Short-Term Traffic Flow Prediction Methods: A Survey

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Abstract. As a major part of a smart transport system, the vehicle management system has become an effective means for traffic management departments to control urban road traffic with the advent of smart transportation technology. The short-term traffic flow forecasting provides drivers with the best route as a core engineering of the car guidance system as well as the very relevant mathematical foundation in the field of intelligent transport, improving the traffic management schemes and managing traffic flow by measuring and projecting path flows. This paper mainly aims at incorporating the current mainstream approaches to avoid short-term traffic flow, including the ARIMA, RNN, Sparse Auto Encoder (SAE) and others. We hope that this article will help those who want to delve into it quickly.

1. Introduction
China’s economy has continued to grow at a high speed. A large number of cars have entered people’s daily lives, and they have also brought problems such as traffic congestion, traffic pollution, and traffic accidents. The intelligent transport system is a means for addressing related problems successfully in the transport sector under the current road conditions. The traffic flow prediction algorithm as the fundamental theoretical research in the intelligent traffic management system is the secret to applying an intelligent traffic management system which is very important. In the past few decades, more and more families have owned their own private cars. At present, the traffic management department mainly adopts the following methods to solve the traffic congestion problem: strengthening the construction of road infrastructure, limiting the number of private cars driving on the road, restricting the entry of vehicles from different places into the city and developing Intelligent Transportation System (ITS).

The advanced intelligent transportation system is inseparable from the processing of basic traffic data. At present, there are many data collection and processing methods in the intelligent transportation field, and also provides multidimensional traffic data for ITS. How to make this data effectively applied to ITS has become the current research’s hot spot. Traffic flow prediction is also a way of traffic data processing. Accurate traffic prediction information can provide traffic managers with a strong basis for traffic decision-making, and also allow drivers to choose more smooth road travel, thereby avoiding or alleviating traffic congestion situation. The forecasting of traffic flow is mainly based on statistical theory of statistics and on smart analysis modeling models.

Profound learning as a new method for machine learning has started to attract wide interest from scientists and businessmen. Deep analysis is a multi-layer detector with several secret surfaces. Through researching a deeply-fledged non-linear network architecture for the realization of complex calculations, the transport system is best preserved and the traffic flow forecast can be further accomplished. Improve smart transportation slowly integrates short-range wireless communications, micro-electronic sensing software, embedded sensor and further developments with the introduction of...
IPv6, wireless communication technology and sensing technology. Intelligent Transportation Internet of Things combines the basic concept of intelligent transportation with the Internet of Things technology industry, bringing a new upgrade to intelligent transportation, but it also brings a huge amount of traffic data, only in Guangzhou, each newly added urban traffic operation data record data exceeds 1.2 billion, and the amount of data generated every day is 150G to 300GB. The traditional method can't solve such a huge amount of data at all. It is an inevitable trend to analyze and forecast traffic big data through deep learning.

This article provides the introduction and some cutting-edge work into major categories in the field of estimation of short-term flows such as the ARIMA model, the RNN model, the Sparse Autoencoder (SAE) model, etc. Section 2 is the summary section of the literature and Section 3 is the conclusion portion of that article. Other paragraphs are indented (BodytextIndented style).

2. Literature review

2.1 ARIMA model

In contrast to ARIMA and the Multilayer Arti-Neural Network (MLanN), Zeng, Dehui et al. [1] suggested a hybrid prediction model. ARIMA is best for linear forecasts and for non-linear forecasts MLFNN is suitable for use. It explored the manner in which a modern algorithm could be used to estimate short-term flux time using the weight of the MLFNN and the ARMAs device parameters. Lippi, Marco et al. [2] proposed a detailed empirical analysis of many methods of numerical and machine learning for short-term traffic flow forecasts. They also suggested 2 different SVR designs for the seasonal kernel to measure the sim.

The data found include both linear and non-linear sections because of the complexities of historical data traffic and the random nature of many unknown variables. The selection of the prediction model is important to improve prediction accuracy. While ARIMA can be used to handle the linear portion of historical load data, and an ANN model can be used to deal with the non-linear portion of the historical load data, Huang, Hongqiong et al. [3] proposed ARIMA-ANN which is a combined model. As seasonal synchronized moving average systems, Williams et al. [4] provided the conceptual foundation for modeling of univariable data streams for traffic conditions. This is based on the Wold decomposition theorem and the assumption that a one-week deferred first seasonal differential for discreet interval conditions results in a somewhat steady transition.

