

**Bi-level Optimization Algorithm for Dynamic Reversible Lane Control based
on Short-term Traffic Flow Prediction**

Chenxi Liu

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Committee:

Yinhai Wang

Jeff Ban

Edward McCormack

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Department of Civil and Environmental Engineering

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Chenxi Liu

University of Washington

Abstract

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Chenxi Liu

Chair of the Supervisory Committee:

Dr. Yinhai Wang

Department of Civil and Environmental Engineering

Traffic congestion is a more and more serious problem in all over the world. Reversible lanes have been used throughout the world to mitigate the effects of congestion and optimize roadway performance for more than 80 years. They have been applied on a variety of roadway types using different control methods to address an assortment of needs. However, the limited traditional control methods can not meet the increasing various demands. To address the needs on freeway scenario, the study introduces a bi-level method based on short-term traffic flow prediction for the dynamic reversible lane control algorithm. The work improves the traditional traffic management method, reversible lane control, from static control to dynamic real-time traffic management. Taking advantage of the development of neural network technology, the input of the algorithm covers not only historical data and real-time data but also the predicted data.

Advanced Bi-directional Long Short-term Memory (Abi-LSTM) model is employed for the short-term traffic flow prediction. For the control algorithm, the study introduces bi-level optimization method to maximize the total traffic flow in both directions which determine the lane deployment. Also, the study considers the user costs in the lower level optimization formula. Finally, the study builds up a simulation to test the effect of the dynamic reversible lane control algorithm.

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Chapter 1. INTRODUCTION

1.1 GENERAL BACKGROUND

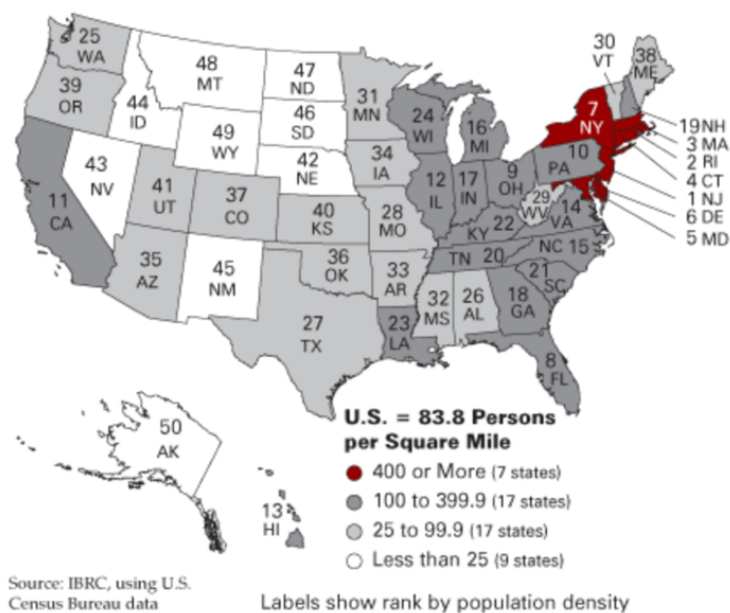


Figure 1.1 Density of population based on land area in US (2005)¹

Since last century, the scales of metropolises have become larger and larger because of the consistent increasing population in urban area. Figure 1.1 shows the density of population based on land area in US (2005). It is clear that most population is concentrated in well-development areas. Even though the large-scale metropolises can provide more job opportunities and promote the development of the economy and technology, it also brought a series of challenges, the most serves of which is transportation problems. The transportation system in metropolis of US for example New York City was mostly built in the last century when the urban planners can never imagine the huge travel demand in the city at present. Therefore, the present road networks cannot handle the overflowed trips and result in serious transportation problems like traffic congestion,

¹ Figure source: IBRC, using U.S. Census Bureau data <http://www.ibrc.indiana.edu/ibr/2006/summer/article1.html>

which not only influence the traffic safety, but also reduce the operation efficiency of the whole city and increase the energy consumption.

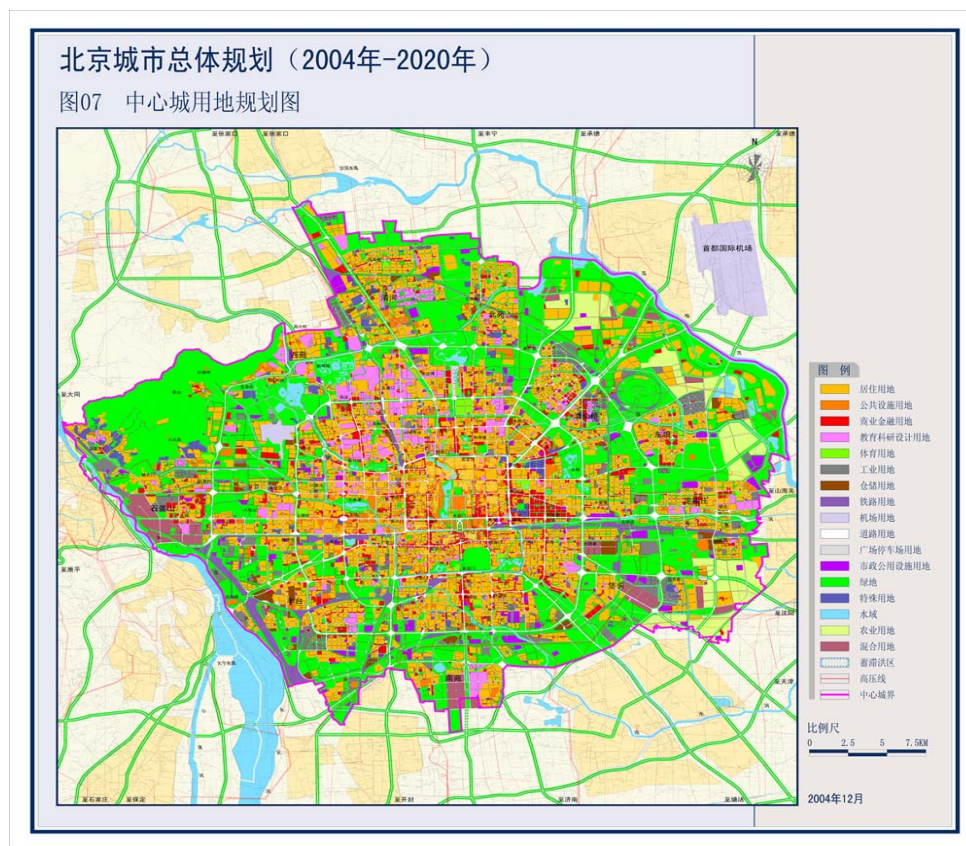


Figure 1.2 Overall Urban Planning Map in Beijing (2004-2020)

Another reason deteriorates the transportation system is the antiquated urban planning, the single core city planning, which lead to the directed travel demands (i.e., unbalanced travel demand in the two directions). Set Beijing as an example, Figure 1.2 shows the overall urban planning map in Beijing (2004 - 2020). It is easy find that the commercial lands (red areas) are concentrated in the north-east of the central area (CBD district), while the residential lands (orange areas) covers all over the city. Therefore, in the morning peak, the concentrated travel demand can cause the heavy traffic congestion in the entering city direction (see Figure 1.3), and vice versa in the evening peak.



Figure 1.3 Morning Peak in Beijing

It is said that the transportation system is the arteries of the city, which determine the development of the city in the future. Therefore, to address the serves transportation problems, multiple traffic control solutions like reversible lanes, traffic signal control, and congestion charging zone have been employed in the metropolises all over the world and get great progress. Thanks to the creative traffic control methods, numeric international metropolises have stood up all over the world in the last century. Set the well-known congestion charging zone in London as an example (see Figure 1.2). A report (Pidgeon et al., 2017) from Transport Commit of London in 2017 shows that between 2002 and 2014, the number of private cars coming into the zone fell by 39% and 29,000 more passengers had entered the charging zone by bus during the morning rush hour, compared to a year before (2016). Another example is the reversible lane in Beijing, China (see Figure 1.3). A research (Cao et al., 2009) shows that the average traffic flow raises 17.3% in the morning rush hours, and the average 12.6% increase of travel speed is also detected.

