.8}$$

for spatial lag $k_l = 2$:

$$\mathbf{W}^{(2)} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & w_{17} \\ 0 & 0 & 0 & 0 & 0 & 0 & w_{27} \\ 0 & 0 & 0 & 0 & 0 & 0 & w_{37} \\ 0 & 0 & 0 & 0 & 0 & 0 & w_{47} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \tag{3.9}$$

3.3 Verification

In this section, a case study is implemented by using my new model. As for the effect evaluation, mean squared error (MSE), mean absolute percentage error (MAPE) and the square of the sample correlation coefficient R-square (R^2) are applied [114]. The formulas are defined by following equations.

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(X_t - \hat{X}_t\right)^2 \tag{3.10}$$

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{X_t - \hat{X}_t}{X_t}\right| \tag{3.11}$$

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 1 - \frac{\sum_t\left(X_t - \hat{X}_t\right)^2}{\sum_t\left(X_t - \bar{X}\right)^2} \tag{3.12}$$

3.3.1 Dataset

In this study, the England Highway traffic flow data at a 15-min interval were chosen, which covers the period of all Wednesdays in May 2015 for seven different roads [115]. The location of seven probers is circled in Fig. 3.2, and the related information is listed in Tab. 3.1. Since the travel delay is calculated based on the distance between the two locations, the too-small distance leads to an insignificant travel delay, which does not meet the experimental requirements, so followed seven locations were chosen as the experimental path. Also, because the available and experimentally required data sets are very limited, this experiment only adopted these seven locations as the predicted roads.

In addition, in my DSTARMA model, travel delay τ is short at the second level, which is almost a real-time value but used dataset is 15-min interval statistic value, so that practical traffic volume $V_i\left(t - \tau_{ik}\right)$ cannot get directly.

For solving this problem, the $V_l\left(t\right)$ $l \in (i, j)$ was calculated as follows,

$$V_l\left(t\right) = V_l\left(t - \tau_{lk}\right) = \frac{V_l\left(t\right)\cdot\left(15 - \tau_{lk}\right)}{15} + \frac{V_l\left(t - 15\right)\cdot\tau_{lk}}{15} \tag{3.13}$$

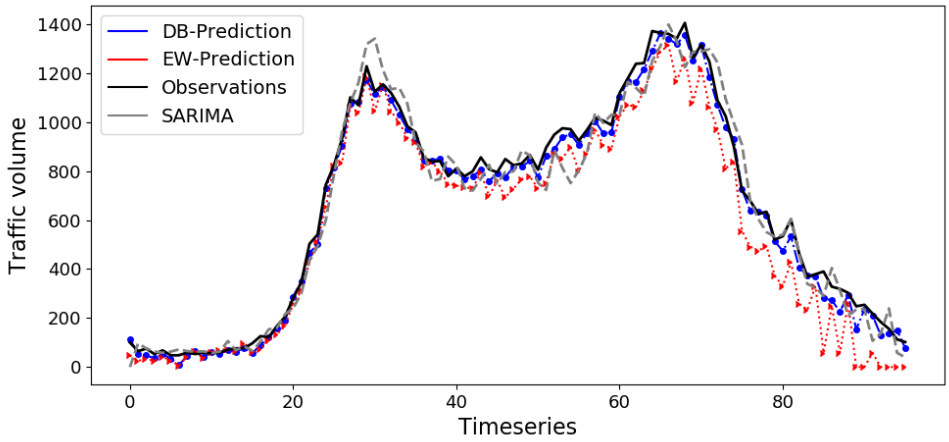
Table 3.1: Location of probers under study

Location	Label	Direction	GPS Ref.
L1	M1/4556B	Southbound	443630;389314
L2	M1/4557M	Southbound	443593;389329
L3	8898/2	Westbound	449965;392404
L4	8898/1	Westbound	449989;392388
L5	M1/4551B	Southbound	444092;389326
L6	M1/4505M	Westbound	448145;387845
L7	M1/4500B	Southbound	448120;387365

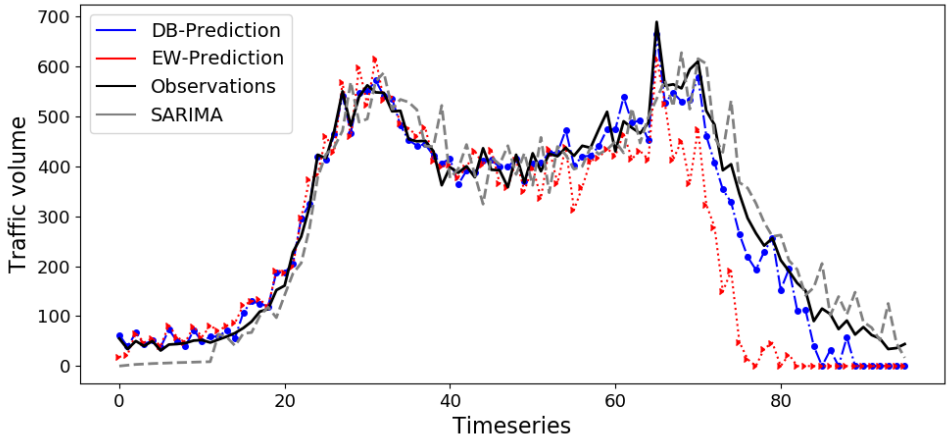
3.3.2 Performance evaluation

In this study, one-day traffic flow for 3 downstream locations ($L5$, $L6$, $L7$) are predicted by traditional equal weighted STARMA (EW-STARMA), DSTARMA and SARIMA. The related indexes for evaluating the quality of these three models are shown in Tab. 3.2. For MSE and MAPE values, both of them display the errors, the deviation degree of prediction values and practical values, which means the lower value, the higher the accuracy. Another indicator is R^2, the closer to 1, the better the effect. From this table, DSTARMA has the lowest MSE, MAPE values but highest R^2 for all three locations. Conversely, EW-STARMA shows the worst prediction effect, lower accuracy than SARIMA. Situations in three locations are slightly different.

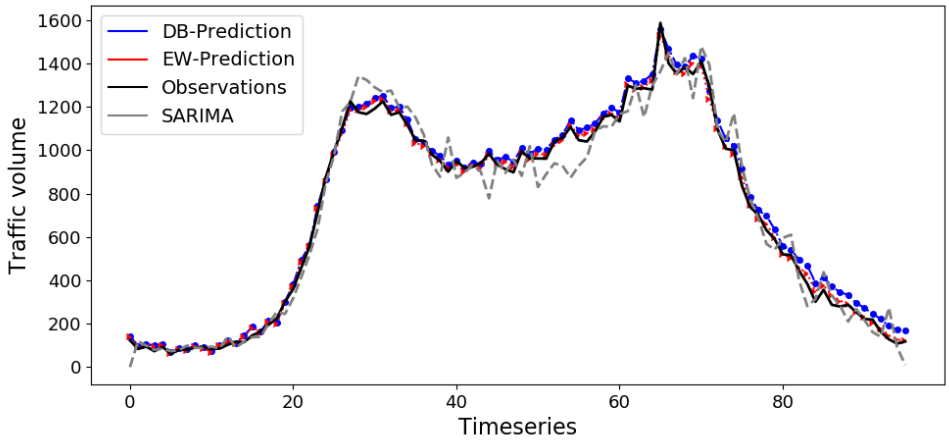
According to Fig. 3.3, it is obvious that $L7$ can be seen as the best fitting effect for all three models. This is because $L7$ sits in the most downstream road segment which is at the bottom of road structure. The unique position makes it have more spatial correlation information than other two locations, and hence with this information, EW-STARMA and DSTARMA perform best, with 0.992 and 0.998 for R^2 respectively. Although $L5$ and $L6$ are the same levels locations, in general, the prediction effect for $L5$ is better than $L6$, especially afternoon to midnight period. There are mainly two reasons for this phenomenon, the number of traffic diversion and traffic complexity nearby. To be more precise, traffic volumes have been separated and included into another irrelevant road segments more than two times when arriving at $L6$, however, only once in $L5$. Besides, the road segment that $L6$ locates in are connected more road branches than $L5$, which requires models have good understanding ability to tackle these complex information, and this also makes the accuracy decrease of $L6$. As for the worse prediction effect for evening period



(a) one-day traffic flow prediction for $L5$



(b) one-day traffic flow prediction for $L6$



(c) one-day traffic flow prediction for $L7$

Figure 3.3: Comparison of Three models for $L7$, $L6$, $L5$

of these two locations, this is because fewer vehicles go through so that less traffic pattern can be captured, and also the worse detection ability of probers in dark environment is another possible factor.

To sum up, DSTARMA shows the best prediction results in this scenario, followed by SARIMA and EW-STARMA. This is ascribed to the strong illustration ability of spatial-temporal relationship of DSTARMA. SARIMA also perform well as its seasonality.

Table 3.2: Prediction Accuracy of DSTARMA

Location	**Model**	**MSE**	**MAPE**	$\mathbf{R^2}$
$L5$	EW-STARMA	12604.95	24.13	0.931
$L5$	**DSTARMA**	**1243.07**	**9.05**	**0.993**
$L5$	SARIMA	5672.30	13.44	0.969
$L6$	EW-STARMA	9363.87	35.82	0.745
$L6$	**DSTARMA**	**1326.12**	**20.51**	**0.964**
$L6$	SARIMA	2760.57	28.29	0.925
$L7$	EW-STARMA	1470.70	8.89	0.992
$L7$	**DSTARMA**	**484.51**	**4.92**	**0.998**
$L7$	SARIMA	6325.88	12.35	0.969

3.4 Conclusion

DSTARMA model is a novel and simple method that takes the travel delay, nature of traffic flow, into consideration, and this makes it better describe spatial-time correlation in road networks. After comparing the classic STARMA with equal weight matrices and SARIMA in daily traffic flow prediction situation, my approach, DSTARMA shows higher reliability and accuracy no matter where the location is. This is owing to its strong interpreting ability for space and time. Specifically, in DSTARMA model, it calculates the travel delay τ between upstream and downstream locations and then adding them into spatially weighted matrices, which is the core of this model. The verification results also prove that DSTARMA is superior to EW-STARMA and SARIMA, with its lowest MSE, MAPE, and highest value for R^2 within the same day for downstream locations' traffic flow prediction. What is more, in this study, the dataset is statistics value, and discretization process may decrease the prediction accuracy. The spatial-temporal weighted matrices distinguish STARMA from other time-series-based models, and good prediction guidance

can have the great impact on whatever data dissemination or vehicular routing scheduling in VANET, so how to improve the matrices facilitating modeling is still a big challenge for future research. In addition, a more diversified road network structure can be incorporated in the future work. For example, it can select a more complex urban road network structure rather than freeway roads, to apply in my new model, because rich data sets facilitate the promotion of this model in multiple scenarios to increase its practical value.

Chapter 4

SSGRU: A Hybrid Traffic Volume Prediction Approach for a Sparse Road Network

This chapter focuses on the optimization of ML-based models. In previous studies, some machine learning (ML)-based models were proposed to predict the traffic volume at a single road segment/position, and these models performed not bad. However, when applied in a more complicated road network, they show low efficiency or need to pay higher computing costs. To solve this problem and further improve the model feature mining ability for ML-based models, an innovative selected stacked gated recurrent units model (SSGRU) is proposed. In addition, this method has been accepted and published in [116].

4.1 Problem statement

Different from the predictions based on the single road, an intact road network traffic volume prediction usually requires the higher mining ability for spatial-temporal information. Considering of this, it assumes that there is a tree-shape road network within n road segments, and for each road, one detector is selected to count the number of vehicles, namely Ln $(n = 1, 2, 3, ...7)$, the same as the road structure shown in Fig. 3.1 of Chapter 3. The traffic flow is the single direction from top to bottom, and the traffic volumes have an impact on each other to a various extent. Traffic flow in the suburbs area is less on-ramp and off-ramp [117], and also the impact from too far level traffic flow on the target location

is very limited or even negligible, so three-layer tree-shaped road network structure was adopted to simulate the real road convergence, which is widely seen situation in real suburb highway.