In order to combine the automotive regressive integrated moving average (ARIMA) and genetic programming (GP) models, Xu, Chengcheng et al. [5] have developed a simple and efficient system of hybrid for traffic prediction. Various aspects of the underlying traffic patterns can be captured by combining different models. The dimensional component of time series traffic flow was modelled by ARIMA. The prototype GP was then used for the selection of the nicht linear component by modeling the residues of the ARIMA model.

Mehdi, Hamid et al. [6] used ARIMA and FUZZY regression combined to forecast traffic on cloud computing to call Fuzzy Autoregressive Integrated Moving Average (FARIMA). Utilizing the SOFA sliding window, they adopt the FARIMA model in order to determine more accurate models. Ding, Qingyan et al. [7] proposed a STARIMA model to estimate the volume of traffic in urban areas for the purposes of self-regression. The methodological framework includes historical traffic data and a network's spatial characteristics.

ARIMA-GARCH is a common hybrid model capable of capturing the linear and nonlinear conditions of time series variance. The Traffic Flow Prediction Model for a General Integrated Movable Autoregressive Average (ARIMA-GARCH) was suggested by Chen, Chenyi et al. [8]. Including a linear ARIMA with the nonlinear GARCH model, the model allows for both stable and conditional traffic heteroscedasticity.

Lin, Jing [9] used wavelets to analyze complicated network traffic. Time series are built and the time series are approximately flattened. Time series uncorrelated. The WAVLET analysis is conducted by using a mathematical model, an independent model wavelet and the multi-fractal model. 

Matlab
and SPSS are used to analyze traffic flow data. Wavelet analytics and ARIMA approaches, which eliminate mistakes and boost viability, are employed to evaluate the sequence for a single branch reconstruction.

To make faster traffic forecasts more precise. Fang, Chao et al. [10] emphasis on controlling the reliability of short-term path forecasts. The improved road charge coefficient is used to divide traffic status and to predict short-term traffic flow by choosing the Kalman filter method and the ARMA algorithm. Wang, Yuqiong [11] proposed an ARIMA and RBF neural network combination model, combining ARIMA's good linear-shape fitness and the RBF neural network's strong nonlinear dynamic mapping efficiency. The frequency of a microwave is measured in real time with the time characteristics of the traffic flow in mind. The results show that the overall mean percentage error of a combined model is smaller and the fitness of a combined model is more efficient.

Table 1 Partial model description

| Paper | Model | Dataset |
|-------|-------|---------|
| [1]   | ARIMA and MLANN | Statistics was gathered on the traffic flow at 7 a.m. in 8 mins. Up to 7 p.m. Every day. |
| [4]   | Seasonal-ARIMA | Data from two highway areas, one in the U.S. and one in the UK. |
| [6]   | FARIMA | Data from two highway sites, one in the US and the other in the UK. |
| [7]   | STARIMA | Data from 1 November to 30 December 2015 received 228 GB applications. |
| [8]   | ARIMA-GARCH | PeMS single loop detector data. |
| [9]   | ARIMA | 1,000 traffic flow data from January 26th to January 20th, 2010 were predicted. |
| [10]  | the kalman filter method and ARMA | Data collected from 1 December 2003 to 5 December 2003 by six second-circle RTMS in Beijing. |
| [11]  | a combined model of ARIMA and RBF | The statistics were calculated for the first eight days of ET (7:30-9:30) from April 15, 2013 to April 19, 2013, April 22 to April 24. |
| [12]  | SDLSTM ARIMA | Data in the work come from the traffic flow data of British Columbia of Canada. |
| [13]  | ARIMA-ANN | PuDong New District of Shanghai highway from 7:00 a.m. to 12:00 a.m. on Dec 28, 2005. |

2.2 RNN based model

Wang, Xiangxue et al. [14] proposed an urban road network traffic forecast framework that would mainly include two modules using data-driven approach. A collection of data processing algorithms are included in the first module. The second section deals with the short-term multi-stage projection. The time series is first split into a variety of averages, with clear understanding of traffic patterns and randomness. Once two time series have been recovered, template learning and avoidance based on a neuronal long-term memory recuperation network (LSTM-RNN). Yang, Bailin et al. [15] suggested an enhanced method that links the significantly long series of times to the current time stage with the high-impact quality and the attention mechanism collects these high-impact traffic flow values. We simultaneously smooth certain information beyond the standard range in order to obtain better results. The experimental results demonstrate that in short-term traffic flow forecasts the proposed prediction model is certainly competitive.