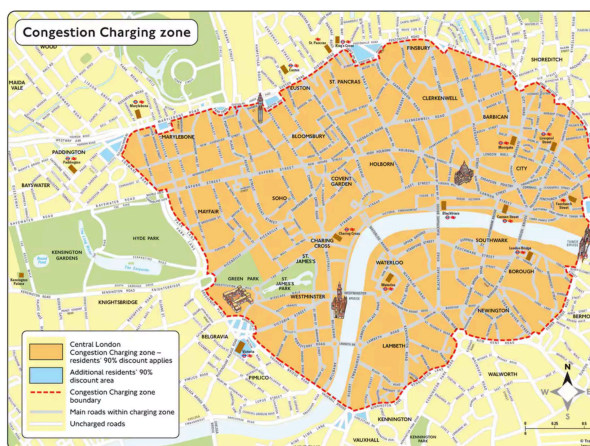
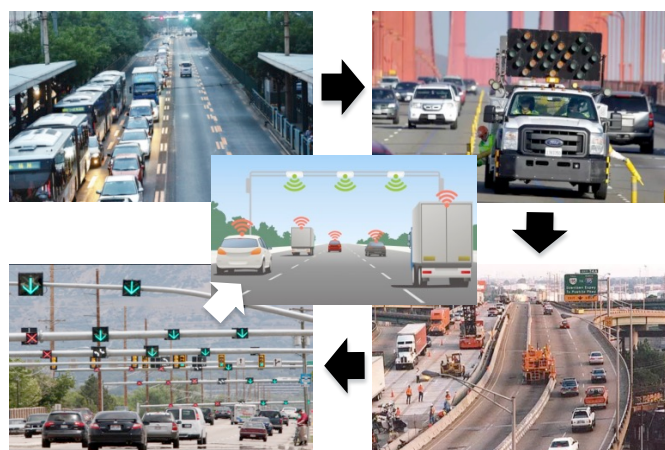


Figure 1.4 Congestion charging zone in London, UK²

Figure 1.5 The first reversible lane in Beijing, China³

Reversible lanes have been used throughout the world to mitigate the effects of congestion and optimize roadway performance for more than 80 years. They have been applied on a variety of roadway types such as arterials, freeways, and bridges using many different methods of control to address an assortment of needs, including the movement of unbalanced directional traffic associated peak commuter periods, emergency evacuations, roadway construction work zones, and other major gatherings and events (Lambert and Wolshon, 2010; Kim and Shekhar, 2008).



² Figure Source: <https://theconversation.com/london-congestion-charge-what-worked-what-didnt-what-next-92478>

³ Figure Source: <http://www.people.com.cn/>

Figure 1.6 Reversible lanes for mitigating traffic congestions

The methods and techniques to operate reversible lane system have also improved significantly from regulatory signs and road markings to dynamic signal controls during the last several decades. Figure 1.6 illustrates some current and future potential applications of reversible lanes for mitigating traffic congestions. San Francisco was used to manually shifted plastic cones on the Golden Gate Bridge. Then it bought a giant “zipper” machine that lifts concrete movable lane barriers and moves them from one lane to another. However, this type of convertible lane management mode deployed in some cities is designed for specific traffic patterns at specific hours, and can not quickly adapt to fluctuations in actual traffic. In these cases, the change in flow must be carefully planned before the event, with little or no room for dynamic changes. With the help of modern computerized traffic control systems, it is possible to quickly and dynamically open and close lanes or entire roads, or even change the directionality of lanes based on real-time usage statistics, such that effective capacity of a road can be dynamically changed based on the demand. Nowadays, dynamic signal control-based reversible lane system has been deployed in several cities all over the world, including Charlotte, Birmingham, Calgary, Montreal, and Vancouver (Guebert et al., 2010; Delanoy et al., 2011). These reversible lanes allow traffic, at different times, to travel in different directions depending on congestion. Traffic is directed by overhead signals with a green arrow or a red X into the correct lanes. However, these reversible lanes are only deployed on a single arterial, freeway or bridge and operated for improving traffic flow mobility only during rush hours. But for large cities, dynamic reversible lanes could be deployed on several coordinated arterials and freeways, thus, network-wide real-time management of dynamic reversible lanes is needed. Additionally, governments are now interested in developing reversible lane system to

maximize flows not only during peak periods or specific events such as emergency evacuation and major gatherings and events, but also addressing fluctuation of traffic flows at anytime.

Reversible lane systems have been proved to bring significant benefits (Golub, 2012). Firstly, they utilize roadway capacity that we often waste which means that when most cars are bunched up going one direction the reversible lane system can allocate more capacity to improve the flow mobility instead of wasting lots of capacity. Second, the costs to build reversible lane systems are far less than build-from-scratch highways even if we had the land. For example, in 2016, Denver put reversible lanes on 13 miles of roads for \$22.2 million plus \$710,000 a year to switch lane directions back and forth. However, the cost per mile a 4-lane highway will run between \$8 to \$10 million in urban areas. Third, it is faster to build reversible lanes. The government only spend around one year to build reversible lane system on an arterial instead of using several years to build more roads. While maximizing resources and improving the traffic mobility quickly and affordably, using reversible lanes to cut congestion raises other issues and still has a large amount of space to improve.

One of the most important issue is the safety. Pedestrians and drivers, especially new visitors from foreign countries may be unfamiliar with the dynamic signal-based reversible road. Motorists who are accustomed to one road pattern may not be focused enough to realize that the pattern differs mornings from evenings. If the signage is not clear and intelligible enough to all the road users, any accidents on the reversible lanes will lead to even worse congestions. Furthermore, rapid changes of lane directions, however, may confuse human drivers. To fully utilize the potential of dynamic lane reversal, we will need to rely on the upcoming availability of computer-aided driving systems and fully autonomous vehicles that will help vehicles to adjust to the rapid changes of lane directions. Connected Vehicle (CV) technology can be applied in the scenario to

assist the drivers drive in the right lane to grantee their safety. In the research, a smart sensor system for transportation will be employed to communicate with the drivers passing by. More details about the smart sensor system will be introduced in section 1.2. Based on the system, the smart dynamic reversible lane system can provide a more efficient and safe service for the drivers.

With the development of Intelligent Transportation System (ITS) recent years, more and more advanced technologies like Computer Vision (CV) have been applied in transportation field to empower the traditional traffic control approaches. For example, equipped with smart sensors, congestion, charging zone in London can detect and record the vehicles entered in the zone and realize automatic charging without any stop, which increase the traffic efficiency a lot. However, comparing with other traffic control solutions like traffic signal management, reversible lane control, got less attention because not only appropriate control algorithm is needed but also the hardware like traffic signs is significant for the safety issue in the reversible lane scenario. To improve the reversible lane performance, the thesis is aimed to introduce a multiple sensor fusion solution based on the products developed by Star Lab, in dynamic reversible lane control to improve traffic flow capacity in the given road.



