When Traffic Flow Prediction and Wireless Big Data Analytics Meet

Yuanfang Chen, Mohsen Guizani, Yan Zhang, Lei Wang, Noel Crespi, Gyu Myoung Lee, and Ting Wu

Abstract

In this article, we verify whether or not prediction performance can be improved by fitting the actual data to optimize the parameter values of a prediction model. Traffic flow prediction is an important research issue for solving the traffic congestion problem in an ITS. Traffic congestion is one of the most serious problems in a city, which can be predicted in advance by analyzing traffic flow patterns. Such prediction is possible by analyzing the real-time transportation data from correlative roads and vehicles. The verification in this article is conducted by comparing the optimized and the normal time series prediction models. With the verification, we can learn that the era of big data is here and will become an important aspect for the study of traffic flow prediction to solve the congestion problem. Experimental results of a case study are provided to verify the existence of the performance improvement in the prediction, while the research challenges of this data-analytics-based prediction are presented and discussed.

Introduction

Traffic flow prediction is an important research issue in an Intelligent Transportation System (ITS), and it can be used as an important measure to solve the traffic congestion problem. Traffic congestion is considered a serious problem in big cities around the world. In a study of 471 U.S. urban areas in 2014 [1], the extra energy cost due to traffic congestion was estimated at $160 billion (3.1 billion gallons of fuel). In addition, long periods of traffic congestion cause the release of more carbon dioxide (CO_2) greenhouse gases into the atmosphere, and increase the number of accidents. This can in turn produce severe public health risks that will dramatically increase medical treatment costs. Predicting traffic flow patterns can help to reduce traffic congestion and therefore reduce the amount of CO_2 emissions as well as save lives. A scenario of using traffic flow prediction to avoid traffic congestion is illustrated in Fig. 1.

Figure 1 illustrates a scenario: how to avoid congestion in an ITS, and what can be achieved by avoiding congestion? In this scenario, the transportation and driving data is collected from various devices of the ITS. The data is then analyzed to assist the navigation of vehicles. Meanwhile, other vehicles that are preparing to hit the road want to know the current traffic conditions to make a decision about whether to start the journey and when? Which routes can be used and which is the best? On this basis, congestion can be reduced to achieve eco-friendly routing (low-carbon transportation). Traffic flow is predictable by analyzing the relevance of traffic conditions between different traffic roads, as shown in Fig. 2.

Figure 2 illustrates the possibility of knowing whether or not there is a potential congestion point in advance. Such knowledge is acquired by predicting the traffic flow on the specific route due to the continuity of traffic flow among different traffic roads. It means that the flow of a traffic road comes from other roads that connect to it.

It is possible to analyze the relevance of the traffic conditions between different traffic roads by tracing the change of traffic flow, and such tracing can be achieved by analyzing the real-time transportation data submitted by the wireless devices embedded into the vehicles and road side units (RSUs) installed in the correlative roads [2].

The trajectory data of vehicles (a kind of transportation data) is the most commonly used by traffic flow prediction. Trajectories provide important information on the mobility of vehicles, where the moving pattern of vehicles characterizes the traffic flow of a transportation system. The trajectory data of vehicles is becoming easily available in current transportation systems due to the prevalence of global positioning system (GPS) and other localization technologies. A trajectory generated by a moving vehicle is usually described by a temporal sequence of spatial locations with their time stamps. These trajectories convey underlying information about how the traffic flow of the transportation system changes.

From the traffic congestion problem to traffic flow prediction, and then further to transportation data about trajectory, the research issue becomes how to analyze and mine trajectory data to solve the congestion problem. Analyzing and mining trajectory data can extract and reveal inherent information or knowledge about potential congestion. It will benefit various applications, for example, it is possible to reduce exhaust emission by congestion knowledge based path planning, and further to enhance the level of public health. Also, improving public security in transportation systems is possible by avoiding traffic accidents caused by congestion. Figure 3 illustrates the gen-

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Yuanfang Chen and Ting Wu (corresponding author) are with Hangzhou Dianzi University, Mohsen Guizani is with the University of Idaho; Yan Zhang (corresponding author) is with the University of Oslo; Lei Wang is with Dalian University of Technology; Noel Crespi and Gyu Myoung Lee are with the Institut Mines-Télécom SudParis.