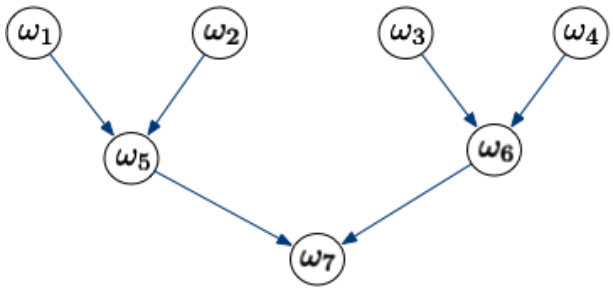


Figure 4.1: Weight assignment for a road network

Similar to the weights set in the last chapter, a set of weights w_{ab}, $a, b \in (1, 2, 3, 4, 5, 6, 7)$ are still used to describe these influential degrees among road segments, shown in Fig. 4.1. Subscript a and b represent any two locations in this road framework. For example, weight vector for Location1 $(L1)$ is in the form of $\mathbf{w}_1 = \{w_{11}, w_{21}, ..., w_{71}\}$, in which w_{a1}, $a \in (2, 3, 4, 5, 6, 7)$, is the impact factor from La to $L1$. Through employing different w_{ab}, it can be easier to catch correlations of all roads. Most of the previous traffic flow predictions only consider a certain road segment. However, roads are interconnected, and traffic information is fluent in real life. Prediction only with the temporal relationship is not able to meet the needs of the more and more complicated transportation system nowadays. So how to expand the prediction view from a single road to a road network and improve the accuracy with a comparatively simple model at the same time is the goal of this chapter.

4.2 Proposed method

In consideration of the hypothesis stated above, a selected stacked GRU model is introduced since GRU has a good ability to handle the time series in a highly efficient way. Also, a stacked structure generates a deep learning procedure to gain a better training effect. There are mainly two parts of this model, and the general structure is shown in Fig. 4.2. A road network including multiple roads is firstly processed by Linear Regression Weight Selected System, obtaining useful roads in this stage.

As for the second stage, stacked GRU learning system, does the model building, forecasting as well as results output. Additionally, traffic flow data selected by the previous

stage are split into training and testing groups. Multiple features (i.e., n features) are simultaneously transported with aim feature into GRUs in layer 1. Manipulated by three GRUs respectively, they get into layer 2, where input dimension change from $n+1$ features to only three features for each GRU in layer 2. Through a fully connected dense layer, the shape of predictions is adjusted to one time series vector and ready to output. Particularly, only five GRUs are used in this model, because traffic flow vibrations in the same area show some similarities and hence a small number of learning units are enough to dig their patterns. What is more, different from many other neural networks such as the convolutional neural network (CNN) [118], which can stack over one hundred layers, RNN, regards only two layers as deep learning network. Because each layer of RNN has a depth in the time dimension, even if the number of RNN layers is small, the overall network size will be pretty significant. Considering the above factors, two-layer and a total of five GRUs are included in this model.

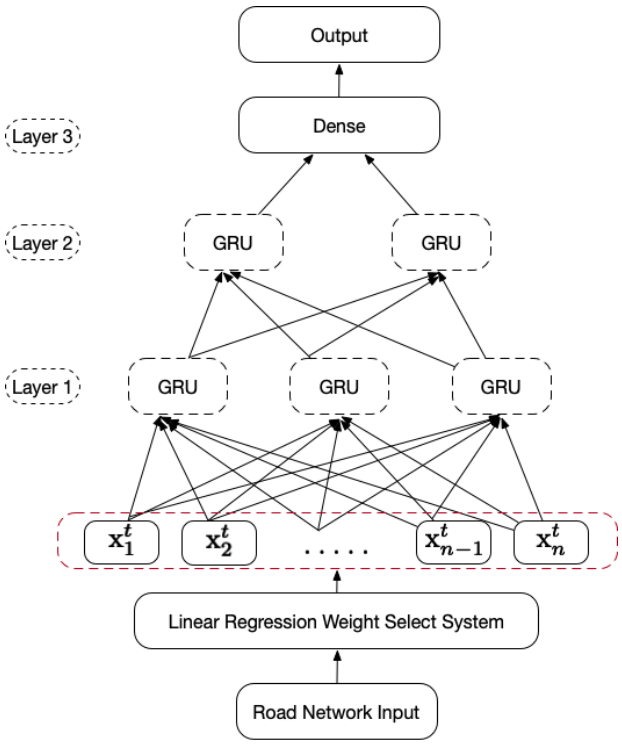


Figure 4.2: SSGRU model structure

4.2.1 Linear Resgression Weigt Selection System

This selection system is responsible for spatial correlation study, selecting high-impact roads. In this period, every roads are given a weight related to the aim road by fitting into a linear regression model. For example, given an aim road x_0, it assumes all n roads in the same area have impacts on it, so their relationship can be described by,

$$x_0 = \omega_1 x_1 + \omega_2 x_2 + \cdots + \omega_n x_n, \tag{4.1}$$

in which, $x_0, x_1 \cdots x_n$ and $\omega_1, \omega_2 \cdots \omega_n$ are both $1 \times t$ vectors, and t is the time length.

Since it is linear regression, the linear function in Eq.(4.1) must be able to fit the data optimally, that is, it must minimize the variance of the data to the fitted line. To represent this variance, a cost function is defined to represent this amount as follows,

$$J(\omega) = \frac{1}{2t} \sum_{i=1}^{t} \left(h_\omega \left(x^{(i)} \right) - x_0^{(i)} \right)^2, \tag{4.2}$$

where, $x^{(i)} \in (x_1, x_2, \cdots, x_n)$. To find a best parameter ω to minimize the cost function, the gradient decent approach is employed based on the following equation,

$$\omega_j = \omega_j - \alpha \frac{1}{t} \sum_{i=1}^{t} \left(h_\omega \left(x^{(i)} \right) - x_0^{(i)} \right) x_j^{(i)}, \tag{4.3}$$

where α is the learning rate and h_ω is the coefficient related to current ω. Finally, for each road, this system will output a suitable weight ω_j, with regards to the aim road x_0. For reduce input size, the weights that lower than 0.5 is drop, as this kind weights has limited even converse impact on aim feature.

4.2.2 Stacked GRU

The principle of stacked GRU is similar with the simple GRU, and its internal structure is shown in Fig. 4.3. As one kind of Recurrent Neural Network (RNN) unit, like LSTM, it is also proposed to solve problems such as gradients in long-term memory and back propagation [119] but with fewer control gates. In my case, the number of current input x^t is n, showing in red dash circle in Fig. 4.2. The hidden state h^{t-1} is passed by the previous node owing the same size with x^t. This hidden state contains information about

the previous node. Combined with x^t and h^{t-1}, GRU will get the output of the current hidden node y^t and the hidden state passed to the next node h^t. Two gate states r and z are calculated from the very beginning by using the formula shown below,

$$r^t = \sigma\left(W^{(r)}x^t + U^{(r)}h^{t-1}\right), \tag{4.4}$$

$$z^t = \sigma\left(W^{(z)}x^t + U^{(z)}h^{t-1}\right), \tag{4.5}$$

in which, $W^{(r)}$, $W^{(z)}$ and $U^{(r)}$, $U^{(z)}$ are weight matrices, and once one h is generated, a ω is produced and added in the matrix. r^t is the state of reset gate at time t, and z^t is the state of update gate at time t. These two gates decide how much to discard previous information and what new information to add and pass to the future. The function σ converts the data to a value in the range of $0 \sim 1$ to act as a gate signal. Reset gate will store the relevant information from the past in h' in Eq.(4.6),

$$h' = \tanh\left(Wx^t + r^t \odot Uh^{t-1}\right), \tag{4.6}$$

where $\odot$ is the Hadamard Product, and $\oplus$ stands for matrix addition.

In this step, h' contains current input data x^t, scaling the data to a range of -1 to 1 by a tanh activation function, to achieve memory purpose. Last but not least procedure of GRU is to figure out current hidden state h^t by Eq.(4.7) and output y^t is the combination of h^t and x^t. When this step is done, the model finish the memory update process, and particularly, the closer the gating signal of z is to 1, the more data represents "memory"; the closer to 0, the more "forgotten".

$$h^t = z^t \odot h^{t-1} + \left(1 - z^t\right) \odot h' \tag{4.7}$$

The first part of this equation is to forget some useless information in the h^{t-1}, similar to the forget gate in LSTM [120]. The second part indicates the selective "memory" of h', which contains current node information. After the first layer GRU finishes their task and each GRU output a prediction sequence, these sequence will be continue input into next layer GRU. Stacked GRU is the upgrade version of GRU, which has a much stronger ability of individual pattern learning, digging into details through layer by layer. For example, after disposing of three GRUs in layer 1, three first-learned results are thrown into all GRUs in the second layer as the Fig. 4.2 shows.

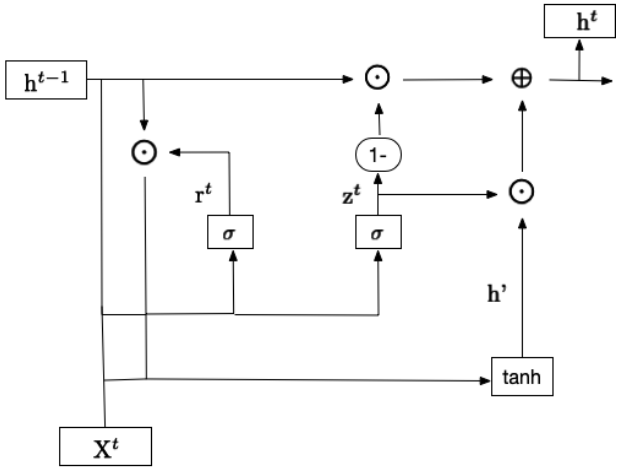


Figure 4.3: Internal structure of GRU

4.3 Verification

In this section, a case study is implemented by using my new model. As for the effect evaluation, Root Mean Square Error (RMSE) and the square of the sample correlation coefficient r-square (r^2) are applied [20]. Details show in Eq.(4.8) and Eq.(4.9).

$$RMSE = \sqrt{\overline{(\hat{x}_t - x_t)^2}} \tag{4.8}$$

$$r^2 = 1 - \frac{\sum_t (x_t - \hat{x}_t)^2}{\sum_t (x_t - \bar{x})^2} \tag{4.9}$$

where, x_t represents the observation values at time t, and $\hat{x}_t$ is the forecasts at time t.

4.3.1 Dataset

In this study, 15-min England highway traffic flow daily data for seven different roads, covering the period of all Wednesdays in May 2015 are used, the same dataset as Chapter 3. Different from previous experiment, two-thirds of data are used for training and the remainder for testing.

4.3.2 Performance evaluation

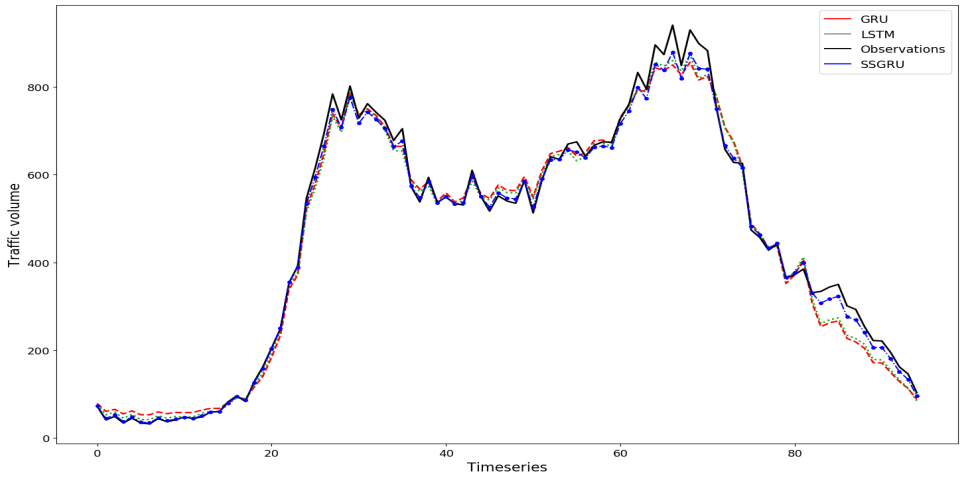
In this study, one-day traffic flow prediction for all seven locations is conducted at an interval of 15-min. To better describe the high performance of my model, the validation work not only tested my new model, but also compared it with other models, such as LSTM, GRU, Stacked GRU (SGRU) and Selected GRU (SEGRU).

The predicted traffic flow for three downstream locations are shown in Fig. 4.4, from which we can see that my method is to perform better in details forecasting. Moreover, according to Fig. 4.5, we can see that RMSE values for all locations of my SSGRU model are the smallest. Notably, the decline for $L5$ is the most dramatic, to almost half amount of the other two methods. This is may because there are more connected fork roads connected with this road, and the linear regression selection system is more helpful to filter the useful roads to make the subsequent learning more effective. As for the $L6$ and $L7$, the performance of these two roads are pretty similar, and both with nearly 10% reduction since the road condition in these two roads are similar. In contrast to RMSE, the index of r^2 shows a slight increase in three locations, become closer to 1, which fully demonstrates that my algorithm performs are the best among three models, and my approach makes the prediction accuracy improved obviously.