Figure 1.7 Smart Road Sticker developed by Star Lab (left: version 1 and right: version 2)

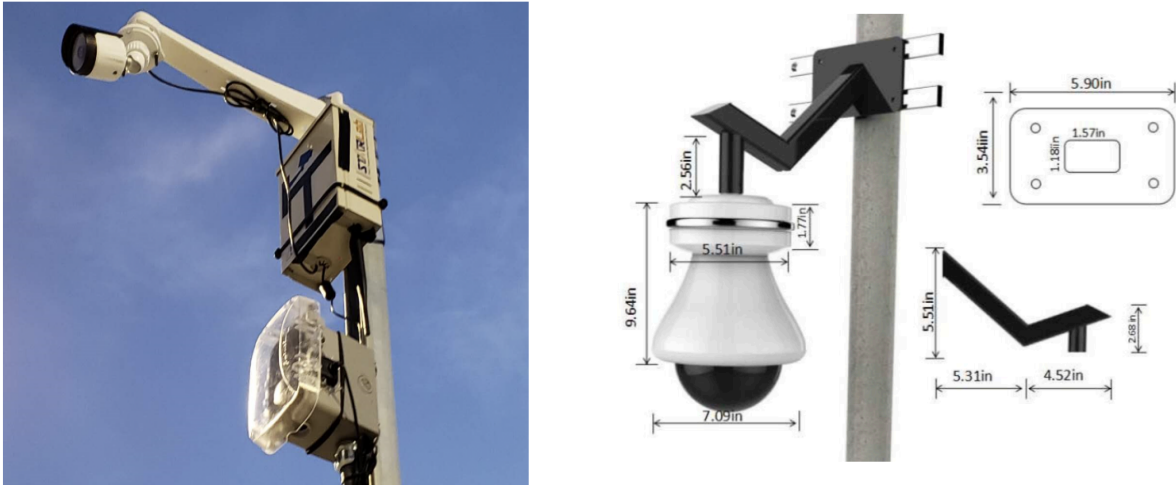


Figure 1.8 MUST Installed in Angle Lake Station Parking Garage

The Smart Road Sticker (SRS) (see Figure 1.7) is an innovated transportation device installed on the road surface for vehicle detection. Taking advantage of sensor fusion, SRS can detect the vehicles passing over it and record its status like travel speed with multiple sensor technologies including magnetic sensor, lightning sensor and ultrasonic sensor. For the recorded data transmission and processing, another advanced device developed by STAR Lab named Mobile Unit for Sensing Traffic (MUST) (see Figure 1.8) can cooperate with SRS for traffic information detection. MUST is a video-based traffic detection and communication device based on Raspberry Pi. It can collect the detection results from external sensors, such as SRS in this study, and the internal video sensors, and send collected data as to the designated server computer in a fast, reliable, and secured way for data storage, processing, computation, and service support.

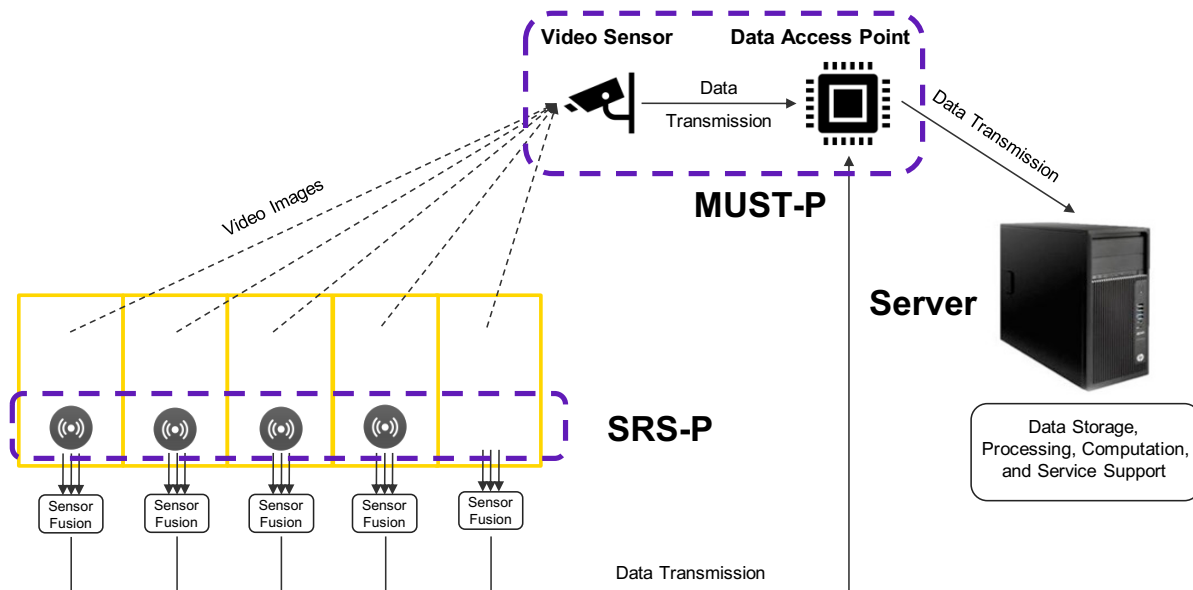


Figure 1.9 Basic Structure of the multi-sensor system in Parking Scenario

Along with the sensor fusion technology, a systematic algorithm has been developed by STAR Lab recent years, which enabled the SRS and MUST specific functions to multiple applications. For example, in a project funded by Sound Transit, about thirty SRS have deployed in Angle Lake Parking Garage for parking slots occupancy status detection. Figure 1.6 shows the basic structure of the parking solution. In the reversible lane scenario, based on the sensor fusion technology and data processing algorithm, SRS can capture not only the traffic flow but also the queue length, traffic flow speed, and number of stops around the intersection, which can realize the real-time reversible lane control. Additionally, the control center can give out commands to the SRS through communication devices and SRS take actions. In the dynamic reversible lane scenario, the LED lights attached to the SRS can change between green and red to give the instruction to the drivers based on the commands from the control center.

1.2 RESEARCH OBJECTIVE

Based on the background introduced in Section 1.1, the truth that reversible lane control has made great achievement in multiple cities all over the world has proved that it is an efficient transportation management method for the directed traffic congestion caused by the urban planning. However, because of the hardware and algorithm limitation, at present, most of the reversible lane control is still a static traffic management method whose reversion time period is predetermined by the Department of Transportation based on the history traffic data. In spite of the control method can release the traffic congestion somehow, it is still lack of flexibility and efficiency. Furthermore, at present, in most cases, the cost on the reversible lane change is still too high to be accepted. Therefore, the study is focused on the real-time dynamic control algorithm for the reversible lane management, which can adjust the number of lanes in each direction based on the real-time data collected by sensor fusion system provided by STAR Lab from University of Washington, Seattle. The purpose of the control algorithm is the maximum traffic flow in the given road section.

There are two challenges need to be addressed in the study. The first challenge is the short-term travel demand forecasting in both directions, and the second challenge is the reversible lane control algorithm based on the near future travel demand forecasting result, which is aimed to maximize the traffic in the given road section.

Data fusion technology is the first challenge we have to face. In the study, both historical data and real-time data are necessary for the precise traffic flow prediction. Therefore, the combination of the two kinds of data is the first challenge we need to address. The study employs Long Short-term Memory (LSTM) model for the traffic flow prediction based on the real-time data and historical data. Additionally, considering the traffic flow in various environment

conditions like sunny condition and rainy condition, the study expands the environment data to a matrix and inserts it into the LSTM model as the attribute module. Based on the environmental data module, the model can produce a more precise traffic flow in the near future.

Secondly, based on the traffic demand result got from the first step, a bi-level program model is applied in the scenario to describe the smart dynamic reversible lane control algorithm. In the bi-level programming model, the upper level is aimed to maximize the through output of the entire road section, and the lower level is focused on minimize the total travel time in the road segment. In the other word, the upper level programming is for the system level optimization and the lower level programming is for the individual level optimization. In the step, the traffic flow which has been predicted in the previous step has been employed as the input of the programming. Based on the predicted traffic flow, the best reversible lane solution will be generated by the bi-level programming algorithm. In the next time period, the new reversible lane plan will be applied to practice, and roadside sensing units will detect the new traffic flow, which can server as the real-time data input in the step 1. Therefore, the traffic flow in the near future will be predicted again by the LSTM model, which can be work as the input of the bi-level programming module for the new reversible lane solution in the next time period.