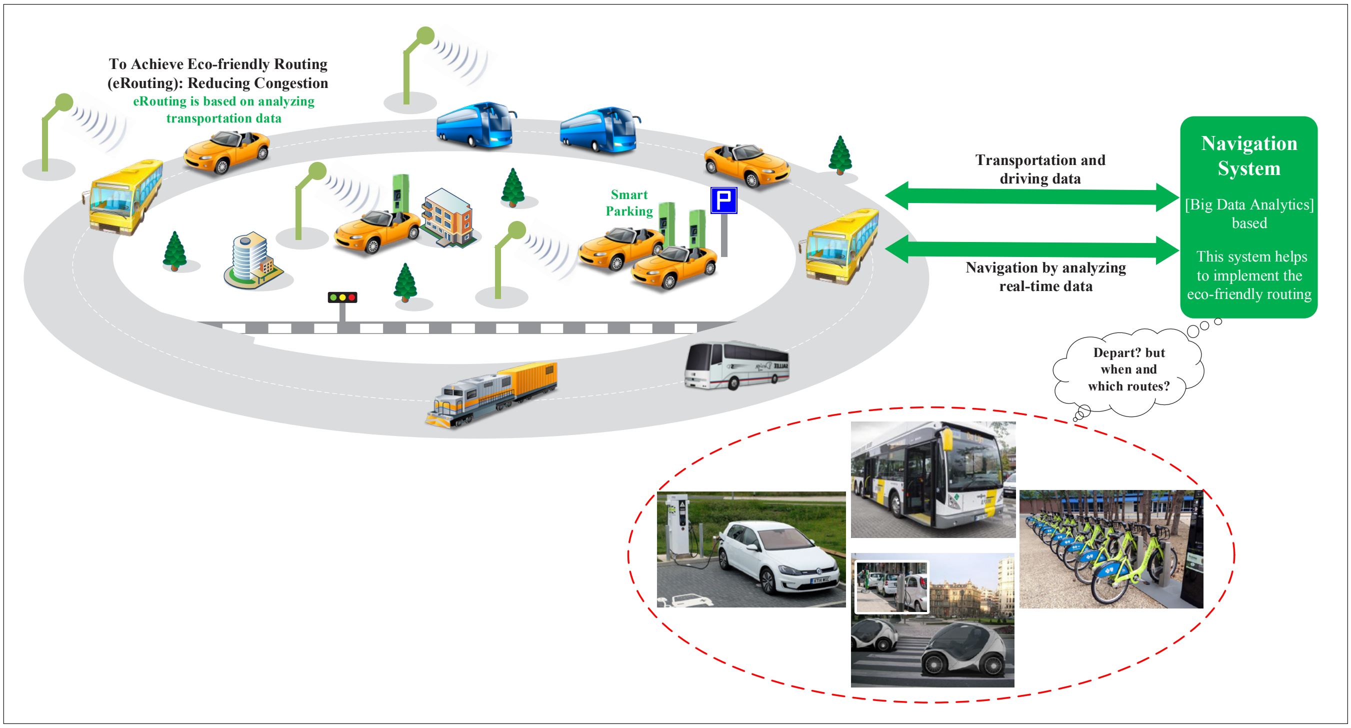

FIGURE 1. Traffic congestion avoidance. This scenario shows how to avoid congestion by analyzing transportation data: Where the data comes from? Where does the data go? How is the data used? What can be achieved by analyzing the data?

eral framework of such data-analytics-based traffic flow prediction. The general framework consists of the following three modules.

Data Collection Module: Transportation data can be collected from vehicle-mounted GPS, WiFi, Bluetooth and RFID. For example, shared bikes can be embedded with GPS, WiFi, Bluetooth, and even RFID to achieve tracking, i.e., when and where the bikes are used, and this tracking can indicate the bikes' traveling trajectories. The trajectory is a kind of spatio-temporal data. In such data, this information is available: location, location semantics, geographical information and time stamp.

Data-Analytics-Based Prediction Module: The collected transportation data is analyzed by deep learning, classification, ranking and regression to acquire useful knowledge as the basis of traffic flow prediction. These four technologies can be used to conduct data-analytics-based prediction: time-series model, deep-learning-based predictor, Markov chain model, and combination of neural networks (NNs) and autoregressive integrated moving average (ARIMA).

Application Module: The predicted results can be used to support many special applications to improve the life experience in cities, for example, transportation planning, transportation management, city planning, and city management.

The main contributions of this article are listed as follows:
- Verify whether or not prediction performance can be improved by fitting actual data to optimize the parameter values of a traffic flow prediction model.
- Survey state-of-the-art prediction methods on traffic flow.
- Present and discuss the research challenges of data-analytics-based traffic flow prediction.