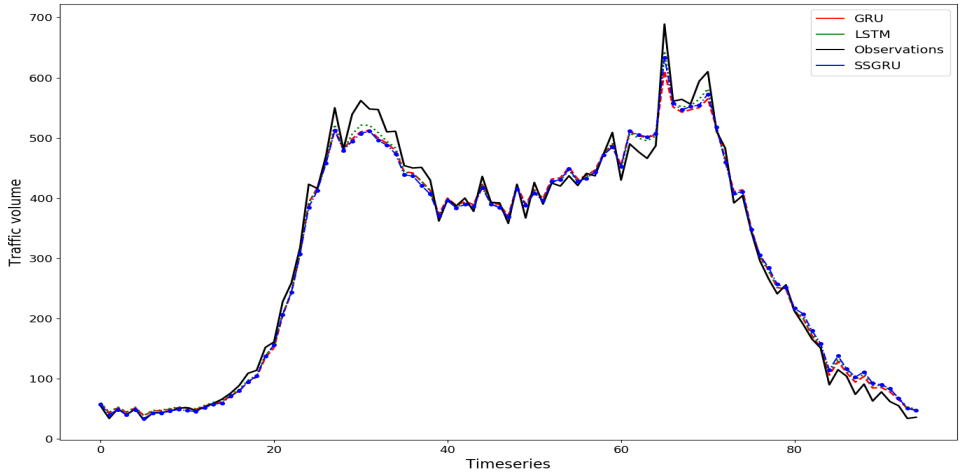
To further prove the advancement of my model, SSGRU was compared with two other similar models. The first one is the GRU with road selection (SEGRU), the second one is the stacked GRU without road selection (SGRU), and the results can be seen in Fig. 4.6. Although the r^2 values of these three models are very close, the RMSE is quite different, in which my model SSGRU always maintains the lowest RMSE. This set of comparisons also illustrates that the combination of data pre-processing and stacking structure can make the prediction effect the best.

4.4 Conclusion

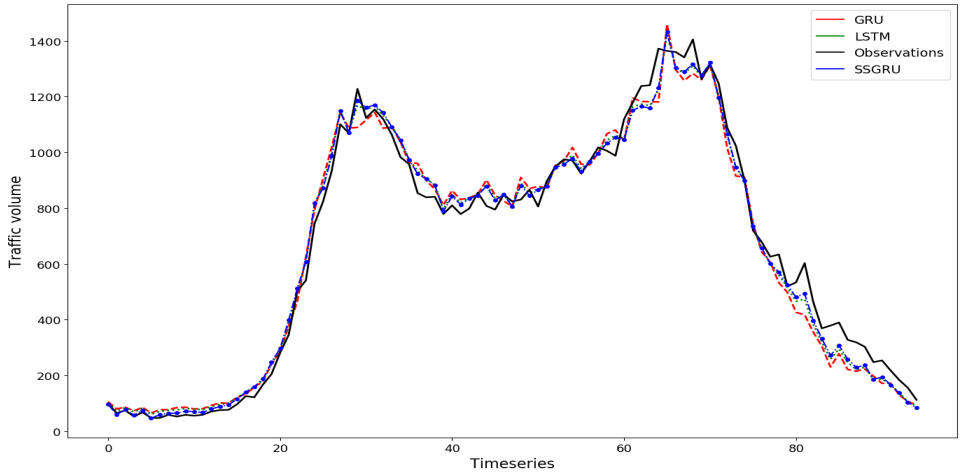
SSGRU is an innovative model, which is good to be fit into a road network, in a simple and easy to understanding manner. The data preprocessing system leaves out low impact roads, which not only reduces the cost of subsequent computational but also improves the prediction accuracy. Besides, the low computational cost and ease of understanding are also advantages of this pre-processing system. Stacked two layers of GRUs give the deep learning ability to data, better digging out the pattern details. In fact, due to the less



(a) one-day traffic flow prediction for $L5$

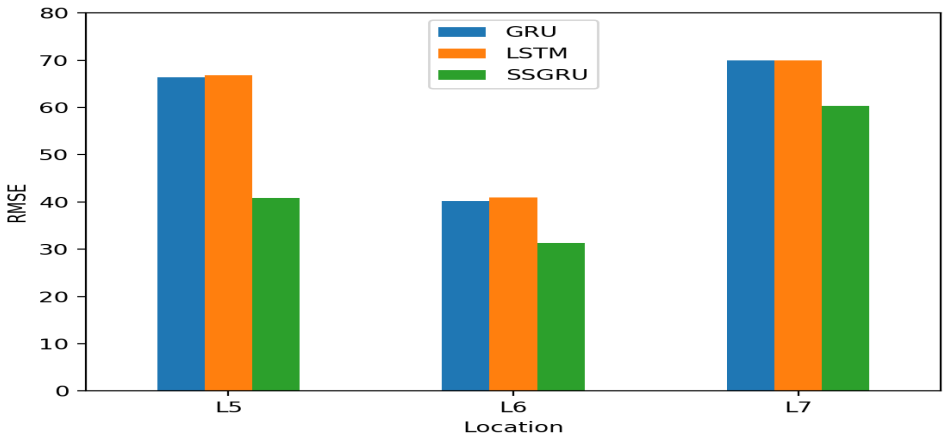


(b) one-day traffic flow prediction for $L6$

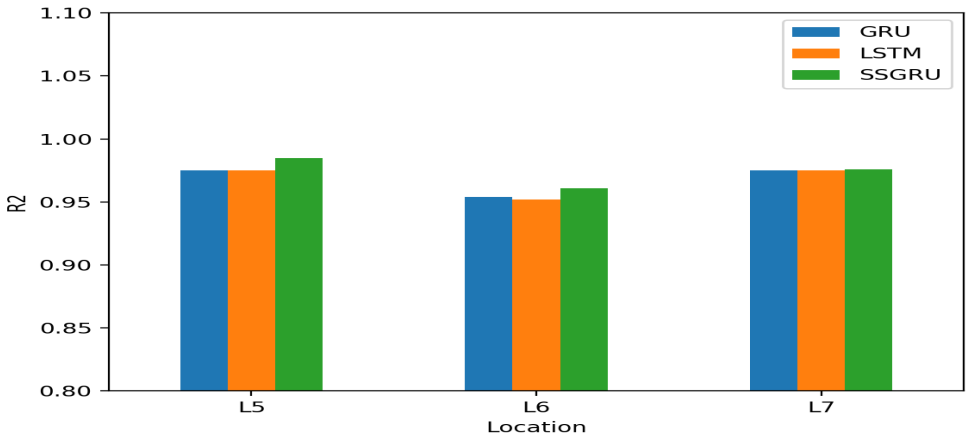


(c) one-day traffic flow prediction for $L7$

Figure 4.4: Comparison of Three models for $L7$, $L6$, $L5$

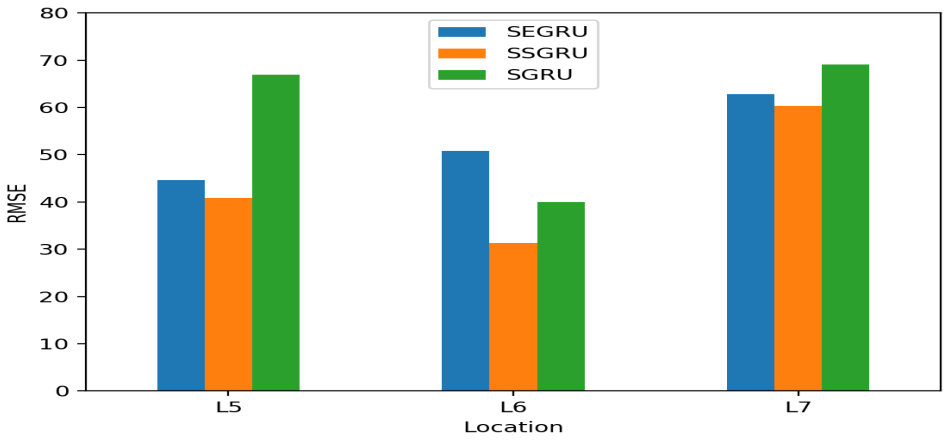


(a) RMSE

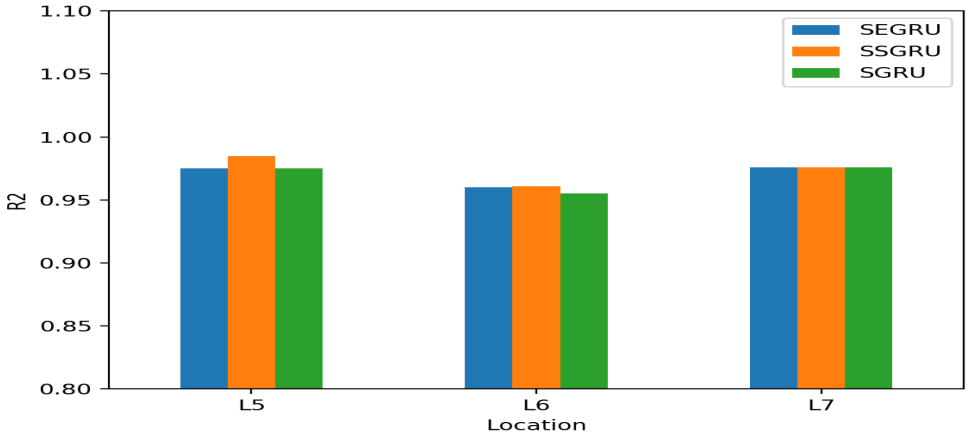


(b) r^2

Figure 4.5: RMSE and r^2 for LSTM, GRU and SSGRU



(a) RMSE



(b) r^2

Figure 4.6: RMSE and r^2 for SEGRU, SGRU and SSGRU

number of gating controls in GRU, the computational complexity is significantly reduced compared with LSTM but with a much better result in my study. In general, this new model is simple, high efficiency and low computational complexity, and last but not least, it conducts prediction from a network perspective instead of an individual one, which is more practical in real life. In fact, with the development of ITS, reliable traffic flow predictions for the urban areas become significant because this information can greatly facilitate traffic management. However, the more complicated urban road features make it is difficult to achieve, so in the next chapter, an innovative approach will be proposed to solve this problem.

Chapter 5

A Delay-Based Deep Learning Approach for Traffic Volume Prediction on a Road Network

Based on the DSTARMA and SSGRU introduced before, a delay-based deep learning framework (MDGRU) will be proposed to improve the accuracy of the short-term traffic flow prediction, in which travel delay is handled in the form of a weighted matrix enrolled into a multivariate input stacked Recurrent Neural Network (RNN). Multivariate input makes this approach has a stronger mining ability for spatial relationships capture, and the stacked structure leads to a more accurate pattern learning process. Moreover, urban and suburban road networks are both tested in this chapter, and the results show that my approach is accurate and reliable.

5.1 Problem statement

Most of the previous studies related to the short-term traffic flow predictions are based on the single road, in which spatial correlations are lost. Therefore, how to improve the accuracy and efficiency of the volume predictions under a specific road network structure is my main task in this chapter. In particular, for better model adpatability, my study is based on two environments, suburban and urban areas.

5.1.1 Suburban scenario

Traffic patterns in suburban areas are comparatively simple and usually set as a fundamental road context in many traffic flow prediction researches. In this paper, to better describe the spatial information, we adopt a tree structure to modeling the real traffic shape shown in Fig. 5.1, since the on-ramp and off-ramp situations are less seen in suburban highways [117] and too long-distance locations barely affect the aim feature. Also, we assume the traffic flow is single direction only, from top to bottom. For this road structure, 7 locations are set, where the $L7$ is the aim feature, and for each location, it has a corresponding weight to describe the spatial correlations. In fact, there are two level influences have an impact on the aim feature: the first level is coming from the $L1, L2, L3$, and $L4$, and $L5, L6$ generates the second-level effect. To better depicting the spatial relationships among different road segments, a set of weights w_{ab} are employed, and it represents the influence of the La to Lb.