1.3 SCOPE OF THE STUDY

The work improves a traditional traffic management method, reversible lane control, from static control to dynamic real-time traffic management. In the study, the Long Short-term Memory (LSTM) model will be employed for the real-time short-term traffic flow prediction. To increase the prediction accuracy, the study embeds the environment factors as a matrix into the model. Based on the predicted travel demand, we maximize the total traffic flow in both directions which

determine the lane deployment. Finally, the validation part, the study introduces VISSIM as the simulation tool to test the effect of the dynamic reversible lane control algorithm.

The algorithm proposed in the paper can provide a solution for the traffic congestion scenario with unbalanced traffic flow, which can improve the traffic capacity of the road. In the work, the contribution of the study can be summarized as three points. The first contribution is the study introduces a new smart traffic sensing system containing Smart Road Sticker (SRS) and Mobile Unit for Sensing Traffic (MUST) into a specific transportation application. Therefore, the introduction of the smart sensing system is the first contribution of the study. Secondly, the study has proposed a complete algorithm to present how to use the new dataset generated by the smart sensing system in the reversible lane control scenario. In the research, the author did the traffic demand forecasting based on the new dataset which inspire the future research working on the data. As a start, the new data can be used in more and more situation to address various traffic problems. Finally, cooperating with the dynamic reversible lane control algorithm proposed in the research can realize the real-time traffic flow control, which have great contribution for the traffic management.

The structure of the thesis is organized as follows: Chapter 1 introduces the general background and the overview of the study. Chapter 2 is the literature review parts which reviews the traffic flow prediction models and dynamic reversible lane control algorithms. In Chapter 3, the study specifies the details of the traffic flow prediction models. And Chapter 4 introduce the bi-level programming model based on the predicted traffic flow. Chapter 5 presents the sample experiment and its results. Finally, in Chapter 6, we conclude the whole study and introduces the future work.

Chapter 2. STATE-OF-THE-ART

2.1 DYNAMIC REVERSIBLE LANE MANAGEMENT

2.1.1 *Overview*

Reversible traffic operations are widely regarded as one of the most cost-effective methods to increase the capacity of an existing freeway, arterial, or bridge. Current researches on reversible lane control are mostly focusing on two aspects, the practice side and the theoretical side. On the practice side, studies were conducted to established guidelines and standards to guide their planning, design, and operation (Lambert and Wolshon, 2010; Krause et al., 2014). On the theoretical side, researches were focused on addressing the optimal control and traffic conflicts during the operation of reversible lane systems in different scenarios (Ampountolas et al., 2018; Wang et al., 2018; Zhao et al., 2015; Bede and Péter, 2011). As a research level study, the thesis is focused on the theoretical side. In the other word, the reversible lane control algorithm is the key point discussed in the paper. The following parts review the reversible lane control algorithm in two aspects: the traditional control algorithm and the bi-level control algorithm.

2.1.2 *Traditional Methods*

Using the National Cooperative Highway Research Program (NCHRP), Wolshon and Lambert (2006a, 2006b) studied the application range of the reversible lane, with a focus on assuring the security of the reversible lane, the influence on the environment, and the design and implementation requirements. They (Lambert and Wolshon, 2010) also studied to measure and evaluate the speed and flow characteristics of reverse-flow traffic streams by comparing them under various operating conditions and locations. It was found that, contrary to some opinions, the flow characteristics of reverse-flowing lanes were generally similar to normally flowing lanes

under a variety of traffic volume, time-of-day, location, and type-of-use conditions. (Frejo et al., 2016) proposes a macroscopic model and two control algorithms for the dynamic operation of reversible lanes on freeways. (Zhao et al., 2014) developed a lane-based optimization model to guide the integrated setting of reversible lanes and other traffic management measures in an arterial to maximize its operational performance. (Dey et al., 2011) introduced the reversible lane implementation for a city corridor at traffic peak periods for the purpose of improving American traffic flow. They also studied the application of the reversible lane in temporary emergency evacuations, traffic maintenance, and other special events. (Sheu, 2001) studied the lanes-transform behavior when a reversible lane has been implemented. They also constructed a random predicting model for lanes-transform behavior. (Zhang et al., 2007) proposed a lane adjustment method for roads with bidirectional traffic imbalance. They constructed a discrete bi-level programming model for allocating lanes in an urban traffic network. Using an ordered sample class and nonparametric regression, (Gong and Kang, 2006) took on the traffic tide phenomenon and proposed a switching algorithm for travelling direction. (Hausknecht et al., 2011) proposed a framework for dynamic lane reversal in which the lane directionality is updated quickly and automatically in response to instantaneous traffic conditions recorded by traffic sensors. (Karoonsoontawong and Lin, 2011) allowed time-varying reversibility with different reversibility durations for various candidate link pairs in the program model, such that the optimal starting times and the optimal reversibility durations for candidate link pairs could be determined for peak-period traffic management on a daily basis. (Wu et al., 2009) introduced flow entropy in the upper level objective function to obtain symmetrical flows. The upper level of Wu's model was to minimize the total system cost and flow entropy and the lower level was a stochastic user equilibrium assignment with an advanced traveler information system. (Xie et al., 2010) and (Xie et al., 2011)

discussed a dynamic evacuation network optimization problem that incorporated lane reversal and crossing elimination strategies.

2.1.3 *Bi-level Programming Method*

In the recent ten years, a new model is applied to the reversible lane control more and more frequently, Bi-level programming methods. Bilevel optimization is defined as a mathematical program, where an optimization problem contains another optimization problem as a constraint. Since 1950, with the development of computing power, bi-level optimization has been applied to more and more applications. Figure 2.1 presents the bilevel network-map showing connections between various applications and theory since 1950s. Each connecting link represents either a topic connected with a subtopic, or an overlap between two subtopics. Comparing with the traditional optimization algorithm, the bi-level programming can be used for the more complex system like smart transportation system. In the transportation system, the system optimization is not the operators' only concern, but also the user time costs. Therefore, transportation system is one of the most important applications of bi-level optimization.

In the reversible lane scenario, the upper level optimization problem is aimed to maximize the through output of the road section, and the lower level optimization problem is focused on minimize the total travel time of the users. In the other word, the upper level is the systematic level optimization and the lower level is the individual level optimization.