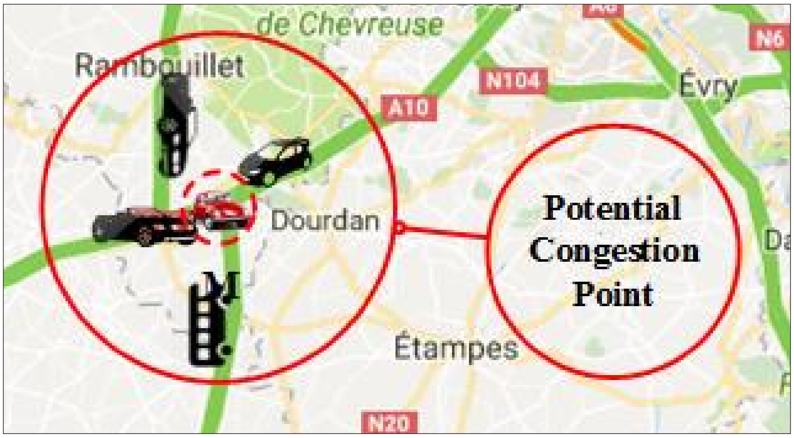

FIGURE 2. In this scenario, the traffic flow in an intersection is predictable. The traffic flow of the intersection comes from the traffic roads connecting at the intersection.

Transportation Data and the State of the Art

What is transportation data and what kind of transportation data is used in this article?

What is transportation data? Transportation data is a kind of data that describe the information related to transportation systems, and it contains various vehicle and road information, for example, the trajectory and speed information of vehicles, and the length information of traffic roads. It is helpful to improve the performance of transportation related applications by analyzing such data, for example.

Traffic flow prediction: This is the attempt to estimate the number of vehicles that will travel on the traffic roads of a transportation system in the future. This prediction enables us to understand and develop an optimal transportation system

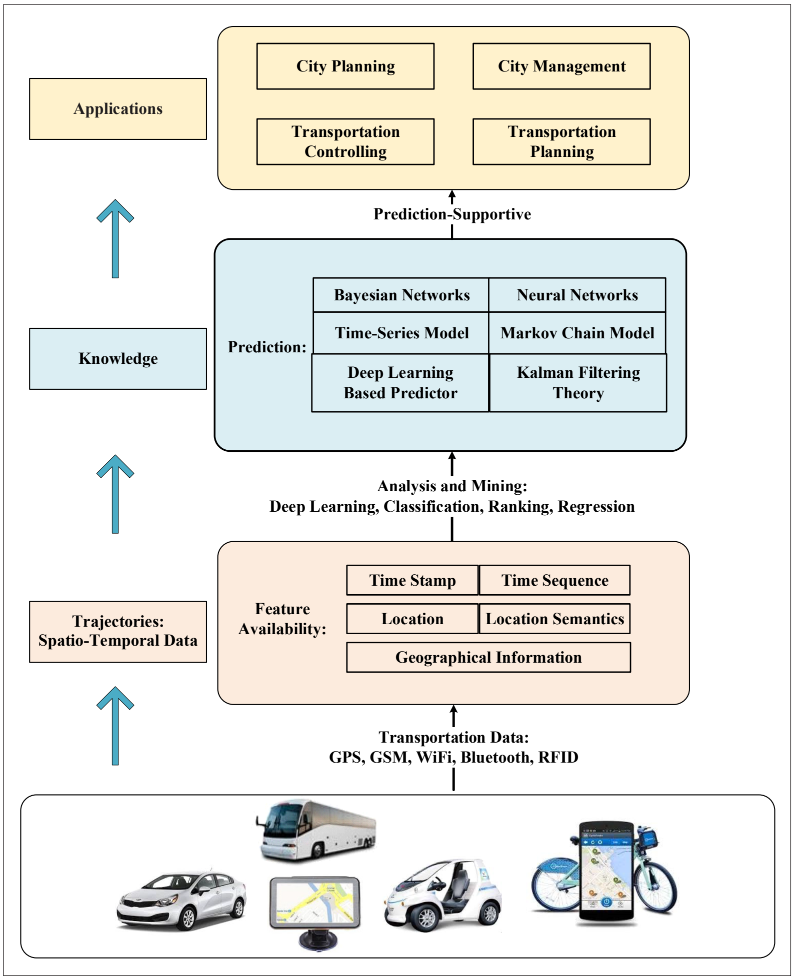

FIGURE 3. General framework of data-analytics-based traffic flow prediction.

with efficient movement of traffic. It will also allow us to minimize traffic congestion by designing optimal overall route planning for vehicles based on the predicted traffic flow. The flow of a traffic road has a connection with the flows of prior roads that are connected to this traffic road. Thus, it is possible to predict the flow of the current traffic road by calculating the potential fractional flows from the prior roads and the previous time period. The potential fractional flow is able to be calculated by analyzing the transportation data (the trajectory and speed data of vehicles).

Transportation planning: This is the process of defining the future design for transportation systems to prepare for the future needs to move people and goods to destinations. In this application, it is possible to acquire the underlying knowledge of transportation systems by mining the transportation data from the systems. With the acquired knowledge, transportation planning will be more reasonable.