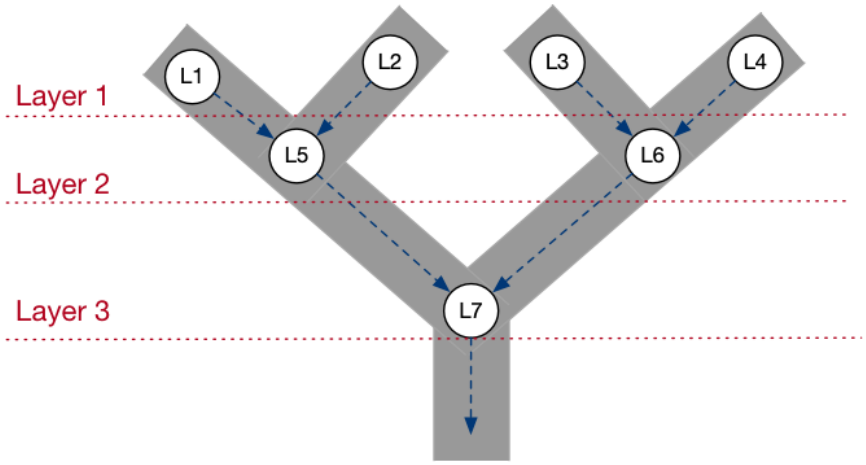


Figure 5.1: Three-layer tree shape unit

When vehicles move from any two neighboring locations, from La to Lb, the time cost is produced, and this time cost is named the travel delay τ_{ab}. With the different distance and speed, travel delay varies. In previous studies, travel delay is neglected, and they more focus on the single road prediction instead of the whole road network. So, how to consider these two issues and further improve the forecasting accuracy and efficiency is my goal in this chapter.

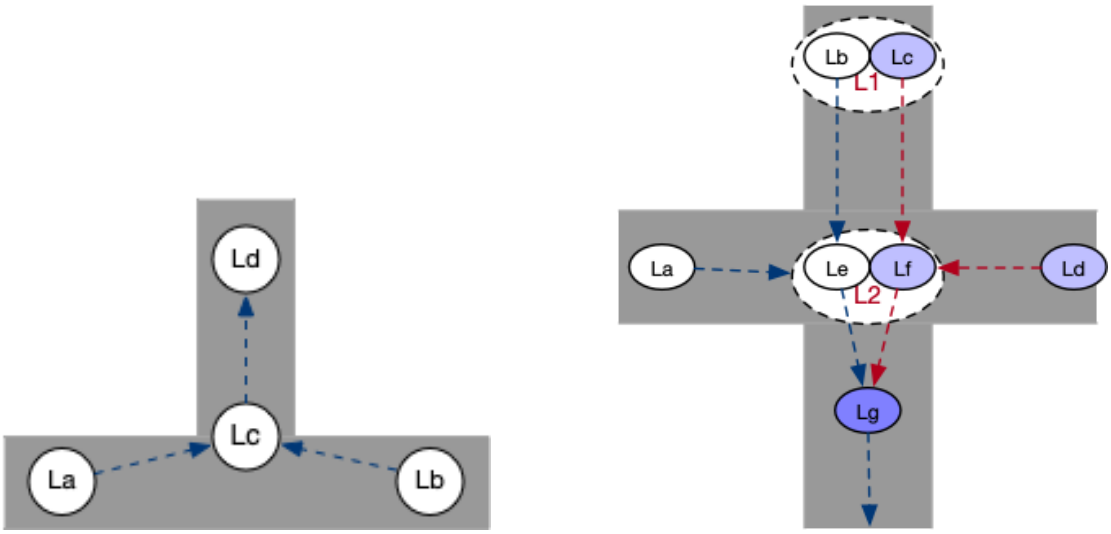
5.1.2 Urban scenario

For the suburban road network, the traffic condition is comparatively simple and easy to describe, so a tree-shape structure is a good model to depict the suburban road networks. However, for the urban road network, the road shapes are more complex, so how to fit this given tree-shaped structure into the urban road network is my primary task, which is accordingly convenient to urban routing and data transmission [121] [2].

In fact, typical urban road structures with m road segments can be decomposed into several binary tree shape units. For example, the T road ($m = 3$) and the crossroad ($m = 4$) can be separated into one and two binary tree units respectively, shown in Fig. 5.2. Further, if expanding the road shape to the star type, the number of binary tree unit N can be calculated based on the equation below.

$$N = \begin{cases} \frac{m-1}{2} & m \in odd, \\ \frac{m}{2} & m \in even, \end{cases} \tag{5.1}$$

in which, $m \geq 3$. For the special case that $m = 1$ or $m = 2$, which is not a road network anymore, and was not in my discussion range.



(a) T-shape Road (b) Cross Road

Figure 5.2: Decomposition of two types of road structure

When in network decomposition, some road segments may be shared by several divided tree units. For example, the crossroad shown in Fig. 5.2, is divided into two binary tree units, and obviously, two middle road segments and four locations are shared. As for the

weights of shared locations, the influence is allocated equally. To be more precise, in this case, a crossroad is separated as tree shape structure, which is the same as the situation in Fig. 3.1. However, Lb, Lc equally share the same location volume, in which $V_b = V_e = 1/2V_1$ and $V_e = V_f = 1/2V_2$. Generally, if there are the number of a shared locations, and the volume recorded by the prober at this area is V_p, so for each shared location, the volume V_{sl} can be calculated as follows.

$$V_{sl} = \frac{1}{a} V_p \tag{5.2}$$

This section illustrates the problem that needs to be resolved, and in the following section, my innovative approaches will be given in a step by step manner.

5.2 Proposed method

My method is based on a deep learning framework, and delay-based GRU is the basic unit in this model, which is used to complete different tasks at different layers. Compared to the shallow learning fashion, deep learning can obtain more patterns and dig out more in-depth information, and this advantage can significantly improve prediction accuracy. Original GRU structure contains two gates, reset gate and update gate respectively. Fewer gates than LSTM makes GRU more efficient in the prediction process but still with the high prediction accuracy. Different from the basic gates in traditional GRU based structures, my MDGRU consists of the two delay-based gates within the three-layer learning structure. What is more, the details for these three RNN units are listed in the Tab. 5.1. As for my two improved gates, they are able to handle the travel delay according to the delay-based weights. So before stepping into the specific MDGRU structures, the concept of delay-based weights, as well as the delay-based GRU, are illustrated, to give a better understanding of MDGRU.

5.2.1 Delay-based Weight

In the previous spatial weights calculation, most of them are worked out in an even fashion. For example, for $L5$ in Fig. 3.1 there are two directly linked locations $L1$ and $L2$ respectively, and contribution weight of each location is average assigned. So the influential from $L1$ to $L5$ (w_{15}) is equal to the $L2$ to the $L5$ (w_{25}), are both 0.5. However, this calculation approach is too naive to fit into the real traffic conditions. In fact, when vehicles move

Table 5.1: Comparision of GRU, LSTM and MDGRU

Unit name	**Gate Number**	**Gate Symble**	**Gate Name**	**Expression**
GRU[122]	2	r, z	r : reset gate z: update gate	$r = \sigma\left(W^{(r)}x_t + U^{(r)}h_{t-1}\right)$ $z = \sigma\left(W^{(z)}x_t + U^{(z)}h_{t-1}\right)$
LSTM[123]	3	i, o, f	i: input gate o: output gate f:forget gate	$i = \sigma\left(W^{(i)}x_t + U^{(i)}c_{t-1}\right)$ $o = \sigma\left(W^{(o)}x_t + U^{(o)}c_{t-1}\right)$ $f = \sigma\left(W^{(f)}x_t + U^{(f)}c_{t-1}\right)$
MDGRU	2	r', z'	r' : delay-based reset gate z: delay-based update gate	$r' = \sigma\left(W^{(r)}\left(x_t \cdot W'\right) + U^{(r)}h_{t-1}\right)$ $z' = \sigma\left(W^{(z)}\left(x_t \cdot W'\right) + U^{(z)}h_{t-1}\right)$

from $L1$ to $L5$, the time cost is produced, and this cost is the travel delay τ, which can be calculated based on the formula shown below.

$$\tau_{ac} = \frac{d_{ac}}{\bar{v}_{ac}} \tag{5.3}$$

, where, d_{ac} is the distance between L_a and L_c, and the average speed is described by the $\bar{v}_{ac}$. Further, assuming the aim feature is Lc, and there only two linked locations nearby, La and Lb. Based on the traffic volume at time t, $V\left(t\right)$, the delay-based weight w' can be obtianed accoding to Eq.(5.4).

$$w'_{ac} = \frac{V_a\left(t - \tau_{ac}\right)}{V_c\left(t\right)} = \frac{V_a\left(t - \tau_{ac}\right)}{V_a\left(t - \tau_{ac}\right) + V_b\left(t - \tau_{bc}\right)} \tag{5.4}$$

After acquiring the delay-based weights, the specific weight matrix $\boldsymbol{w}'$ can be represented. For example, assuming the $L7$ is the aim feature, then its delay-based weight matrix $\boldsymbol{w}'_7$ is as followed.

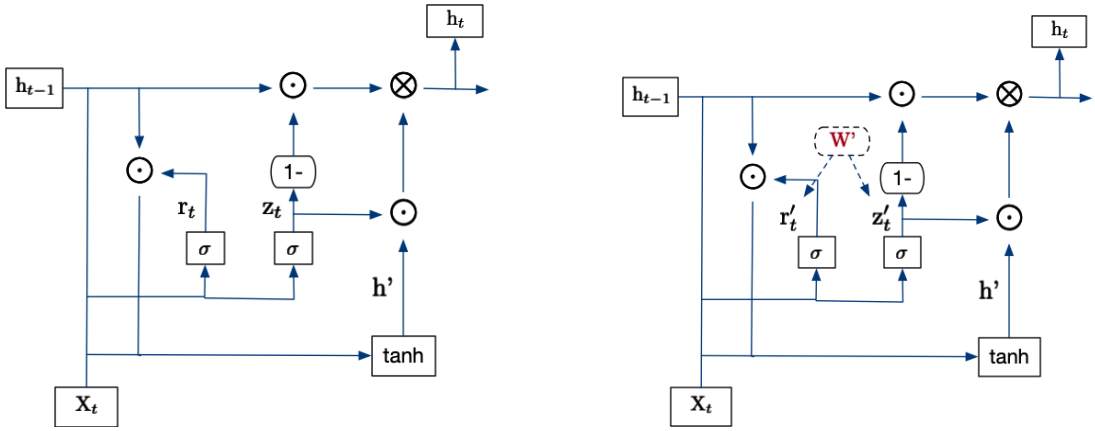
$$\boldsymbol{w}'_{\boldsymbol{7}} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ w'_{17} & w'_{27} & w'_{37} & w'_{47} & w'_{47} & w'_{57} & w'_{67} \end{pmatrix} \tag{5.5}$$

, for which, generally the second level locations such as $L1, L2, L3$ as well as $L4$ have

limited influences on $L7$, due to the off-ramp or on-ramp situations commonly seen in middle locations $L5, L6$. So for further reducing the computation burden, the directly linked features are considered only. And for the whole road network the delay-based matrices is $W' = [\mathbf{w}'_a, \mathbf{w}'_b, \cdots, \mathbf{w}'_n]$, which is comprised of the delay-based weight matrix of all locations.

5.2.2 Delay-based GRU

Different from the ordinary GRU shown in Fig. 5.3, which only contains two gates, r and z. A delay-based GRU introduces the delay-based weight matrix in its control gates, which is based on the followed equations.



(a) Simple GRU structure

(b) Delay-based GRU structure

Figure 5.3: Two types of GRU structures

$$r'_t = \sigma\left(W^{(r)}\left(x_t \cdot W'\right) + U^{(r)} h_{t-1}\right) \tag{5.6}$$

$$z'_t = \sigma\left(W^{(z)}\left(x_t \cdot W'\right) + U^{(z)} h_{t-1}\right) \tag{5.7}$$

$$h_t = z'_t \odot h_{t-1} + (1 - z'_t) \odot h' \tag{5.8}$$

, in which the σ is a function that transforms data between 0 to 1, and $\odot$ is the Hadamard Product. Moreover, $W^{(r)}$, $W^{(z)}$ and $U^{(r)}$, $U^{(z)}$ are the original weights related to the two control gates.

5.2.3 MDGRU

To tackle the travel delay in a more sensible and efficient way, Multivariate Delay-based GRU (MDGRU) is given. By adding a delay based weight in each GRU, and canceling the data preprocessing system used by many previous GRU-based researches, MDGRU is coming out. MDGRU model choose the deep learning as its core prediction structure, and the structure is shown in Fig. 5.4. There are three layers included in this structure, in which the first layer is hired to handle the spatial relationships, and the second layer is to temporal patterns mining. The last layers are for reshape and output final result.