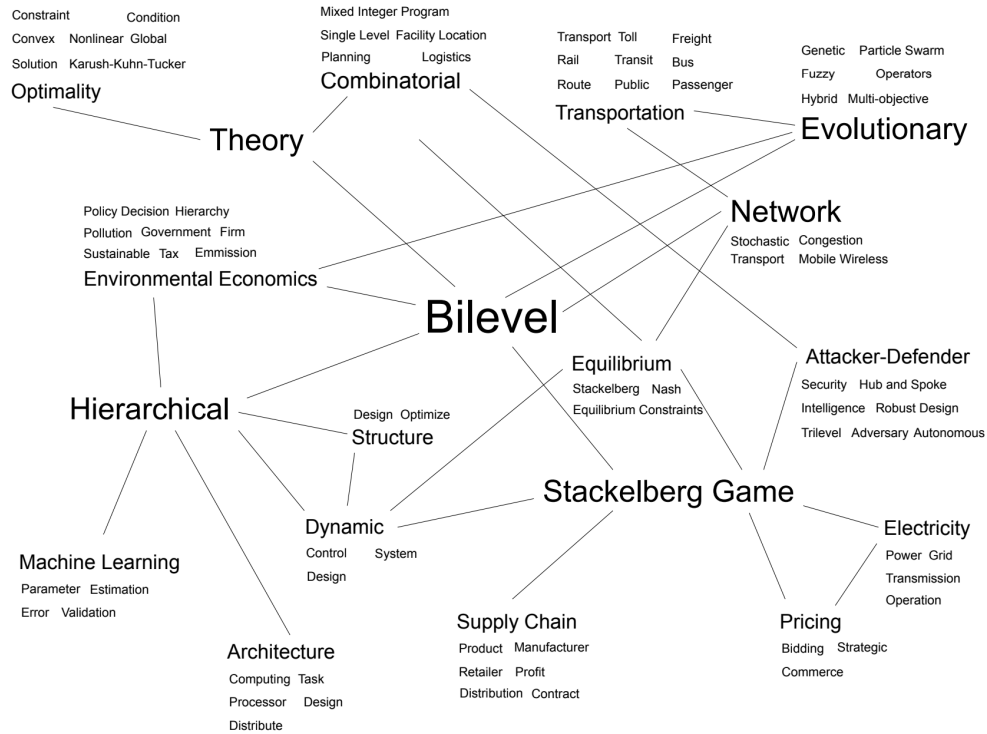


Figure 2.1 Bi-level network-map showing connections between various applications⁴

A bi-level network optimization model was formulated in which the upper level aimed at optimizing the network evacuation performance subject to the lane-reversal and crossing-elimination constraints and the lower level conveyed a cell transmission-based dynamic traffic assignment problem. An integrated Lagrangian relaxation and tabu search method was designed for approximating the optimal problem solutions. (Levin and Boyles, 2016) developed a cell transmission model for dynamic lane reversal with autonomous vehicles. (Sheu et al., 2001) studied the lanes- transform behavior when a reversible lane has been implemented. They also constructed a random predicting model for lanes-transform behavior. (Zhang et al., 2007) proposed

⁴ Sinha, Ankur, Pekka Malo, and Kalyanmoy Deb. "A review on bilevel optimization: from classical to evolutionary approaches and applications." *IEEE Transactions on Evolutionary Computation* 22.2 (2017): 276-295.

a lane adjustment method for roads with bidirectional traffic imbalance. They constructed a discrete bi-level programming model for allocating lanes in an urban traffic network. Using an ordered sample class and nonparametric regression, (Gong and Kang, 2006) took on the traffic tide phenomenon and proposed a switching algorithm for travelling direction. (Hausknecht et al., 2011) proposed a framework for dynamic lane reversal in which the lane directionality is updated quickly and automatically in response to instantaneous traffic conditions recorded by traffic sensors. (Karoonsoontawong and Lin, 2011) allowed time-varying reversibility with different reversibility durations for various candidate link pairs in the program model, such that the optimal starting times and the optimal reversibility durations for candidate link pairs could be determined for peak-period traffic management on a daily basis. (Wu et al., 2009) introduced flow entropy in the upper level objective function to obtain symmetrical flows. The upper level of Wu's model was to minimize the total system cost and flow entropy and the lower level was a stochastic user equilibrium assignment with an advanced traveler information system. (Zhang et al., 2016) discussed a dynamic evacuation network optimization problem that incorporated lane reversal and crossing elimination strategies.

(Chu et al., 2017) proposed the Dynamic Lane Reversal-Traffic Scheduling Management (DLRTSM) Scheme for CAVs. It collects the travel requests from the CAVs and determines their optimal schedules and routes on dynamically reversible lanes.

While a lot of studies have been done on improving the operations of reversible lane, very limited number of published researches have considered the integration optimization of dynamic reversible lane control, CAV routings, and traffic signal phase and timing for mixed traffic.

2.2 TRAFFIC DEMAND FORECASTING

2.2.1 *Overview*

In transport engineering, prediction of travel demand based on direct observations of the network (e.g. from traffic counts and other traffic measurements) is a classical and widely adopted procedure, both in off-line planning and in on-line (real-time) applications (Lu et al., 2013; Ma et al., 2017). In literature, demand estimation has been initially studied assuming static conditions for the simulation process, that is to say, based on specific assumptions underlying the impact of congestion on route choice. When such conditions do not hold, demand estimates must reflect both time variability and network patterns. (Carrese et al., 2017) investigated the dynamic demand estimation and prediction for traffic urban networks by adopting new data sources. (Peng-peng et al., 2018) analyses the state change of traffic flow on the road network and establishes the dynamic traffic diversion model, inducing the redistribution of traffic demand. Considering the changes in the amount of origin–destination (O-D) demand, diversion rate is introduced into the basic theory of dynamic traffic flow model, and then established a dynamic traffic flow model based on dynamic demand change.

Moreover, current technologies can provide a great heterogeneity of traffic data, referring to data of different nature collected both locally (sections) and on wide spatial coverage: pavement-embedded sensors, roadside radars and cameras provide measures of flows and speeds at nodes and along links; Advanced Vehicle Identification (AVI), ground-based radio navigation, cellular geo-location and GPS provide a new kind of information about travel times and drivers' route choice that integrate usual information on traffic flows at count sections. Examples of applications of different kind of traffic measurements in the dynamic demand estimation problem (DDEP) can be found in (Balakrishna et al., 2007); (Ashok and Ben-Akiva, 2000); (Tavana, 2001). (Cipriani et

al., 2014) showed a preliminary analysis on the contribution provided by link flows, link speeds and path travel times in the DDEP: results point to the value of information quality and quantity, as well as to ways to improve the demand usually when a sample of path travel time measurements is considered. Several contributions deal with the adoption of AVI data (Dixon and Rilett, 2002; Antoniou et al., 2006; Zhou and Mahmassani, 2007), bluetooth (BT) and mobile phone data (Sohn and Kim, 2008; Barceló et al., 2013). The inclusion of users' route choice data collected by probe vehicles (Floating Car Data, FCD) is warranting increased interest due to their potential added value in solving the DDEP as well as in explaining the real choice mechanism of road users: FCD have been used by Ásmundsdóttir (2008), Ásmundsdóttir et al. (2010) and Zhao et al. (2010), both to derive a priori matrices and to correct them in the dynamic procedure. Specifically, in the first two contributions, FCD are used to derive a priori matrices and to analyze route choices and trip length distributions to be adopted during the dynamic demand estimation by an entropy maximization approach. In the latter, static O-D demand has been generated based on Remote Traffic Microwave Sensors data (RTMS) and, successively, the time-varying O-D demands have been generated using the resulting time-varying splitting rates by a combined application of FCD and RTMS data. Link travel speeds and link flows derived from FCD have been adopted by Yamamoto et al. (2009) and Cao et al. (2013) in the dynamic O-D matrices estimation problem solved by means of a bi-level generalized least squares (GLS) method. In Morikawa and Miwa (2006), the driver's dynamic route choice behavior using FCD have been analyzed with the aim of providing some fundamental knowledge on modelling dynamic behavior for a better representation in dynamic assignment model.

However, the accuracy of traffic demand estimation is largely relied on the quality of the data which could be significantly different from different places. This research is going to

develop a generalized data-driven method framework by integrating the most frontier traffic demand estimation methods while addressing the heterogeneity and uncertainty in the mixed CAVs.