What kind of transportation data is used in this article? In this study, trajectory data of vehicles is used, which is a kind of series transportation data. The data can be used to calculate and predict the traffic flow of a transportation system. It is collected from the transportation system in England. This transportation system has 2501 traffic roads[1] covering 300 miles of England highways and arterial roads, which is illustrated in Fig. 4.

The important part of trajectory data is the location information. With the location information, trajectory data can provide actual semantics to enable such data to be used for traffic flow prediction. Flow information of a traffic road is acquired by counting the number of vehicles being driven on the current road. Thus in trajectory data, location information is required to filter out the vehicle driving records on the current road rather than other roads. Moreover, for traffic flow prediction, the traffic flow of the current road converges from the traffic flow of prior roads, so the location information becomes important to track the traffic flow changes. Trajectory data relies on localization technology to provide location information. The commonly used measurement methods of localization to generate location-containing trajectory data include GPS, WiFi, GSM, Bluetooth, and RFID.

State-of-the-art Prediction Methods: Many kinds of techniques have been proposed to address the traffic flow prediction problem. The details are summarized in Table 1.

Many specific methods have been proposed to make predictions in different situations, and it emerges that traditionally there is no single best method for every situation. It is better to combine several suitable techniques to improve the accuracy of prediction when considering different situations, meaning that traditional traffic flow prediction methods are not able to satisfy most real-world application requirements. During the last five years, some studies have tried to use data analytics to solve the traffic flow prediction problem, and the results demonstrate that such schemes are feasible and are able to improve the accuracy of prediction, such as the method proposed in [12]. Such a data-analytics-based prediction method is able to satisfy the requirements of different applications by analyzing the data from each corresponding specific application.

Performance Comparison

This section compares the performance of two kinds of time series prediction models: optimized time series prediction and normal time series prediction. To verify this fact, the prediction performance of a prediction model can be improved by fitting data to optimize model parameters. The ARIMA model is used in this study to make this verification. Predicting a stationary time series by ARIMA depends on the parameters (p, d, q) of the ARIMA:

- The parameter p is the number of auto-regressive (AR) terms, for example, if p is 5, the predictors for $x(t)$ will be $x(t - 1)$, ..., $x(t - 5)$.
- The parameter q is the number of moving average (MA) terms. MA terms are lagged prediction errors in the prediction equation, for example, if q is 5, the predictors for $x(t)$ will have such lagged prediction errors $e(t - 1)$, ..., $e(t - 5)$, where $e(i)$ is the difference between the moving average and the actual value at the ith instant.
- The parameter d is the number of differences when the time series becomes stable.

An important concern here is how to determine the values of p and q. Determining the values of p and q will affect the performance of the prediction model. This study uses the Bayesian Information Criterion (BIC) to determine the

[1] A two-way highway/arterial road is counted as two traffic roads.

optimum values of parameters p and q to avoid over-fitting, when fitting a model by training data. BIC is a criterion for model selection among a finite set of models, and the model with the lowest BIC value is preferred. It is based, in part, on the likelihood function. Comparative results are illustrated in Fig. 5. Each curve is the average of the results from 2501 traffic roads.

The root-mean-square error (RMSE) of a model with respect to the "traffic flow" is defined as the square root of the mean square error between the values actually observed and the values predicted by a model. The RMSE estimated from the optimized ARIMA is less than the estimated result from the normal ARIMA. The prediction accuracy of the time series model ARIMA is able to be obviously improved by optimizing relevant parameters.

Figures 5a and 5b show the comparative results with the data of two selected dates, March 15, 2015 and March 31, 2015. By comparing both calculated RMSE values, the value calculated from the optimized ARIMA model is much better than the value calculated from the normal ARIMA model: (i) in the results with the data of March 15, 2015, the RMSE value of the optimized ARIMA model is 5.382, and the RMSE value of the normal ARIMA model is 64.05; (ii) in the results with the data of March 31, 2015, the RMSE value of the optimized ARIMA model is 15.03, and the RMSE value of the normal ARIMA model is 130.07. Figure 5c provides the average results for 31 days of March, 2015: the RMSE value of the optimized ARIMA model is 11.298, and the RMSE value of the normal ARIMA model is 87.65. It is observed that improving the performance of a prediction model is possible by optimizing model parameters with analyzing sequential transportation data.

FIGURE 4. Flow information of traffic roads is acquired by analyzing the trajectory data of the vehicles driving on these traffic roads. The update period of this information is 15 minutes. Highways and arterial roads are marked by different color depths; the deeper color denotes a heavier traffic load on the corresponding road.

Research Challenges

The pattern prediction of traffic flow, which is supported by data analytics, strongly relies on the transportation data that records the vehicle mobility of transportation systems. Meanwhile, using transportation information may cause privacy issues.