The Long Shortened Speed Memory (LSTM) and Neural Network (NN) gated recurring units (GRU) and experiments show that deep-learning LSTM and GRU (ARIMA) methods like LSTM are a better way than the Auto Regressive Integrated Moving Average (ARIMA). Shafqat, Wafa et al. [17]
submitted a short-term traffic flow forecast for ITS road transport control via RNN (Recurrent Neural Networks). Prediction of precise flow of traffic at any given time interval, which is essential to assist and to manage road conditions in intelligent cities. The applied system uses profound learning technology for precise predictions at any given time of traffic flow. In order to achieve more effective traffic speed reduction than existing solutions, Lv, Zhongjian et al. [18] suggested the new LC-RNN design. The RNN and CNN models were used in a logical integration to learn more concrete patterns of time series which can respond to the traffic dynamics in the area.

Huang, Bohan et al. [19] used the BRNN traffic prediction model to improve traffic forecasts and to have a better effect in comparison to the LSTM and GRU models. The data indicate that the MAE and RMSE are both the lowest, that is to say, the prediction accuracy is the highest model and an efficient model of traffic forecast if the BRNN model predicts speed within three, speed in six and speed in 12 phases.

Liu, Boyi et al. [20] are recommending the SDLSTM solution in order to address the algorithm issue of the approximation of the traffic flows, which in medium and long term slots have no better effect. First of all, the method of calculating a time singularity flow ratio has been established, the neural LSTM network has been improved by using the Time Singularity ratio as a system of automatic data, addresses the issue of overadaptation in the neural LSTM network and adapts data traffic. The new approach for Wei, Wangyang et al. [21] to forecast traffic flow was implemented as the AutoEncoder Long Short term memory prevention (AE-LSTM). The AutoEncoder is used to collect upstream and downstream traffic data for the internal fluid relationship. In order to predict complicated linear flux information the LSTM network also makes use of its traffic and background knowledge.

Jia, Yuhan et al. [22] developed a deep faith network (DBN) and Long Shorter (LSTM) to forecast urban flow considering impacts of rainfall. Under several weather conditions combined with precipitation, DBN and LSTM will study the traffic characteristics. Experimental results show that, given the additional rainfalls variable and enhancements compared to the original deep learning system, the deep learning predictors are more reliable than the existing predictors. Therefore, LSTM exceeds DBN to capture time series characteristics of traffic flow information.

In a short-term forecast of traffic flows, Tian, Yongxue [23] suggested the LSTM RNN design. In short-term traffic flow forecasts, it is probable that LSTM RNN saves long history input data and decides the optimal time set automatically. The data collected from pEMS are used in our proposed experiments to evaluate the effectiveness of the RNN LSTM framework in a comparable manner to four other conventional prediction systems. Mike et al. [24] suggested a long-term, memory-based approach with travel time prediction attention mechanism. In a tree structure, they present the proposed model. In order to build the complexity of a long-lasting short-term memory, the proposal model replaced the tree structure with the focus system to model long-lasting reliance. The focus mechanism is on each long short-term memory unit's output layer. The time of departure is used as component of the attention mechanism and the time of departure mechanism is integrated in the proposed model.

Wei, Wangiang et al. [25] suggested the hybrid long-short-term memory network (LSTM) focused on the LSTM designs. Afterwards, the LSTM hybrid neural network architecture and parameters are tested on various conditions of traffic and the final version compared with other standard models is measured. The LSTM hybrid model is clearly less reliable than other models, but the time of operation of the LSTM hybrid model is only slightly longer than that of the LSTM model. The flows from each traffic segment and intersection are further estimated on the basis of the hybrid LSTM model in the actual traffic network.

### Sparse Autoencoder (SAE) model

Jin, Yinli et al. [26] presented a new combination of the model and method of dropout with a deep learning stacked self-encoder (SAE). The role and pattern in the data is modeled and the output date is not linear. The greedy layering approach is also used to optimize that layer's parameters and to achieve
the best prevention performance, the network is done. The short-term traffic forecasting approach for
deep learning was proposed by Zhao, Xinran et al. [27]. A nominee has been chosen for the traffic
information from the Second Ring Road, Beijing, China, and microwave detectors. A stacked auto
encoder neural network (SAE-DNN) model is deployed to forecast short-term traffic conditions.