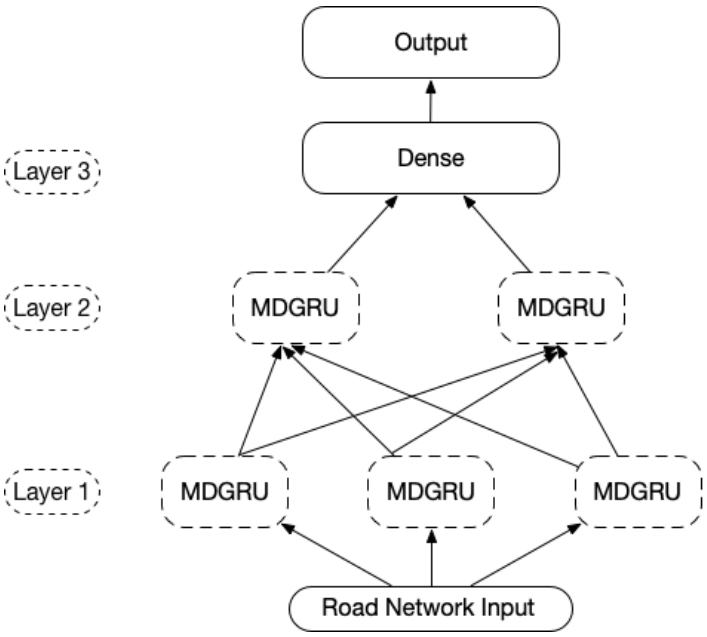


Figure 5.4: MDGRU structure

Compared with the most deep learning models, MDGRU is more compact, which gets rid of the data-preprocessing system and disposes of the raw data directly. The dimension of the dataset is gradually reduced, where precisely, the $n \times t$ input matrice is fed, and after the first layer disposal, the dimension is down to $3 \times t$. And then the $2 \times t$ matrice produced by Layer 2 is reshaped by the dense layer, and finally, a $1 \times t$ prediction vector is prepared for output.

For this optimized system that is based on the trial-and-error method, the traffic flow of an intact road network can be efficiently used to make a short-term traffic flow prediction. By replacing the GRU to the delay-based GRU as its main prediction unit, and based on a deep learning structure, MDGRU has ability to not only prediction the whole road network, but also solve the travel delay problem.

5.3 Verification

To further test my innovative methods, in this section, a case study is implemented. My proposed methods, MDGRU is used to predict short-term traffic flow, and two kinds of road conditions are covered as well, urban and suburban road networks in a step-by-step fasion. What is more, some error evaluation figures such as mean absolute error (MAE), the square of the sample correlation coefficient r-square (r^2) and Root Mean Square Error (RMSE) shown in Eq.(5.9)-Eq.(5.11) are employed to judge the model performance at the end.

$$MAE = \frac{\sum_{i=1}^{n} |y_t - x_t|}{n} \tag{5.9}$$

$$RMSE = \sqrt{\overline{(y_t - x_t)^2}} \tag{5.10}$$

$$r^2 = 1 - \frac{\sum_t (x_t - y_t)^2}{\sum_t (x_t - \bar{x}_t)^2} \tag{5.11}$$

5.3.1 Suburban scenario

5.3.1.1 Dataset

The used suburban data source is based on the England highway system, and 15-min interval traffic flow is adopted, and they cover all Wednesdays in May 2015 for seven different roads respectively, the same dataset used in Chapter.3.

In addition, since the real travel delay τ is pretty short at the second level, which is almost a real-time value, so the $V_a(t - \tau_{ac})$ can not be obtained directly for the raw dataset. For getting over this problem, the practical traffic volume can be calculated based on the equation below.

$$V_a(t - \tau_{ac}) = \frac{V_a(t) \cdot (15 - \tau_{ac})}{15} + \frac{V_a(t - 15) \cdot \tau_{ac}}{15} \tag{5.12}$$

5.3.1.2 Results for Suburban context

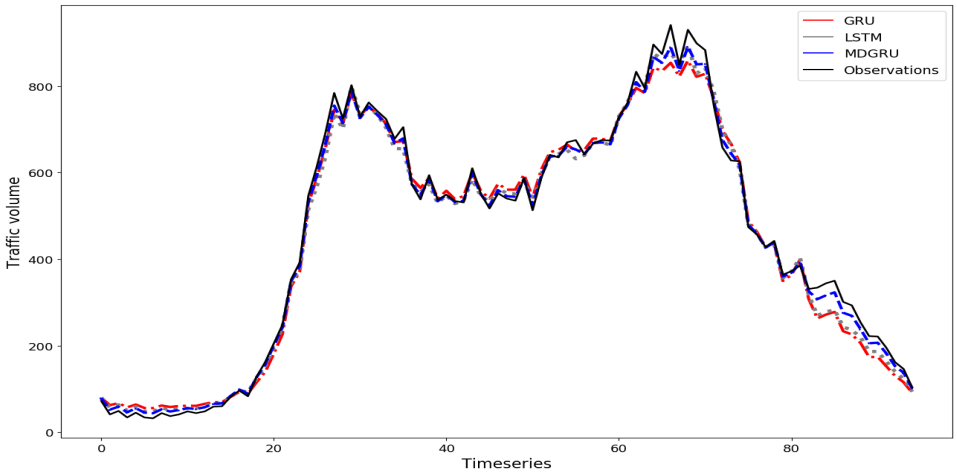
In this study, one-day traffic flow with the 15-min interval of three downstream locations $L5, L6, L7$ are predicted. For further proving the superiority of my method, two popular

and widely used machine learning models, GRU and LSTM are compared under the same situations.

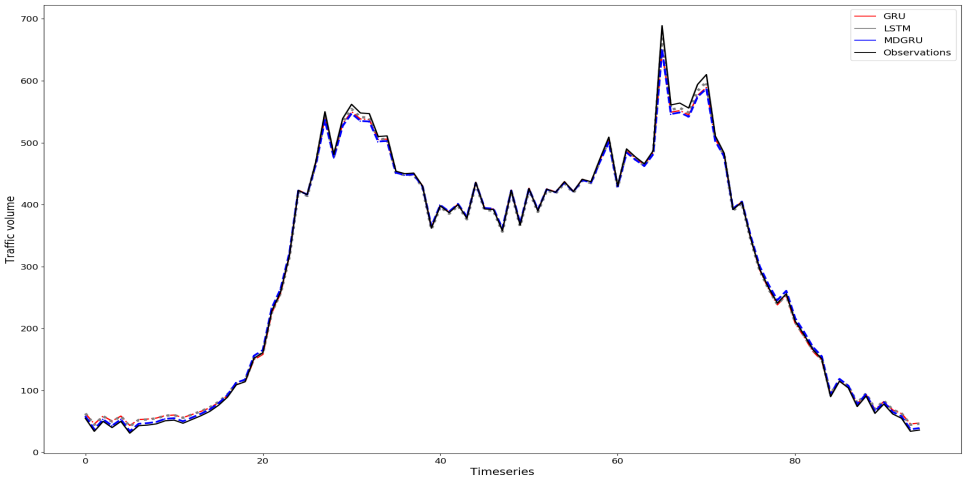
Table 5.2: Prediction Accuracy of Suburban road network

Location	**Model**	**MAE**	**RMSE**	$\mathbf{r^2}$
$L5$	GRU	49.145	66.169	0.975
$L5$	**MDGRU**	**38.128**	**51.689**	**0.986**
$L5$	LSTM	48.819	66.377	0.975
$L6$	GRU	31.683	43.714	0.946
$L6$	**MDGRU**	**28.986**	**40.019**	**0.964**
$L6$	LSTM	33.701	48.742	0.951
$L7$	GRU	49.781	69.480	0.972
$L7$	**MDGRU**	**44.140**	**59.857**	**0.990**
$L7$	LSTM	49.791	69.161	0.974

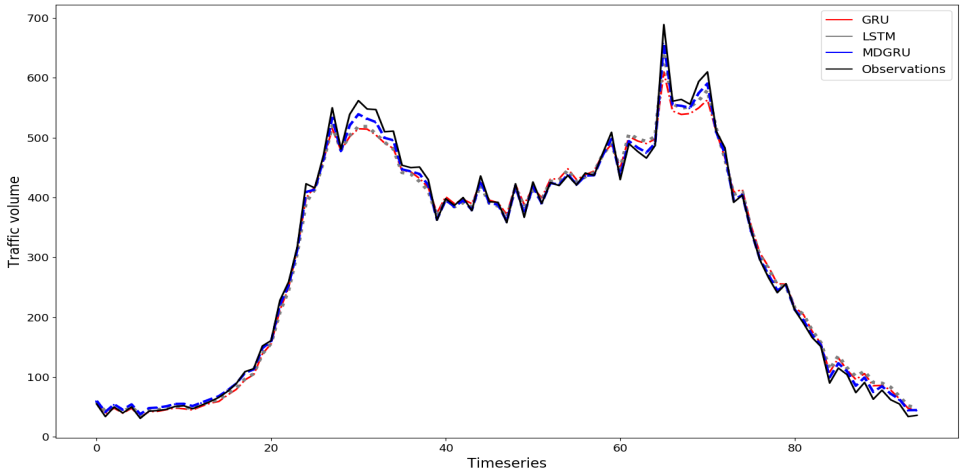
As for the suburban context, the prediction results are shown in Tab. 5.2, and Fig. 5.5, from which it can be found that MDGRU has the highest prediction accuracy for all locations. With nearly 20% decrease of MAE and RMSE in $L5$, MDGRU shows its stronger forecasting ability than the other two methods. Particularly, the r^2 for $L7$ rises up to 0.990, which is pretty close to the 1.0, while GRU and LSTM only reach to 0.972 and 0.974 individually. For the $L6$, MDGRU still has the best prediction accuracy, 28.986 for MAE and 40.019 for RMSE, both lower than values generated by fundamental GRU and LSTM. In addition, for $L6$, it has slightly worse accuracy than $L5$ and $L7$, and the reason for this is that there are more road segments connected with $L6$, so the on-ramp and off-ramp probability are higher than other two locations. From the results shown in Fig. 5.5, it can be found that my MDGRU model has the best performance along all day, especially at the afternoon to midnight period. The reason for this phenominon is that the traffic volume at that time is large, accordingly the patterns are comparatively hard to capture. So, the accuracy of three models at this time period are all decrease with varing degrees. Particularly, the most slight deviation is happend in my MDGRU model, which means my model has the more powerful prediction ability than the others. When compared the general prediction results of three downstream locations, the best fiiting effect is the $L6$, since $L6$ has the least connected road segments nearby and off-ramp (on-ramp) situations.



(a) one-day traffic flow prediction for $L5$



(b) one-day traffic flow prediction for $L6$



(c) one-day traffic flow prediction for $L7$

Figure 5.5: Comparison of three models for $L7$, $L6$, $L5$ under Suburban context

5.3.2 Urban scenario

5.3.2.1 Dataset

The dataset for urban context is also gathered from the England highway system, which includes all Wedneys of March in 2016, the real road structure is shown in Fig. 5.6. As for the specific probes information, it can be found in the Tab. 5.3.

Table 5.3: Location of probers under Urban area

Location	Label	Direction	GPS Ref.
L1	M25/5020B	Southbound	502165;185062
L2	M25/5015M	Southbound	502465;184604
L3	M4/2283K	Westbound	504071;178384
L4	M25/4946M	Westbound	504633;177982
L5	M25/4947B	Southbound	504598;177987
L6	M25/4943B	Westbound	504484;177607
L7	M25/4938B	Southbound	504234;177169

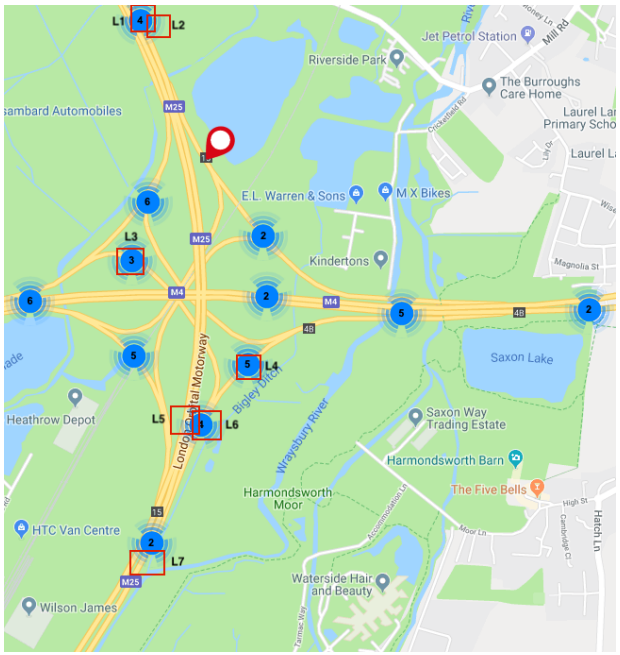


Figure 5.6: Urban Road Network Structure

5.3.2.2 Results for Urban context

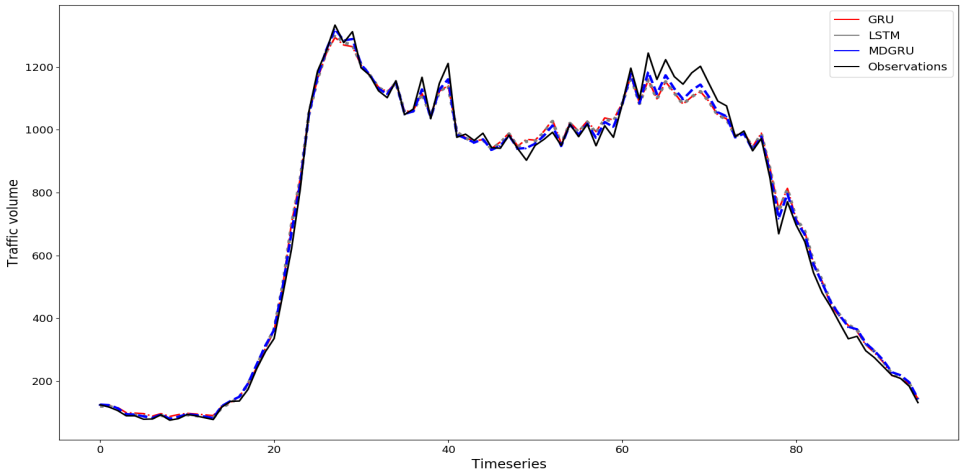
Three methods under the urban road network are also compared, and the result is shown in Tab. 5.4. Compared with the suburban context, the urban road network is more complicated and volatile. However, for the urban context, MDGRU has a bigger improvement than under suburban road condition. With almost 35% and 15% decrease of MAE and RMSE for $L6$ and the other two locations, MDGRU shows its stronger adaptability for unstable conditions. Besides, even though in complex road conditions, the r^2 values produced by MDGRU for three locations are all beyond 0.97, which proves the outstanding stability of my new method.