In this section, we provide the research challenges on traffic flow prediction from these two aspects: data and data-based prediction.

Data:

Privacy Protection: It is necessary and important to protect personal privacy information that is contained in transportation data. Such information includes the locations, driving trajectories, properties and vehicles' plate numbers. It is a worthy research challenge to protect this information when the transportation data is analyzed to obtain useful information and knowledge.

Mobility: In transportation systems, understanding and predicting mobility patterns is the basis of studying and solving the traffic congestion problem, and traffic flow is an important reflection for mobility in transportation systems. Mobility produces large amounts of spatio-temporal data, and this kind of data is accompanied with time and location information. Analyzing the spatio-temporal data is a research challenge as the basis of understanding, learning and predicting the patterns of mobility and traffic flow. Spatio-temporal data is a kind of time series data. To analyze this kind of data, a time series analysis model is necessary, and in different scenarios of traffic flow prediction, the objective functions are different because of the different requirements, and how to combine a time series analysis model with an objective function for special requirements is another important challenge that requires further investigation.

Vehicle: The vehicles in a transportation system produce large amounts of trajectory data. This kind of data can be used to mine vehicle behaviors and relations. If we know the behaviors of vehicles and the relations between these vehicles, it is possible to predict the change of traffic flow and then to avoid congestion by traffic control and management. For example, if there is congestion at a certain intersection and the relevant vehicles have the same destination, these vehicles have great possibility to use the same route, and the congestion will happen again at the next intersection, if there are no control measures in advance.

Big Data: The mobility of vehicles produces large amounts of spatio-temporal trajectory data. To analyze this kind of data, big data analytics is needed. Such analytics is different from traditional data analysis [14]. For example, deep learning and NNs can be used to analyze such big data, but how to learn such data to extract useful information and knowledge, and learning for what, are worthy challenges that need to be studied.

Wireless Big Data: The collection of big data from intelligent transportation systems (the trajectory data of vehicles) is by wireless devices. These devices can be wireless sensor nodes that are embedded on the traffic road surfaces to detect passing vehicles. There will be problems with missing data in this kind of wireless data because of unpredictable problems, for example, sensor node failure. In some scenarios, if the critical data is missing or has errors, it will make the analysis results greatly deviate from making correct conclusions. For example, if the data from a device is not correct and the data is used to perform analysis, the result will be incorrect and cannot be used as useful information or knowledge to aid decision making. Ensuring the integrity of the wireless big data information is still a great challenge that needs to be addressed by experts in the field.

City Data Based Prediction: The prediction with analyzing transportation data can help in city planning and management. For example, designing intelligent traffic lights to achieve automatic traffic flow global scheduling. Such scheduling is based on the understanding and prediction of global traffic conditions, so it is important to know how does the current traffic flow impact the traffic conditions during the next time period, which is called prediction. It is still a challenge that needs researchers' attention.

In the data-driven prediction [15], apart from accuracy, computation complexity is one of the main challenges. With data-driven prediction it is still easy to encounter problems in computation complexity, even if its accuracy can be improved with increasing the size of the data.

Conclusion

Transportation data is the sampling of dynamics of moving objects in the temporal and spatial dimensions. Analysis and mining of such time series data is becoming a promising way to discover the underlying knowledge of vehicular activities, vehicles' relations and even city dynamics. It helps to well understand and predict the pattern of traffic flow that is an important aspect of traffic dynamics. Traffic flow prediction can be