2.2.2 *Traditional Method*

Current technologies can provide a great heterogeneity of traffic data, referring to data of different nature collected both locally (sections) and on wide spatial coverage: pavement-embedded sensors, roadside radars and cameras provide measures of flows and speeds at nodes and along links; Advanced Vehicle Identification (AVI), ground-based radio navigation, cellular geo-location and GPS provide a new kind of information about travel times and drivers' route choice that integrate usual information on traffic flows at count sections. Examples of applications of different kind of traffic measurements in the dynamic demand estimation problem (DDEP) can be found in Balakrishna et al. (2007); Ashok and Ben-Akiva (2000); Tavana (2001). Cipriani et al. (2014) showed a preliminary analysis on the contribution provided by link flows, link speeds and path travel times in the DDEP: results point to the value of information quality and quantity, as well as to ways to improve the demand usually when a sample of path travel time measurements is considered. Several contributions deal with the adoption of AVI data (Dixon and Rilett, 2002; Antoniou et al., 2006; Zhou and Mahmassani, 2007), bluetooth (BT) and mobile phone data (Sohn and Kim, 2008; Barceló et al., 2013). The inclusion of users' route choice data collected by probe vehicles (Floating Car Data, FCD) is warranting increased interest due to their potential added value in solving the DDEP as well as in explaining the real choice mechanism of road users: FCD have been used by Ásmundsdóttir (2008), Ásmundsdóttir et al. (2010) and Zhao et al. (2010), both to derive a priori matrices and to correct them in the dynamic procedure. Specifically, in the first two contributions, FCD are used to derive a priori matrices and to analyze route choices and trip

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2.2.3 *Machine Learning Method*

In transport engineering, prediction of travel demand based on direct observations of the network (e.g. from traffic counts and other traffic measurements) is a classical and widely adopted procedure, both in off-line planning and in on-line (real-time) applications (Lu et al., 2013; Ma et al., 2017). In literature, demand estimation has been initially studied assuming static conditions for the simulation process, that is to say, based on specific assumptions underlying the impact of congestion on route choice. When such conditions do not hold, demand estimates must reflect both time variability and network patterns. Carrese et al. (2017) investigated the dynamic demand estimation and prediction for traffic urban networks by adopting new data sources. Peng-peng et al. (2018) analyses the state change of traffic flow on the road network and establishes the dynamic traffic diversion model, inducing the redistribution of traffic demand. Considering the changes in

the amount of traffic flow demand, diversion rate is introduced into the basic theory of dynamic O-D model, and then established a dynamic traffic flow model based on dynamic demand change.

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Chapter 3. REALTIME TRAFFIC DEMAND FORECASTING

3.1 OVERVIEW

The toll data is the fundamental source of transportation planning and management research no matter in urban or rural area. (Mussonne et al., 2010). Taking advantage of traffic flow data, many studies have great achievements in traffic flow characteristics recognition (Wang et al.,2010) and driver behavior analysis (Dsa Miska et al.,2009). In practice, traffic flow prediction can be applied to multiple traffic flow and infrastructure management in expressway such as performance evaluation, investment decision-making, traffic volume balancing, deployment of personnel and resources and congestion mitigating (Mussonne et al., 2010), (Wang et al.,2010), (Dsa Miska et al.,2009). However, the attributes of the toll data like continuity and granularity have great impact on the final result, which indicates a reliable and concise methods to collect the toll data is significant.

The generation of the toll data of expressway usually faces considerable difficulties (Wang et al.,2010), traditional methods like field survey and observation methods are not applicable to expressway condition. However, the enclosed expressway system provides (i.e., vehicles must pass through the toll gates when they enter or exit the expressway) in China a favorable condition to record the toll data. In the process, the toll data generated by the toll stations contains the detailed information about trips including vehicle type, entry and exit gates ID, entry and exit time, and toll. Therefore, the entry and exit toll gate sites can be considered as the origins and destinations of the trips separately within the network. As a result, the data generated by the toll system can be regarded as a kind of toll data essentially (Qu et al., 2014), and it can reflect the spatial characteristics of the traffic flow in the enclosed network.

Many studies have proved that enclosed system generated toll data has satisfied performance in numeric applications of expressway, which has been applied in many expressway related flow analytics (Qu et al., 2014). The traffic flow matrices data generated by trip records and vehicle information in toll stations can be used for traffic process identification, demand characteristics understanding (Dsa Miska et al., 2009), mobility performance evaluation (Qu et al., 2014), the traffic flow parameters estimation (Zhao et al., 2014), travel time prediction and reliability evaluation (El Faouzi et al., 2010) (Yamazaki et al., 2012) in the network. Additionally, some studies focus on the weight data in the toll system, which can assist the researchers learn more about the vehicle types in the network (Zhang et al., 2012).

In review of the existing studies, multiple attempts have been made for traffic flow prediction in the enclosed expressway network, of which are based on Automatic Vehicle Identification (AVI) system (Asakura et al., 2000) or loop data (Mussone et al., 2010). For the studies employ toll data (or vested traffic flow data), we can classify them into three categories:

- 1) Linear theoretical models based on historical average models, time series models and Kalman filtering models (Asakura et al., 2000).
- 2) Nonlinear statistics models based on nonparametric regression models and chaotic theoretical models (Du et al., 2009).
- 3) Machine learning prediction models based on neural network, support vector machine etc. (Lorenzo et al., 2013).

In summary, existing studies, especially the neural network modeling method has made great progress in expressway traffic flow prediction, however, further exploration is still needed on the following issues:

- 1) Most studies considered the case of one single road only (Wang et al., 2007) or a simple road network (Kikuchi et al., 2000), while the model design research for large-scale, complex road networks is rare.
- 2) Some studies have carried out the design and application of neural network models based on link counts data (Lorenzo et al., 2013), but the applicability of traffic flow prediction at different time granularities still needs further discussion.
- 3) Some studies have realized neural network model design for traffic flow prediction in the selected link instead of the complete network (Remya et al., 2013), however, to understand the characteristics of traffic flow in practice, the network-scale study is necessary.
- 4) For traffic flow matrix prediction based on an artificial neural network, the influence of city attributes like GDP is rarely considered, which may impact the accuracy of the results neural network modeling.

The artificial neural network like Recurrent Neural Network (RNN) was widely used in transportation field for traffic flow estimation and prediction. RNN is a well-known kind of neural network can model sequential information by maintaining a chain-like structure and internal memory with loops (Jozefowicz et al., 2015) and is widely used in traffic information prediction. Taking advantage of RNN, a series of research about travel behavior recognition, trajectory prediction (Van Lint et al., 2005) (Elhenawy et al., 2014) (Ye et al., 2012) have been developed recently. However, one technology challenge blocks the progress: the chain-like structure and deep loops deteriorate the process of model training, which lead the loss function (i.e., the deviance between the training results and the true records) of RNN hard to converge. There are multiple attempts for the challenges and the Long Short-Term Memory (LSTM) neural network (Hochreiter et al., 1997) is one of the successful attempts.

The LSTM neural network firstly proposed in 1997 [ibid] is a special form of RNN that is capable of learning long-distance dependencies. Compared with the other neural networks, LSTM has a better applicability in processing sequence data and identifying trends. A multi-layered LSTM was introduced to present an end to end sequence learning that makes the minimal assumptions on the sequence structure (Sutskever et al., 2014). Therefore, the translation result can be closer to the nature language with less misunderstandings. In the application of traffic data prediction field, the LSTM is also proven to handle spatio-temporal data. A Spatial-Temporal LSTM network was once used to capture the transportation trajectories features, which can memory and summarize the changes of GPS data sequence (Zheng et al., 2009). Another point to note is the LSTM applied in computer vision and machine translation filed shows that it can deal with several different data sequence and memory sequence characteristics.

3.2 STUDY DATA

In the study, we used the toll data and the weather data in the freeway system for the traffic flow prediction.

3.2.1 *Toll Data*

The primary purpose of toll data collecting is to fully document the individual trip process and related details of the vehicle's use of road to support charging behavior. The toll amount of a complete driving process usually needs to be determined by factors such as distance, vehicle type (sometimes including weight), driving time, etc. The typical data structure of a typical charging record (take Guangdong Province as an example) is shown in Table 3.1. Some fields not related

to this paper are not listed here, such as axle weight, payment method, whether it is a free vehicle, data upload time, etc.