The prediction curves for urban area in Fig. 5.7 further illustrates the stronger prediction ability of MDGRU. For all three locations, $L5, L6$ and $L7$, MDGRU shows the best fitting effect. The prediction accuracy for these three models on urban context all fall down, due the more complexity prediction enviroments carring more noises and useful information. Even though, compared to GRU and LSTM, my model shows its high reliability, has the slightest deteriorate for all error values amongß three locations.

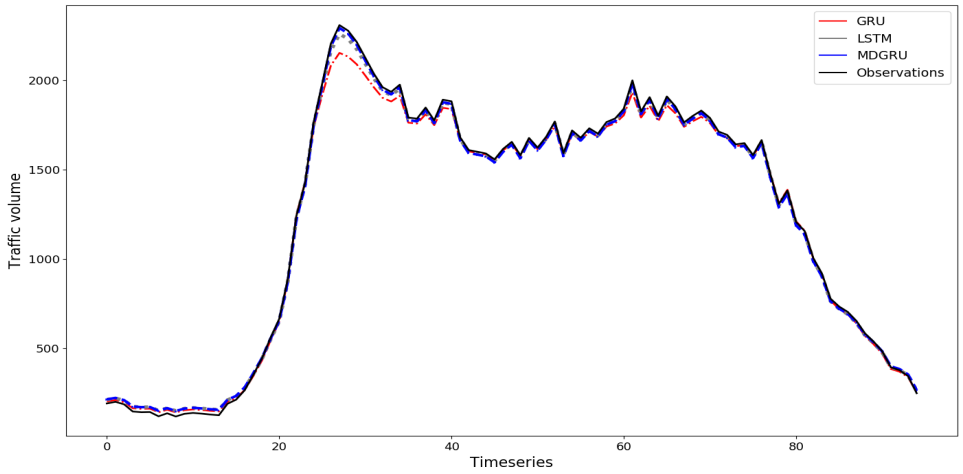
To sum up, the results for both suburban and urban road networks, MDGRU has high accuracy and stable performance, and the improvement for the latter is more obvious. Despite the accuracy for the urban roads are lower than the roads located in suburban area, the r^2 values are all higher than 0.96 by using the MDGRU model; as for another error evaluation standards, MAE and RMSE, the values generated by MDGRU are all greatly lower than the values derived from GRU and LSTM.

5.4 Conclusion

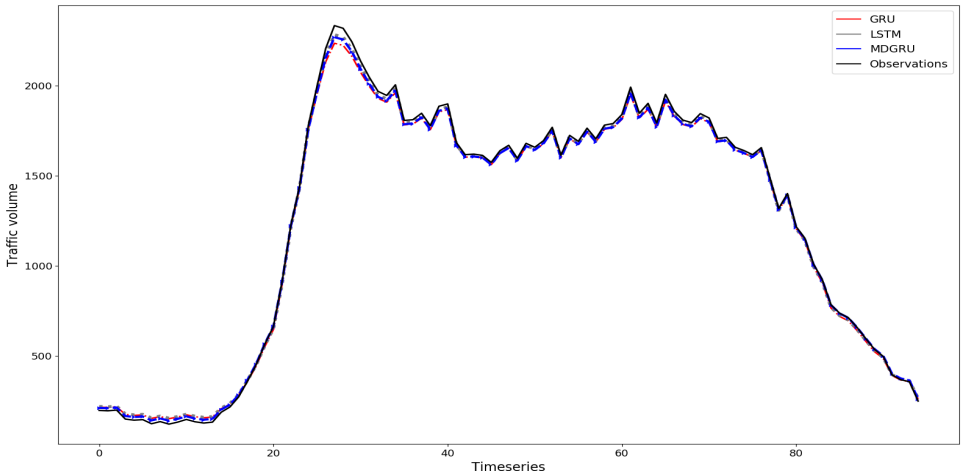
In this chapter, based on the basic GRU, a deep learning model is come up with, namely MDGRU, to solve the travel delay problem in road networks. In my model, the three-layer structure is adopted with a diminishing dimension, for which the first layer is used to mine the spatial correlations and the second layer is responsible for the traffic patterns learning with time. Particularly, my model is an optimized GRU model, which contains mult-task delay-based GRUs. Delay-based weights participate in the prediction process, used to takle the travel delay problem, and they are fed into simple GRU to form the delay-based GRU. Simply, the travel delay is treated as the form of delay-based weight matrice to be fed into the simple GRU, and also the advantage of this proposed model is that it can handle



(a) one-day traffic flow prediction for $L5$



(b) one-day traffic flow prediction for $L6$



(c) one-day traffic flow prediction for $L7$

Figure 5.7: Comparison of three models for $L7$, $L6$, $L5$ under Urban context

Table 5.4: Prediction Accuracy of Urban road network

Location	**Model**	**MAE**	**RMSE**	$\mathbf{r^2}$
$L5$	GRU	58.329	79.612	0.962
$L5$	**MDGRU**	**52.013**	**74.216**	**0.971**
$L5$	LSTM	57.837	79.205	0.963
$L6$	GRU	80.282	108.916	0.974
$L6$	**MDGRU**	**53.179**	**73.198**	**0.977**
$L6$	LSTM	80.298	107.842	0.974
$L7$	GRU	80.354	107.575	0.964
$L7$	**MDGRU**	**69.258**	**90.282**	**0.974**
$L7$	LSTM	80.252	108.469	0.972

the whole road network dataset just one time and no need to do any pre-processing data works. Compared with previous short-term traffic flow prediction studies, MDGRU model has a more simple structure but higher efficiency.

For better illustrating the great adaptability and stability for most of the road networks, two kinds of road contexts are employed, roads in suburban and urban areas. Different from the simplicity of suburban road shape, in the urban area, the shapes of which are more complex. The introduce of binary tree unit is greatly deal with this problem through the road network decomposition. Generally, most of the commonly seen road shapes can be separated into several binary tree units, and the final impact is the sum of influence from these units. Through a 15-min traffic flow prediction by using three test models, GRU, LSTM, and MDGRU, respectively, the superiority of my MDGRU is shown. To be more specific, the three error evaluation figures MAE, RMSE and r^2 of MDGRU are all the lowest among three models for both two road conditions.

This method not only figures out the travel delay problem in most of the road networks but simplify the deep learning inner structure. By using this method, the prediction accuracy is obviously improved, and the computation cost is reduced at the same time. Particularly, for making approach more general, it is extended to urban road networks, and the experiment shows its great adaptability. In my study, due to the limitation of a valid dataset, the experiment only based on the three-week traffic flow data, so for the future work, the data source can be more abundant. Also, bi-direction traffic flow is a potential problem that may affect prediction accuracy, which is deserved to discuss.

Chapter 6

Conclusion and Future Work

In this thesis, three models are proposed to improve the spatiotemporal feature mining ability and adaptability for both statistical-based and ML-based models. In the first model, based on the statistics model (VARIMA) and considers travel delay, DSTARIMA dramatically improves the classic statistic-based models feature capture ability, especially for non-linear patterns. The results show it has higher prediction accuracy than other classic statistic-based models. To further enhance the adaptability of ML-based models, SSGRU is designed, in which a data preprocessing system is introduced, and the whole training process is under a deep learning structure. As for the final scheme, MDGRU, which is inspired by the SSGRU and DSTARIMA. Notably, this model considers the travel delay, and moreover, it extends the prediction scenario to a more complicated road environment, which makes this model have better adaptability and more practical in the real world.

Although the proposed three models enhance the model feature mining ability and adaptability to some extent, there are still many potential works for the future. The first one is to reduce the model complexity in a proper way. To be more precise, model complexity generally can be judged from two aspects, the structure complexity, and computation complexity. Ordinarily, with the increase of model structure complexity, the computation complexity will rise accordingly. In fact, the hybrid models are leading a new trend, but in some models, improperly combination of too many algorithms gives much burden on prediction procedure and causes a low prediction efficiency and accuracy. The second one is finding a more reliable data source and properly fixing the flaw dataset. The limitation of the valid data source is another problem needed to be solved, for which data missing as well as error are main concerns [124]. Currently, they are many data sources used in traffic flow predictions, such as Highways England [115], Caltrans Performance Measurement

System (PeMs) [125], Maryland 511 (MD) [126], etc. However, the traffic flow interval of these data sources is generally based on the 15-min, which also is a limitation for shorter interval studies. Besides, how to adapt these three models into hybrid city road networks that involve highways and paths is also a potential work in the future.

To sum up, in this thesis both statistic-based and ML-based models are improved within two aspects, the model mining ability, and adaptability. Besides, some fundamental concepts and potential future works about the short-term traffic flow predictions are also briefly illustrated at the very beginning and at the end respectively.

References

[1] Maram Bani Younes and Azzedine Boukerche. A performance evaluation of an efficient traffic congestion detection protocol (ecode) for intelligent transportation systems. *Ad Hoc Networks*, 24:317–336, 2015.

[2] Hengheng Xie, Azzedine Boukerche, and Antonio AF Loureiro. A multipath video streaming solution for vehicular networks with link disjoint and node-disjoint. *IEEE Transactions on Parallel and Distributed Systems*, 26(12):3223–3235, 2014.

[3] Azzedine Boukerche, Jan M Correa, Alba Cristina Magalhaes Melo, and Ricardo P Jacobi. A hardware accelerator for the fast retrieval of dialign biological sequence alignments in linear space. *IEEE Transactions on Computers*, 59(6):808–821, 2010.

[4] Azzedine Boukerche, Richard WN Pazzi, and Jing Feng. An end-to-end virtual environment streaming technique for thin mobile devices over heterogeneous networks. *Computer Communications*, 31(11):2716–2725, 2008.

[5] Abdelhamid Mammeri, Azzedine Boukerche, and Zongzhi Tang. A real-time lane marking localization, tracking and communication system. *Computer Communications*, 73:132–143, 2016.

[6] Abdelhamid Mammeri, Azzedine Boukerche, and Guangqian Lu. Lane detection and tracking system based on the mser algorithm, hough transform and kalman filter. In *Proceedings of the 17th ACM international conference on Modeling, analysis and simulation of wireless and mobile systems*, pages 259–266, 2014.

[7] Cesar Hernandez, Diego Giral, and Fredy Martinez. Radioelectric spectrum prediction based in arima and sarima time series models. *International Journal of Applied Engineering Research*, 13(22):15688–15695, 2018.

[8] Azzedine Boukerche, Horacio ABF Oliveira, Eduardo F Nakamura, and Antonio AF Loureiro. Localization systems for wireless sensor networks. *IEEE wireless Communications*, 14(6):6–12, 2007.

[9] A Boukerch, Li Xu, and Khalil El-Khatib. Trust-based security for wireless ad hoc and sensor networks. *Computer Communications*, 30(11-12):2413–2427, 2007.

[10] Hirotugu Akaike. A new look at the statistical model identification. In *Selected Papers of Hirotugu Akaike*, pages 215–222. Springer, 1974.

[11] Chris Chatfield. *The analysis of time series: an introduction*. Chapman and Hall/CRC, 2016.

[12] William D Penny. Comparing dynamic causal models using aic, bic and free energy. *Neuroimage*, 59(1):319–330, 2012.