Techniques	Advantages and limitations
Bayesian networks	**Advantages:** Bayesian networks can fully take into account the causal relationship among variables [3], for example, the spatial and temporal variables of traffic, and the speed of traffic flow, and thus can be employed to model and analyze the traffic flow between upstream and downstream road links [4]. Moreover, Bayesian networks can make good use of information from adjacent roads to analyze the trend of the target road. The proposed Bayesian networks in [5] have the ability to cope with the data-incomplete problem. **Limitations:** Bayesian networks may not be possible to use Bayesian networks in cases where the relationships of the traffic flow between upstream and downstream road links are unavailable [6].
Neural networks	**Advantages:** Traffic flow can be considered as both a temporal and a spatial phenomenon. Dependence on time and space has been established in the traffic flow prediction methods, especially in highly congested and densely urban environments. Neural networks show the ability in modeling the temporal and spatial variability of traffic flow [7]. Moreover, Neural networks are empirical (data-driven) and self-adaptive, and have the ability to capture the underlying relationships without the need of priori assumptions regarding the problem examined. Because of their ability to learn from data, even if the underlying relationships are not apparent, their non-linear nature and their ability to generalize make them useful in working with the data with noise, an often seen phenomenon when modeling time series from real-time traffic prediction applications [8]. **Limitations:** Because of limited knowledge about a given specific dataset, researchers have to rely on time-consuming and questionably efficient data training to train and achieve the optimized neural network.
Time-series models	**Advantages:** Time-series models are used to represent the time series of traffic flow data, and they can identify the pattern of the data, and further extrapolate the pattern into the future. For example, (i) autoregressive integrated moving average (ARIMA) models [9]. They can be fitted to time series data either to better understand the data or to predict future points in the series. ARIMA models are applied in some cases where data shows evidence of non-stationarity, where an initial differencing step (corresponding to the "integrated" part of the model) can be applied one or more times to eliminate the non-stationarity. (ii) seasonal autoregressive integrated moving average (SARIMA) models [10]. Fitted SARIMA models can provide equations that can be used to conduct single and multiple interval prediction. **Limitations:** Time-series models are not suited for the prediction which is based on this kind of data: (i) there is the information deficiency problem in the data, and (ii) the filling of data is problematic as the situation is complex. Moreover, even if huge data with enough information is available, the requirement of specialized software for time series modelling, and the time-consuming model development process, may restrict the use of time-series models in problems dealing with real-time data such as traffic flow.
Markov chain models	**Advantages:** Markov chain models have been used and have shown their strength in a series which has the attribute that, given the current and N–1 preceding states, the future state is independent of the states prior to the given states, which is an N-order Markov chain. It is easily seen that the current and preceding states of the traffic flow can show the trend in the future interval [11]. **Limitations:** In case of incomplete data, Markov chain models are not suitable to predict the traffic flow in road networks.
Deep learning based predictor	**Advantages:** The deep learning based predictor can learn the spatial and temporal inherent correlations of traffic records, and even generic traffic flow features. It is useful to improve the performance of prediction for traffic flow [12]. **Limitations:** The same as the other data-driven prediction methods for traffic flow prediction, the use of the deep learning based predictor requires huge traffic flow data for model development. It may not be possible to use the deep learning based predictor in cases where sufficient data is unavailable. Moreover, because the deep learning models are low in explanatory power, the interpretability of models is mentioned as one of the barriers in adapting more sophisticated machine learning models in practice.
Kalman filtering theory	**Advantages:** To overcome the incomplete data problem, Kalman filtering theory (KFT) is proposed and evaluated, which requires only limited input data, and is with desired accuracy [13]. **Limitations:** In the prediction with the Kalman filtering theory, selection of parameters is very important as it can directly impact the performance of prediction. However, there is still no effective way to deal with such a selection.

TABLE 1. Typical techniques to address the traffic flow prediction problem.

exploited in a wide range of potential applications to make a city smarter, safer, more livable, and can help reduce congestion and pollution. However, it remains challenging to analyze time series data to acquire useful knowledge for problem solving, because of data heterogeneity and data incompleteness in a complex and dynamic transportation system. So, in this article we have introduced transportation data. Then, we discussed state-of-the-art prediction methods. We conducted experiments in order to compare the optimized time series prediction model with the normal time series prediction model. Our results show that prediction performance is able to be improved by fitting actual data to optimize the parameters of the prediction model. In addition, we have discussed typical techniques to address the traffic flow prediction problem. Finally, we listed challenges that can provide leads to future researchers in this area.

References

[1] D. Schrank *et al.*, "2015 Urban Mobility Scorecard," The Texas A&M Transportation Institute and INRIX, Tech. Rep., 2015.

[2] A. Al-Fuqaha *et al.*, "Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications," *IEEE Commun. Surveys & Tutorials*, vol. 17, no. 4, 2015, pp. 2347–76.

[3] Z. Zhu *et al.*, "Short-Term Traffic Flow Prediction with Linear Conditional Gaussian Bayesian Network," *J. Advanced Transportation*, vol. 50, no. 6, 2016, pp. 1111–23.

[4] E. Castillo, J. M. Menéndez, and S. Sánchez-Cambronero, "Predicting Traffic Flow Using Bayesian Networks," *Transportation Research Part B: Methodological*, vol. 42, no. 5, 2008, pp. 482–509.

[5] S. Sun, C. Zhang, and G. Yu, "A Bayesian Network Approach to Traffic Flow Forecasting," *IEEE Trans. Intelligent Transportation Systems*, vol. 7, no. 1, 2006, pp. 124–32.

[6] S. Sun, C. Zhang, and Y. Zhang, "Traffic Flow Forecasting Using a Spatiotemporal Bayesian Network Predictor," *Proc. Int'l. Conf. Artificial Neural Networks*, Springer, 2005, pp. 273–78.

[7] K. Y. Chan *et al.*, "Neural-Network-Based Models for Short-Term Traffic Flow Forecasting Using a Hybrid Exponential Smoothing and Levenberg–Marquardt Algorithm," *IEEE Trans. Intelligent Transportation Systems*, vol. 13, no. 2, 2012, pp. 644–54.