Field Name	Field Type	Data Example	Remarks Example
Entry Gate No	Int	006	
Entry Lane No	Int	12	
Entry Time	Date	2017/9/1 20:54:00	
Exit Gate No	Int	002	
Exit Lane No	Int	2	
Exit Time	Date	2017/9/1 22:31:00	
Exit Lane Type	Int	1	'0'-ETC, '1'-Non_ETC
Vehicle Type	Int	5	
Vehicle License	String	“粤A96534”	
Vehicle Kind	Int	0	'0'-Car, '1'-Truck

Table 3.1 Toll data format

The toll system will generate a large amount of flow data in a short period of time. Due to various situations, the toll data will generate abnormal data which may affect the result. Data for the following cases will be deleted in this paper to reduce interference.

- Data redundancy: multiple record of data reflects the same trip.
- Inaccurate Data: Data cannot be identified as a specific toll gate site, and the OD information cannot be extracted.
- Data anomaly: Data records are contrary to normal trip rules, including entering and leaving the expressway from the same gate, the travel time is zero, etc.

Although the traffic flow information formed by the toll data is continuous, for the sake of simplicity, in this study, the toll data are combined use the same traffic flow data and summarized into 4 different time intervals: per 15 minutes, per 30 minutes, per 45 minutes and per 60 minutes.

3.2.2 *Attributes Data*

The attribute data mainly includes information for the location, travel generation and attraction of the Origin and Destination gate. In this paper, the attribute data mainly includes the GDP, the population, the motor vehicle ownership, and the location information of the city where the toll gate located. The first three attribute data can be obtained by matching the geographic coordinates of the toll gate with the city's administrative boundary. Location information It mainly includes two sub-variables:

- (1) whether the toll gate is in an urbanized area;
- (2) whether the toll gate is at the edge of the entire expressway network (ie, a toll gate on the provincial boundary). The 0-1 variable is used to assign the location information.

3.3 NETWORK STRUCTURE

The Neural-Network used for predicting this OD matrix is a Modular Plug-in Neural Network. The architecture shows in the Figure1. Basically, it is consisted by three modules, the Feature Extension Module (FEM), the Memory Module (MM), and the Prediction Module (PM). The Feature Extension Module (FEM) is responsible for extract and convert features of a serious of OD pair, using embedding and concatenate method. Memory Module is based on Bi-LSTM to capture the time dependency of the OD pair changes. The Prediction Module is responsible for converting the neural network out put into OD flow sequence.

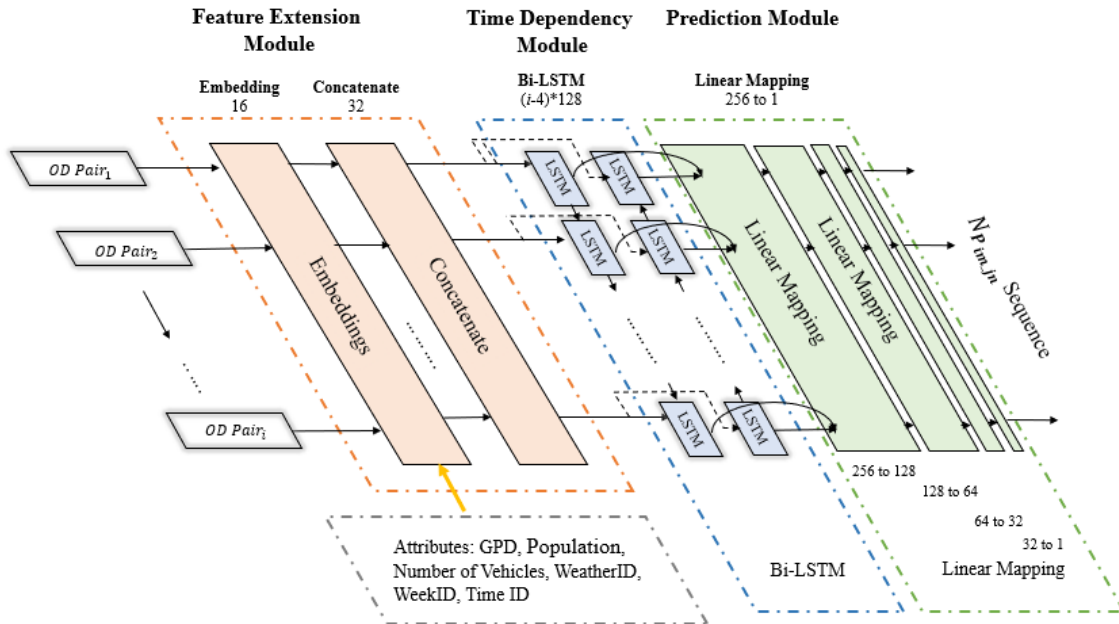


Figure 3.1 The structure of advanced Bi-direction LSTM

3.3.1 Network establishment

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3.3.2 Feature Extension Module

As mentioned before, the OD distribution of express way is affected by tons of factors, such as time, location, weather situation, the located city economic situation, the located city population etc. An effective method to combine these and incorporate these factors in our neural network.

Here, GDP, Population, Number of vehicles, weather condition (rainy/snowy/sunny etc.), the time stamp (0-96) are necessarily added here. However, the format of these factors is not fit to neural network directly. For the GDP, Population, Number of vehicles used here, a normalization process is necessary. Here, researchers use the mean-standard method. The Mean-SD is used to avoid the shifting of the weights in the network caused by extreme values and the training process will be accelerated either.

$$\hat{x}^{(k)} = \frac{x^{(k)} - E[x^{(k)}]}{\sqrt{Var[x^{(k)}]}} \quad (1)$$

Embedding is an effective way to transform discrete categorical attributes into a low-dimensional vector. Here, (Gal et al, 2016) inspired us to achieve the process, using a mathematical mapping method from each categorical into a vector of \mathbf{R}^{m*1} . In our research, \mathbf{P}_{im_jn} is embedding into a space of \mathbf{R}^{16} , called $V_{\mathbf{P}_{im_jn}}$; and the attributes sets are also embedding into a space of \mathbf{R}^{16} , called $V_{\text{attribute}_{im_jn}}$.

Concatenate here is used to combine both information vector into a whole vector before capture the time dependency. \odot represents concatenate:

$$\hat{\mathbf{P}}_{im_jn} = V_{\mathbf{P}_{im_jn}} \odot V_{\text{attribute}_{im_jn}} \quad (2)$$

3.3.3 *Memory Module*

In many real-world tasks, especially traffic flow prediction, in OD prediction problems, the input of the network is not only related to the input at the current moment, but also related to the output of the past period of time. Such prediction problems often have the length of time series data is generally not fixed, the correlation between adjacent data is very strong, and there is an accumulation effect. Recurrent Neural Network (RNN) is a kind of neural network with short-term memory ability. In a circulating neural network, neurons can not only receive information from other neurons, but also accept their own information to form a network structure with loops.