[13] Paul B Wigley, Patrick J Everitt, Anton van den Hengel, JW Bastian, Mahasen A Sooriyabandara, Gordon D McDonald, Kyle S Hardman, CD Quinlivan, P Manju, Carlos CN Kuhn, et al. Fast machine-learning online optimization of ultra-cold-atom experiments. *Scientific reports*, 6:25890:1–6, 2016.

[14] Dean Croushore. Frontiers of real-time data analysis. *Journal of economic literature*, 49(1):72–100, 2011.

[15] Nicholas G. Polson and Vadim O. Sokolov. Deep learning for short-term traffic flow prediction. *Transportation Research Part C: Emerging Technologies*, 79(Supplement C):1–17, 2017.

[16] Douglas M Hawkins. The problem of overfitting. *Journal of chemical information and computer sciences*, 44(1):1–12, 2004.

[17] Harry Fisch, Grace Hyun, Robert Golden, Terry W Hensle, Carl A Olsson, and Gary L Liberson. The influence of paternal age on down syndrome. *The Journal of urology*, 169(6):2275–2278, 2003.

[18] Erich L Lehmann and George Casella. *Theory of point estimation*. Springer Science & Business Media, 2006.

[19] Arnaud De Myttenaere, Boris Golden, Bénédicte Le Grand, and Fabrice Rossi. Mean absolute percentage error for regression models. *Neurocomputing*, 192:38–48, 2016.

[20] Tianfeng Chai and Roland R Draxler. Root mean square error (rmse) or mean absolute error (mae)?–arguments against avoiding rmse in the literature. *Geoscientific model development*, 7(3):1247–1250, 2014.

[21] Salvador García, Alberto Fernández, Julián Luengo, and Francisco Herrera. A study of statistical techniques and performance measures for genetics-based machine learning: accuracy and interpretability. *Soft Computing*, 13(10):959, 2009.

[22] Hirotugu Akaike. Autoregressive model fitting for control. In *Selected Papers of Hirotugu Akaike*, pages 153–170. Springer, 1998.

[23] James Durbin. Efficient estimation of parameters in moving-average models. *Biometrika*, 46(3/4):306–316, 1959.

[24] Wen-chuan Wang, Kwok-wing Chau, Dong-mei Xu, and Xiao-Yun Chen. Improving forecasting accuracy of annual runoff time series using arima based on eemd decomposition. *Water Resources Management*, 29(8):2655–2675, 2015.

[25] Mohammad Valipour. Long-term runoff study using sarima and arima models in the united states. *Meteorological Applications*, 22(3):592–598, 2015.

[26] Ping-Feng Pai and Chih-Sheng Lin. A hybrid arima and support vector machines model in stock price forecasting. *Omega*, 33(6):497–505, 2005.

[27] Osamah Basheer Shukur and Muhammad Hisyam Lee. Daily wind speed forecasting through hybrid kf-ann model based on arima. *Renewable Energy*, 76:637–647, 2015.

[28] Marco Lippi, Matteo Bertini, and Paolo Frasconi. Short-term traffic flow forecasting: An experimental comparison of time-series analysis and supervised learning. *IEEE Transactions on Intelligent Transportation Systems*, 14(2):871–882, 2013.

[29] Sangsoo Lee and Daniel B Fambro. Application of subset autoregressive integrated moving average model for short-term freeway traffic volume forecasting. *Transportation Research Record*, 1678(1):179–188, 1999.

[30] Ni Lihua, Chen Xiaorong, and Huang Qian. Arima model for traffic flow prediction based on wavelet analysis. In *The 2nd International Conference on Information Science and Engineering*, pages 1028–1031. IEEE, 2010.

[31] Guoqiang Yu and Changshui Zhang. Switching arima model based forecasting for traffic flow. In *2004 International Conference on Acoustics, Speech, and Signal Processing*, volume 2, pages 429–432. IEEE, 2004.

[32] Honghui Dong, Limin Jia, Xiaoliang Sun, Chenxi Li, and Yong Qin. Road traffic flow prediction with a time-oriented arima model. In *2009 Fifth International Joint Conference on INC, IMS and IDC*, pages 1649–1652. IEEE, 2009.

[33] Chenyi Chen, Jianming Hu, Qiang Meng, and Yi Zhang. Short-time traffic flow prediction with arima-garch model. In *2011 IEEE Intelligent Vehicles Symposium (IV)*, pages 607–612. IEEE, 2011.

[34] Mascha Van Der Voort, Mark Dougherty, and Susan Watson. Combining kohonen maps with arima time series models to forecast traffic flow. *Transportation Research Part C: Emerging Technologies*, 4(5):307–318, 1996.

[35] Jianhua Guo, Wei Huang, and Billy M Williams. Adaptive kalman filter approach for stochastic short-term traffic flow rate prediction and uncertainty quantification. *Transportation Research Part C: Emerging Technologies*, 43:50–64, 2014.

[36] Xianglong Luo, Liyao Niu, and Shengrui Zhang. An algorithm for traffic flow prediction based on improved sarima and ga. *KSCE Journal of Civil Engineering*, 22(10):4107–4115, 2018.

[37] Fan Zhang, Robson E De Grande, and Azzedine Boukerche. Accuracy analysis of short-term traffic flow prediction models for vehicular clouds. In *Proceedings of the 13th ACM Symposium on Performance Evaluation of Wireless Ad Hoc, Sensor, & Ubiquitous Networks*, pages 19–26. ACM, 2016.

[38] Wanli Min and Laura Wynter. Real-time road traffic prediction with spatio-temporal correlations. *Transportation Research Part C: Emerging Technologies*, 19(4):606–616, 2011.

[39] Yao-Jan Wu, Feng Chen, Chang-Tien Lu, and Shu Yang. Urban traffic flow prediction using a spatio-temporal random effects model. *Journal of Intelligent Transportation Systems*, 20(3):282–293, 2016.

[40] Dmitry Pavlyuk. Short-term traffic forecasting using multivariate autoregressive models. *Procedia Engineering*, 178:57–66, 2017.

[41] Mohamed El Esawey. Estimation of daily bicycle traffic volumes using spatiotemporal relationships. *Journal of Transportation Engineering, Part A: Systems*, 143(11):04017056:1–11, 2017.

[42] Everette S Gardner Jr. Exponential smoothing: The state of the art—part ii. *International journal of forecasting*, 22(4):637–666, 2006.

[43] M Xie, GY Hong, and C Wohlin. A study of the exponential smoothing technique in software reliability growth prediction. *Quality and reliability engineering international*, 13(6):347–353, 1997.

[44] Ahmad Nazim and Asyraf Afthanorhan. A comparison between single exponential smoothing (ses), double exponential smoothing (des), holt's (brown) and adaptive response rate exponential smoothing (arres) techniques in forecasting malaysia population. *Global Journal of Mathematical Analysis*, 2(4):276–280, 2014.

[45] Hao-Fan Yang, Tharam S Dillon, Elizabeth Chang, and Yi-Ping Phoebe Chen. Optimized configuration of exponential smoothing and extreme learning machine for traffic flow forecasting. *IEEE Transactions on Industrial Informatics*, 15(1):23–34, 2019.

[46] Kit Yan Chan, Tharam S Dillon, Jaipal Singh, and Elizabeth Chang. Neural-network-based models for short-term traffic flow forecasting using a hybrid exponential smoothing and levenberg–marquardt algorithm. *IEEE Transactions on Intelligent Transportation Systems*, 13(2):644–654, 2012.

[47] Kit Yan Chan, TS Dillon, J Singh, and Elizabeth Chang. Traffic flow forecasting neural networks based on exponential smoothing method. In *2011 6th IEEE Conference on Industrial Electronics and Applications*, pages 376–381. IEEE, 2011.

[48] Kaouther Abrougui, Azzedine Boukerche, and Richard Werner Nelem Pazzi. Design and evaluation of context-aware and location-based service discovery protocols for vehicular networks. *IEEE Transactions on Intelligent Transportation Systems*, 12(3):717–735, 2011.

[49] Azzedine Boukerche, Ioannis Chatzigiannakis, and Sotiris Nikoletseas. A new energy efficient and fault-tolerant protocol for data propagation in smart dust networks using varying transmission range. *Computer communications*, 29(4):477–489, 2006.

[50] Aleksander Sładkowski and Wiesław Pamuła. *Intelligent transportation systems-problems and perspectives*, volume 303. Springer, 2016.

[51] Omar Y Al-Jarrah, Paul D Yoo, Sami Muhaidat, George K Karagiannidis, and Kamal Taha. Efficient machine learning for big data: A review. *Big Data Research*, 2(3):87–93, 2015.

[52] Kevin Beyer, Jonathan Goldstein, Raghu Ramakrishnan, and Uri Shaft. When is "nearest neighbor" meaningful? In *International conference on database theory*, pages 217–235. Springer, 1999.

[53] Mark A Friedl and Carla E Brodley. Decision tree classification of land cover from remotely sensed data. *Remote sensing of environment*, 61(3):399–409, 1997.

[54] Bin Yu, Xiaolin Song, Feng Guan, Zhiming Yang, and Baozhen Yao. k-nearest neighbor model for multiple-time-step prediction of short-term traffic condition. *Journal of Transportation Engineering*, 142(6):04016018:1–10, 2016.

[55] Simon Oh, Young-Ji Byon, and Hwasoo Yeo. Improvement of search strategy with k-nearest neighbors approach for traffic state prediction. *IEEE Transactions on Intelligent Transportation Systems*, 17(4):1146–1156, 2015.

[56] Ming Ni. Using social media to predict traffic flow under special event conditions. Master's thesis, University at Buffalo, 2013.

[57] Lun Zhang, Qiuchen Liu, Wenchen Yang, Nai Wei, and Decun Dong. An improved k-nearest neighbor model for short-term traffic flow prediction. *Procedia-Social and Behavioral Sciences*, 96:653–662, 2013.

[58] Filmon G Habtemichael and Mecit Cetin. Short-term traffic flow rate forecasting based on identifying similar traffic patterns. *Transportation research Part C: emerging technologies*, 66:61–78, 2016.

[59] Hongyu Sun, Henry X Liu, Heng Xiao, Rachel R He, and Bin Ran. Short term traffic forecasting using the local linear regression model. In *82nd Annual Meeting of the Transportation Research Board*, 2003.

[60] Marti A. Hearst, Susan T Dumais, Edgar Osuna, John Platt, and Bernhard Scholkopf. Support vector machines. *IEEE Intelligent Systems and their applications*, 13(4):18–28, 1998.

[61] Haowei Su, Ling Zhang, and Shu Yu. Short-term traffic flow prediction based on incremental support vector regression. In *Third International Conference on Natural Computation*, volume 1, pages 640–645. IEEE, 2007.

[62] Manchun TAN, Yingjun LI, and Jianmin XU. A hybrid arima and svm model for traffic flow prediction based on wavelet denoising. *Journal of Highway and Transportation Research and Development*, 7:126–133, 2009.

[63] QH Xu and Rui Yang. Traffic flow prediction using support vector machine based method. *Journal of Highway and Transportation Research and Development*, 22(12):131–134, 2005.

[64] Xinxin Feng, Xianyao Ling, Haifeng Zheng, Zhonghui Chen, and Yiwen Xu. Adaptive multi-kernel svm with spatial–temporal correlation for short-term traffic flow prediction. *IEEE Transactions on Intelligent Transportation Systems*, 20(6):2001–2013, 2018.

[65] Zengxiao Chi and Lin Shi. Short-term traffic flow forecasting using arima-svm algorithm and r. In *2018 5th International Conference on Information Science and Control Engineering*, pages 517–522. IEEE, 2018.

[66] Chih-Chung Chang and Chih-Jen Lin. Libsvm: A library for support vector machines. *ACM Trans. Intell. Syst. Technol.*, 2(3):27:1–27, 2011.

[67] Zhifeng Hao, Shu Yu, Xiaowei Yang, Feng Zhao, Rong Hu, and Yanchun Liang. Online ls-svm learning for classification problems based on incremental chunk. In *International Symposium on Neural Networks*, pages 558–564. Springer, 2004.

[68] Andrej Karpathy, Justin Johnson, and Li Fei-Fei. Visualizing and understanding recurrent networks. [Online]. Available: https://arxiv.org/abs/1506.02078, Jun 2015. Accessed on: Sept., 2019.

[69] Zhiyong Cui, Kristian Henrickson, Ruimin Ke, and Yinhai Wang. Traffic graph convolutional recurrent neural network: A deep learning framework for network-scale traffic learning and forecasting. [Online]. Available: https://arxiv.org/abs/1802.07007, Nov. 2018. Accessed on: Sept., 2019.