[8] K. Y. Chan and T. S. Dillon, "On-Road Sensor Configuration Design for Traffic Flow Prediction Using Fuzzy Neural Networks and Taguchi Method," *IEEE Trans. Instrumentation and Measurement*, vol. 62, no. 1, 2013, pp. 50–59.

[9] R. N. Calheiros *et al.*, "Workload Prediction Using ARIMA Model and its Impact on Cloud Applications' QoS," *IEEE Trans. Cloud Computing*, vol. 3, no. 4, 2015, pp. 449–58.

[10] B. M. Williams and L. A. Hoel, "Modeling and Forecasting Vehicular Traffic Flow as a Seasonal ARIMA Process: Theoretical Basis and Empirical Results," *J. Transportation Engineering*, vol. 129, no. 6, 2003, pp. 664–72.

[11] G. Yu *et al.*, "Short-Term Traffic Flow Forecasting Based on Markov Chain Model," *Proc. IEEE Intelligent Vehicles Symposium*, 2003, IEEE, 2003, pp. 208–12.

[12] Y. Lv *et al.*, "Traffic Flow Prediction with Big Data: A Deep Learning Approach," *IEEE Trans. Intelligent Transportation Systems*, vol. 16, no. 2, 2015, pp. 865–73.

[13] J. Guo, W. Huang, and B. M. Williams, "Adaptive Kalman Filter Approach for Stochastic Short-Term Traffic Flow Rate Prediction and Uncertainty Quantification," *Transportation Research Part C: Emerging Technologies*, vol. 43, 2014, pp. 50–64.

[14] M. Chen *et al.*, "5GSmart Diabetes: Towards Personalized Diabetes Diagnosis with Healthcare Big Data Clouds," *IEEE Commun. Mag.*, vol. 56, no. 4, 2018, pp. 16–23.

[15] M. Chen *et al.*, "Data-Driven Computing and Caching in 5G Networks: Architecture and Delay Analysis," *IEEE Wireless Commun.*, vol. 25, no. 1, 2018, pp. 70–75.