A new combination of deep learning SAE model and dropout process is proposed by Jin, Yinli, et
al. [28] to boost forecast accuracy. The historic flow of the Xi’an, Shaanxi, Chinese city ring road was
collected from the K27+ 000 vehicle detector every 5 minutes. The possible function, pattern and
input date are modeled with a nonlinear algorithm.

Zhao, Peize, et al. [29] are working on a promising prediction model called Layerwise’s Recurring
Autoencoder (LRA) to forecast traffic across a large area and to meet the challenges listed, in order to
provide temporary traffic correlations and a model of recurring neural networks (RNNs), a three-layer
autoencoder (SAE) architecture is used. The CNN model is also used to extract information on spatial
traffic within the topology of transport to make forecasting more precise. In the best way we are aware
of this, in large areas of a group of cities there is no general and efficient method for traffic flow
prediction.

Lv, Yisheng et al. [30] suggested a detailed training method of traffic flow forecasting for the
stacked autonomous encoder (SAE). The proposed method would effectively define the latent traffic
flow, for example spatial and temporal interrelationships, compared to the previous methods, which
only considered the limited traffic framework. They implemented the egotistically unattended learning
algorithm in a beautiful layer to pretrain the deep network and configured beautifully to maximize the
anticipated design parameters.

2.4 Other models
In the scope of the Bayesian Information Criterion (BIC), Zhao, Shuxu et al. [31] used the traffic flow
data collected in the Linzi district of Zibo, Shandong and the GPS data of key urban roads, which was
a penalty item for the choice of a classic HMM model and optimal status, thus reducing system
complexity and structural improvement in terms of predicting time-series structure. The Global Space-
Temporal Network (GSTNet) has been proposed by Fang, Shen et al. [32]. In order to capture global
correlations between space-time dynamics consisting of several layers of space-time frames, a multi-
resolution, sequence-related time and global space module are included in each block that
simultaneously retrieves dynamic time dependencies and global spatial correlations.

Goudarzi, Shidrokh et al. [33] used traffic data in the self-organizing vehicular networks to predict
traffic volumes. The method involves multiple layers of auto encoders on a small Boltzmann (RBM)
computer, based on the Deep Belief Network (DBN) generative probabilistic methodology. Goudarzi,
Shidrokh et al. [33] used the DBN of three layers to learn key inputs for a traffic flow prediction
model by removing time series RRU’s data. Rajabzadeh, Yalda et al. [34] have developed a prediction
of real-time data flow using an adaptive model to capture insecurity by a two-stage approach. First, to
evaluate the basic line in recent days, and then to take account of the stochastic changes intraday by an
adaptive and real-time method.

Sun, Shiliang et al. [35] proposed the new approach to Bayesian traffic flow forecasts. A Bayesian
network is the movement of traffic between the related transport links. A Gaussian mixture model
(GMM) with parameters estimated by means of the CEM algorithm is described as a joint probability
distribution of the core (data used for projections) and the core (data expected). A deep architecture
consisting of two sections was proposed at Huang, Wenhao et al. [36]: the lower-beliefs (DBN) and
the top multi-task regression layer. A DBN for uncontrolled functional learning is used here. It can
learn effective traffic prediction features in an unattended manner that have been examined and proven
effective for numerous areas, for example the classification of images and audio. A multi-task
regression layer is used above the DBN for supervised prediction to integrate multi-task learning (MTI)
with the deep architecture. Shang, Qiang et al. [37] focused on improving estimation precision and
employed SSA to process traffic flow noise sequence. On the basis of a common Spectrum Analysis
(SSA) and an extremely learning machine kernel (KELM), a SSA-KELM hybried system was
developed. The following is used for KELM Trainings Traffic Flow: restoration of the process is an optimal input strategy to give the system and design gravity parameter check (GSA) optimisation.

Table 2 Partial model description

| Paper | Model      | Dataset                                                                 |
|-------|------------|-------------------------------------------------------------------------|
| [31]  | HMM        | Data collected in Linzi District of Zibo City.                          |
| [32]  | GSTNet     | Datasets are the transaction records of Beijing Subway and Bus System.  |
| [34]  |            | The Tehran Road information and the PeMS Server for open-access.        |
| [37]  | SSA-KELM   | Two loop detectors were installed on the expressway, Lianqian W Rd, in Xiamen, China. |

3. Conclusion
The paper primarily includes the following three main categories: ARIMA model, RNN model and Sparse Auto Encoder (SAE), in the short-term traffic forecasting field. The main task of this paper is to explain short-term approaches of estimating traffic flows. This article is hoped to help those who want to immerse themselves in this folder rapidly.

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