[70] Yipeng Liu, Haifeng Zheng, Xinxin Feng, and Zhonghui Chen. Short-term traffic flow prediction with conv-lstm. In *2017 9th International Conference on Wireless Communications and Signal Processing*, pages 1–6. IEEE, 2017.

[71] Zheng Zhao, Weihai Chen, Xingming Wu, Peter CY Chen, and Jingmeng Liu. Lstm network: a deep learning approach for short-term traffic forecast. *IET Intelligent Transport Systems*, 11(2):68–75, 2017.

[72] Yuankai Wu, Huachun Tan, Lingqiao Qin, Bin Ran, and Zhuxi Jiang. A hybrid deep learning based traffic flow prediction method and its understanding. *Transportation Research Part C: Emerging Technologies*, 90:166–180, 2018.

[73] Bo Zhao and Xinran Zhang. A parallel-res gru architecture and its application to road network traffic flow forecasting. In *Proceedings of 2018 International Conference on Big Data Technologies*, pages 79–83. ACM, 2018.

[74] Razvan Pascanu, Tomas Mikolov, and Yoshua Bengio. On the difficulty of training recurrent neural networks. In *International conference on machine learning*, pages 1310–1318, 2013.

[75] Yongxue Tian and Li Pan. Predicting short-term traffic flow by long short-term memory recurrent neural network. In *2015 IEEE international conference on smart city/SocialCom/SustainCom (SmartCity)*, pages 153–158. IEEE, 2015.

[76] Danqing Kang, Yisheng Lv, and Yuan-yuan Chen. Short-term traffic flow prediction with lstm recurrent neural network. In *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*, pages 1–6. IEEE, 2017.

[77] Rui Fu, Zuo Zhang, and Li Li. Using lstm and gru neural network methods for traffic flow prediction. In *2016 31st Youth Academic Annual Conference of Chinese Association of Automation (YAC)*, pages 324–328. IEEE, 2016.

[78] Shengdong Du, Tianrui Li, Xun Gong, and Shi-Jinn Horng. A hybrid method for traffic flow forecasting using multimodal deep learning. [Online]. Available: https://arxiv.org/abs/1803.02099, Mar. 2019. Accessed on: Sept., 2019.

[79] aguang Li, Rose Yu, Cyrus Shahabi, and Yan Liu. Diffusion convolutional recurrent neural network: Data-driven traffic forecasting. [Online]. Available: https://arxiv.org/abs/1707.01926, Feb. 2018. Accessed on: Sept., 2019.

[80] Huaxiu Yao, Xianfeng Tang, Hua Wei, Guanjie Zheng, Yanwei Yu, and Zhenhui Li. Modeling spatial-temporal dynamics for traffic prediction. *arXiv preprint arXiv:1803.01254*, 2018.

[81] Brian L Smith and Michael J Demetsky. Short-term traffic flow prediction models-a comparison of neural network and nonparametric regression approaches. In *Proceedings of IEEE International Conference on Systems, Man and Cybernetics*, volume 2, pages 1706–1709. IEEE, 1994.

[82] Wenhao Huang, Guojie Song, Haikun Hong, and Kunqing Xie. Deep architecture for traffic flow prediction: deep belief networks with multitask learning. *IEEE Transactions on Intelligent Transportation Systems*, 15(5):2191–2201, 2014.

[83] Eleni I Vlahogianni, Matthew G Karlaftis, and John C Golias. Temporal evolution of short-term urban traffic flow: a nonlinear dynamics approach. *Computer-Aided Civil and Infrastructure Engineering*, 23(7):536–548, 2008.

[84] Ming-bao Pang and Xin-ping Zhao. Traffic flow prediction of chaos time series by using subtractive clustering for fuzzy neural network modeling. In *2008 Second International Symposium on Intelligent Information Technology Application*, pages 23–27. IEEE, 2008.

[85] Alessandro Attanasi, Lorenzo Meschini, Marco Pezzulla, Gaetano Fusco, Guido Gentile, and Natalia Isaenko. A hybrid method for real-time short-term predictions of traffic flows in urban areas. In *2017 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*, pages 878–883. IEEE, 2017.

[86] Danping Wang, Kunyuan Hu, Maowei He, and Hanning Chen. Cooperative differential evolution with dynamical population for short-term traffic flow prediction problem. *International Journal of Performability Engineering*, 14(4):785–794, 2018.

[87] Dongjie Zhu, Haiwen Du, Yundong Sun, and Ning Cao. Research on path planning model based on short-term traffic flow prediction in intelligent transportation system. *Sensors*, 18(12):4275:1–15, 2018.

[88] Yisheng Lv, Yanjie Duan, Wenwen Kang, Zhengxi Li, and Fei-Yue Wang. Traffic flow prediction with big data: a deep learning approach. *IEEE Transactions on Intelligent Transportation Systems*, 16(2):865–873, 2015.

[89] Junwei Ge, Chun Yang, and Yiqiu Fang. Recommended algorithm of latent factor model fused with user clustering. In *2018 3rd International Conference on Automation, Mechanical Control and Computational Engineering*, 2018.

[90] Andrew C Harvey. *Forecasting, structural time series models and the Kalman filter*. Cambridge university press, 1990.

[91] Mohinder S Grewal. *Kalman filtering*. Springer, 2011.

[92] Hui Liu, Hong-qi Tian, and Yan-fei Li. Comparison of two new arima-ann and arima-kalman hybrid methods for wind speed prediction. *Applied Energy*, 98:415–424, 2012.

[93] SR Stein and John Evans. The application of kalman filters and arima models to the study of time prediction errors of clocks for use in the defense communication system (dcs). In *44th Annual Symposium on Frequency Control*, pages 630–635. IEEE, 1990.

[94] Yuanchang Xie, Yunlong Zhang, and Zhirui Ye. Short-term traffic volume forecasting using kalman filter with discrete wavelet decomposition. *Computer-Aided Civil and Infrastructure Engineering*, 22(5):326–334, 2007.

[95] Luis Leon Ojeda, Alain Y Kibangou, and Carlos Canudas De Wit. Adaptive kalman filtering for multi-step ahead traffic flow prediction. In *2013 American Control Conference*, pages 4724–4729. IEEE, 2013.

[96] Selvaraj Vasantha Kumar. Traffic flow prediction using kalman filtering technique. *Procedia Engineering*, 187:582–587, 2017.

[97] Samuel Karlin. *A first course in stochastic processes*. Academic press, 2014.

[98] Gareth O Roberts. Markov chain concepts related to sampling algorithms. *Markov chain Monte Carlo in practice*, 57, 1996.

[99] Sean R. Eddy. Profile hidden markov models. *Bioinformatics (Oxford, England)*, 14(9):755–763, 1998.

[100] Guoqiang Yu, Jianming Hu, Changshui Zhang, Like Zhuang, and Jingyan Song. Short-term traffic flow forecasting based on markov chain model. In *IEEE IV2003 Intelligent Vehicles Symposium. Proceedings (Cat. No. 03TH8683)*, pages 208–212. IEEE, 2003.

[101] Shiliang Sun, Guoqiang Yu, and Changshui Zhang. Short-term traffic flow forecasting using sampling markov chain method with incomplete data. In *IEEE Intelligent Vehicles Symposium, 2004*, pages 437–441. IEEE, 2004.

[102] Yan Qi and Sherif Ishak. A hidden markov model for short term prediction of traffic conditions on freeways. *Transportation Research Part C: Emerging Technologies*, 43:95–111, 2014.

[103] Cristiano Rezende, Abdelhamid Mammeri, Azzedine Boukerche, and Antonio AF Loureiro. A reliable synchronous transport protocol for wireless image sensor networks. *Ad Hoc Networks*, 17:1–17, 2014.

[104] Azzedine Boukerche, Horacio ABF Oliveira, Eduardo F Nakamura, and Antonio AF Loureiro. Secure localization algorithms for wireless sensor networks. *IEEE Communications Magazine*, 46(4):96–101, 2008.

[105] Felipe Boeira, Mikael Asplund, and Marinho P. Barcellos. Vouch: A secure proof-of-location scheme for vanets. In *Proceedings of the 21st ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems, MSWiM 2018*, pages 241–248, 2018.

[106] Sergio Correia, Azzedine Boukerche, and Rodolfo I Meneguette. An architecture for hierarchical software-defined vehicular networks. *IEEE Communications Magazine*, 55(7):80–86, 2017.

[107] Osama Abumansoor and Azzedine Boukerche. A secure cooperative approach for nonline-of-sight location verification in vanet. *IEEE Transactions on Vehicular Technology*, 61(1):275–285, 2011.

[108] Xu Han, Daxin Tian, Xuting Duan, Zhengguo Sheng, Yunpeng Wang, and Victor C. M. Leung. Optimized anonymity updating in VANET based on information and privacy joint metrics. In *Proceedings of the 8th ACM Symposium on Design and Analysis of Intelligent Vehicular Networks and Applications, MSWIM 2018*, pages 63–69, 2018.

[109] Renê Oliveira, Carlos Montez, Azzedine Boukerche, and Michelle S Wangham. Reliable data dissemination protocol for vanet traffic safety applications. *Ad Hoc Networks*, 63:30–44, 2017.

[110] Yanjie Tao, Peng Sun, and Azzedine Boukerche. A novel travel-delay aware short-term vehicular traffic flow prediction scheme for vanet. In *Proceedings of IEEE Wireless Communications and Networking Conference (WCNC)*, 2018.

[111] Helmut Lütkepohl. Forecasting with varma models. *Handbook of economic forecasting*, 1:287–325, 2006.

[112] Richard McCleary, Richard A Hay, Erroll E Meidinger, and David McDowall. *Applied time series analysis for the social sciences*. Sage Publications Beverly Hills, CA, 1980.

[113] Jyoti Prakash Singh, Paramartha Dutta, and Amlan Chakrabarti. *Time Series Analysis*, pages 9–13. Springer Singapore, Singapore, 2018.

[114] Subrata Bhowmik, Abhishek Paul, Rajsekhar Panua, Subrata Kumar Ghosh, and Durbadal Debroy. Performance-exhaust emission prediction of diesosenol fueled diesel engine: An ann coupled morsm based optimization. *Energy*, 153:212–222, 2018.

[115] Highways-England. Highways england network journey time and traffic flow data. [Online].Available:https://data.gov.uk/dataset/highways-england-network-journey-time-and-traffic-flow-data, 2016. Accessed on: Sept., 2019.

[116] Yanjie Tao, Peng Sun, and Azzedine Boukerche. A hybrid stacked traffic volume prediction approach for a sparse road network. In *Proceedings of IEEE Symposium on Computers and Communications (ISCC)*, 2019.

[117] Lei Zhang. Do freeway traffic management strategies exacerbate urban sprawl? the case of ramp metering. *Transportation Research Record*, 2174(1):99–109, 2010.

[118] Miroslav Malik, Sharath Adavanne, Konstantinos Drossos, Tuomas Virtanen, Dasa Ticha, and Roman Jarina. Stacked convolutional and recurrent neural networks for music emotion recognition. [Online]. Available: https://arxiv.org/abs/1706.02292, Jun 2017. Accessed on: Sept., 2019.

[119] Haşim Sak, Andrew Senior, and Françoise Beaufays. Long short-term memory recurrent neural network architectures for large scale acoustic modeling. In *Fifteenth annual conference of the international speech communication association*, 2014.

[120] Ming Tan, Cicero dos Santos, Bing Xiang, and Bowen Zhou. Lstm-based deep learning models for non-factoid answer selection. [Online]. Available: https://arxiv.org/abs/1511.04108, March 2016. Accessed on: Sept., 2019.

[121] Renfei Wang, Cristiano Rezende, Heitor S Ramos, Richard W Pazzi, Azzedine Boukerche, and Antonio AF Loureiro. Liaithon: A location-aware multipath video streaming scheme for urban vehicular networks. In *2012 IEEE Symposium on Computers and Communications (ISCC)*, pages 000436–000441. IEEE, 2012.

[122] Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555*, 2014.

[123] Klaus Greff, Rupesh K Srivastava, Jan Koutník, Bas R Steunebrink, and Jürgen Schmidhuber. Lstm: A search space odyssey. *IEEE transactions on neural networks and learning systems*, 28(10):2222–2232, 2016.

[124] Azzedine Boukerche and Samer Samarah. An efficient data extraction mechanism for mining association rules from wireless sensor networks. In *2007 IEEE International Conference on Communications*, pages 3936–3941. IEEE, 2007.

[125] pems.dot.ca.gov. Pems data source - caltrans - state of california. [Online].Available:http://pems.dot.ca.gov, 2016. Accessed on: Sept., 2019.

[126] Maryland.gov. Maryland 511 traffic. [Online].Available:https://www.maryland.gov/Pages/default.aspx, 2019. Accessed on: Sept., 2019.