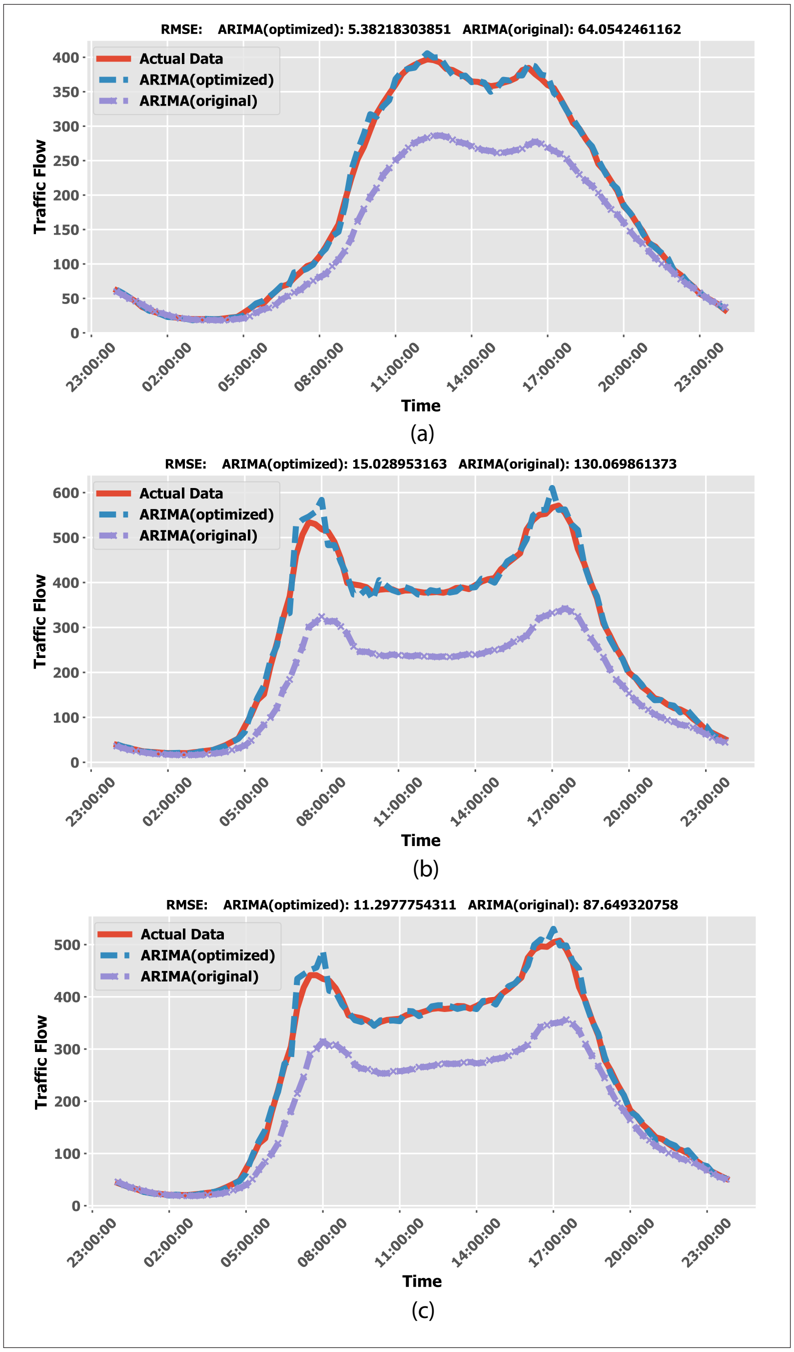

FIGURE 5. Compared with normal ARIMA, optimized ARIMA achieves better prediction results in the aspect of the changing trend and values of traffic flow. Root-mean-square errors (RMSEs) are marked in each subfigure to indicate the prediction performance of normal and optimized ARIMA models. a) Actual traffic flow data of March 15, 2015, and the predicted results by normal and optimized ARIMA models. b) Actual traffic flow data of March 31, 2015, and the predicted results by normal and optimized ARIMA models. c) Average results for 31 days of March: actual traffic flow and the predicted results by normal and optimized ARIMA models.

Biographies

Yuanfang Chen [S'09-M'15] received her Ph.D. and M.S. degrees from Dalian University of Technology, China, and a second Ph.D. degree from the University Pierre and Marie CURIE, France. She currently works at Hangzhou Dianzi University as a Professor. She was an assistant researcher at the Illinois Institute of Technology, USA with Prof. Xiangyang Li. She has been invited as the Session Chair of several conferences, an associate editor of *Industrial Networks and Intelligent Systems*, and the guest editor of MONET.

Mohsen Guizani [S'85-M'89-SM'99-F'09] received the B.S., M.S. and Ph.D. degrees from Syracuse University. He is currently a professor and the ECE Department Chair at the University of Idaho. His research interests include wireless communications, mobile cloud computing, security and smart grid. He is the author of nine books and more than 500 publications. He was the Chair of the IEEE ComSoc Wireless Technical Committee. He has received multiple IEEE paper awards and IEEE ComSoc service awards. He served as an IEEE Computer Society Distinguished Speaker from 2003 to 2005.

YAN ZHANG [SM'10] is a full professor at the University of Oslo. He is an editor of several IEEE publications, including *IEEE Communications Magazine*, *IEEE Network*, *IEEE Transactions on Green Communications and Networking*, *IEEE Communications Surveys & Tutorials*, and *IEEE Internet of Things*. His current research interests include next generation wireless networks leading to 5G and cyber physical systems. He is an IEEE VTS Distinguished Lecturer.

LEI WANG is currently a full professor and vice dean of the School of Software, Dalian University of Technology, China. He received his B.S., M.S. and Ph.D. degrees from Tianjin University, China, in 1995, 1998, and 2001, respectively. He was a member of technical staff with Bell Labs Research China (2001-2004), a senior researcher with Samsung, South Korea (2004-2006), a research scientist with Seoul National University (2006-2007), and a research associate with Washington State University, Vancouver, WA, USA (2007-2008).

NOEL CRESPI holds M.S. degrees from the Universities of Orsay (Paris 11 and Kent, UK), a Ph.D and an Habilitation from UPMC (Paris Sorbonne University). From 1993 he worked at CLIP, Bouygues Telecom, and at Orange Labs in 1995. He joined Institut Mines-Telecom in 2002 and is currently a professor and Program Director. He is also an adjunct professor at KAIST, South Korea, an affiliate professor at Concordia University, Canada, and guest researcher at the University of Goettingen, Germany.

GYU MYOUNG LEE holds a Ph.D. degree from KAIST in Korea. He has been with the Liverpool John Moores University (LJMU), UK, as a reader from 2014 and with KAIST, Korea, as adjunct professor from 2012. He has been actively working for standardization in ITU-T, IETF and oneM2M, etc. In ITU-T, he currently serves as a WP chair in SG13, a Rapporteur of Q16/13 and Q4/20 as well as the chair of FG-DPM.

TING WU is currently a professor at Hangzhou Dianzi University. He is the Dean of the School of Cyberspace, Hangzhou Dianzi University, a committee member of the Secrecy and Management Department at the Ministry of Education, and the director of the Chinese Confidential Association. He has been invited as the principal investigator in the 863 Project, and a member of the 973 Program.