Bidirectional LSTM (BiLSTM) is a novel improved version of LSTM network used in EODPNN. In BiLSTM, two LSTM layers pass the data sequence on two opposite directions, one forward direction and another backward direction. The output is concatenated both layers into a long vector including both direction time dependency features. Both former step input and later step input information are combined. The Figure 3.2 below shows Bi-LSTM structure. Six unique weights are used repeatedly here, which are correspond to: input to the forward and backward hidden layers (w_i, w_m), and hidden layers to the hidden layer itself (w_j, w_n), forward and backward hidden layer to output layer (w_k, w_o)

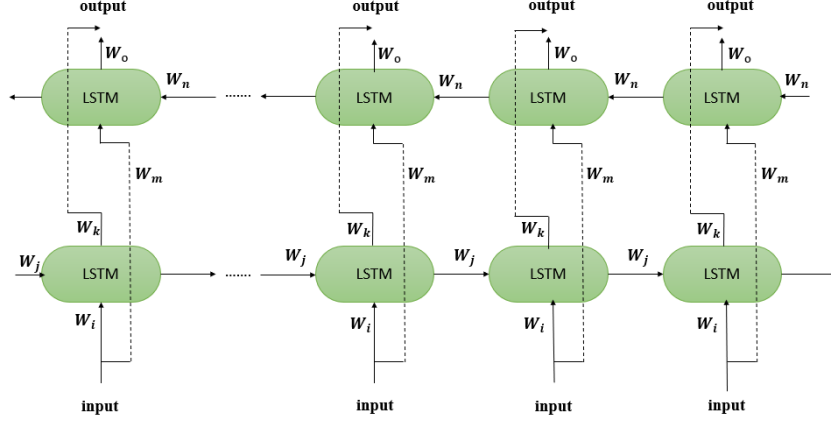


Figure 3.2 Bidirectional LSTM (BiLSTM) Network

In our module, the output sequence $Output_{BiLSTM}$ can be shown as

$$Output_{FP_{BiLSTM}} = \sigma_{rnn}(W_i \cdot Input_{FP} + W_j \cdot h_{i-1} + W_k \cdot Output_{FP}) \quad (3)$$

$$Output_{BP_{BiLSTM}} = \sigma_{rnn}(W_m \cdot Input_{BP} + W_n \cdot h_{i-1} + W_o \cdot Output_{BP}) \quad (4)$$

$$Output_{BiLSTM} = Output_{FP_{BiLSTM}} \odot Output_{BP_{BiLSTM}} \quad (5)$$

h_{i-1} is the hidden state represent after processed the $i-1$ _th time stamp in BiLSTM network. σ_{rnn} is the activation function researcher used here. $W_i, W_j, W_k, W_m, W_n, W_o$, are learnable parameter matrices located in two different direction and they are all illustrated in the figure 4.

3.3.4 Prediction Module

This module is responsibility for transforming the vector into a $N_{P_{im,jn}}$ data sequence.

Four Linear Mapping Layer are used here, transform the vector from 256 to 128, and then 64, 32 and output sequence. The active function of each layer if is Leaky ReLU function.

3.4 MODEL TRAINING

Here the mean absolute error (MAE), the mean absolute percentage error (MAPE) and root mean squared error (RMSE) are used to train this network based on different training strategy. MAE measures the average magnitude of the errors of OD prediction numbers. RMSE is a quadratic scoring method which also used to measure the average magnitude of the OD prediction distribution and useful to represent the large errors and the extreme values. MAPE represents the percentage of the error and always use as a measurement to show the overall performance of the whole network. ε is used to prevent the 0-denominator and here ε is 3. Three loss-function in details:

$$MAE = \frac{1}{N} \sum_{i,m,j,n} |N_{P_{im_jn}} - \widehat{N_{P_{im_jn}}}| \quad (6)$$

$$MAPE = \frac{1}{N} \sum_{i,m,j,n} \left| \frac{N_{P_{im_jn}} - \widehat{N_{P_{im_jn}}}}{N_{P_{im_jn}} + \varepsilon} \right| * 100\% \quad (7)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i,m,j,n} (N_{P_{im_jn}} - \widehat{N_{P_{im_jn}}})^2} \quad (8)$$

Chapter 4. BI-LEVEL PROGRAMMING METHOD

4.1 OVERVIEW

This research component aims to identify, from a theoretical perspective, the effects of lane reversal on a single road. In the study, we only focus on the freeway reversible lane scenario, one of the simplest scenarios. Because in the study, the method idea we proposed is the most important rather than the application scenarios. In the future work, we only consider the corridor and network system in both freeway and local roads. But at present, the master thesis focuses only on the new control algorithm in freeway reversible lane application.

In the Chapter 3, the paper introduces the LSTM model for the traffic flow prediction. The short-term prediction results will be the inputs of the bi-level optimization. In the following paragraphs, we will set a simple example to demonstrate the algorithm.

Consider a road segment between two toll gates I_1 and I_2 . Let R be the road between I_1 and I_2 , $L_{1,2}$ be the set of lanes from I_1 and I_2 , and $L_{2,1}$ be the set of lanes from I_2 to I_1 . We assume a freeway road segment scenario (see Figure 4.1) as an example. In Figure 4.1, $L_{1,2} = \{l_1, l_2\}$ and $L_{2,1} = \{l_3, l_4\}$. The capacity of a lane l , denoted by $c(l)$, is the maximum rate at which vehicles enter the lane and is measured by the number of vehicles per hour. We assume the capacity of a set L of lanes, denoted by $c(L)$, is the sum of the capacities of all lanes ($c(L) = \sum_{l \in L} c(l)$). For simplicity, the effect of lane changing which potentially reduces the capacity of L is ignored. This is one of the most important assumptions in the study.

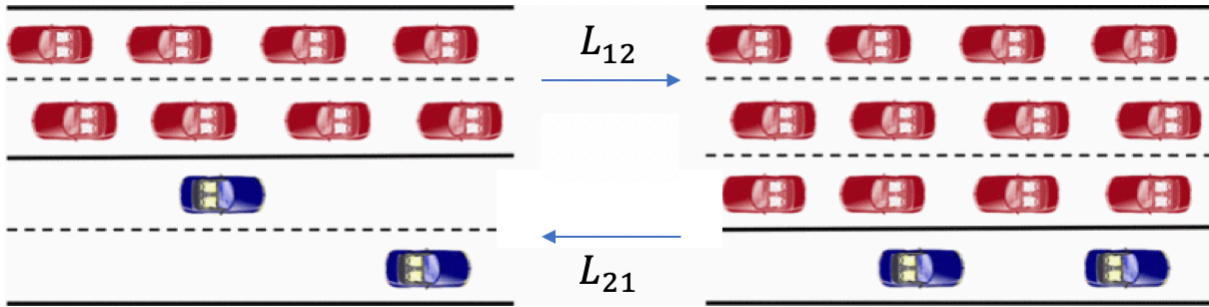


Figure 4.1 Reversible lane schematic diagram

In the section, we have to give out some definitions will be used in our algorithm.

Assume both I_1 and I_2 are sources at which vehicles are generated to travel along R at the target traffic rates $\beta(I_1)$ and $\beta(I_2)$ respectively. But the effective traffic rates $\lambda(L_{1,2})$ and $\lambda(L_{2,1})$ at which vehicles actually enter the road are limited by the capacity of the lanes. More precisely, $\lambda(L_{1,2}) = \min\{\beta(I_1), c(L_{1,2})\}$ and $\lambda(L_{2,1}) = \min\{\beta(I_2), c(L_{2,1})\}$. If $\lambda(L_{1,2}) = c(L_{1,2})$, we say $L_{1,2}$ is saturated. If $\beta(I_1) > c(L_{1,2})$, $L_{1,2}$ is oversaturated by an amount of $\beta(I_1) - c(L_{1,2})$. Clearly, if $L_{1,2}$ is oversaturated, $L_{1,2}$ is saturated. $L_{1,2}$ is undersaturated by an amount of $c(L_{1,2}) - \beta(I_1)$ if $\beta(I_1) < c(L_{1,2})$. Similarly, the saturation of $L_{2,1}$ can be defined in the same manner. For a short summary:

- 1). $\beta(I)$: The target traffic rates along road section R from source I
- 2). $\lambda(I)$: The effective traffic rates along road section R from source I
- 3). $c(I)$: The maximum traffic rates along road section R from source I

The throughput of the road R is the sum of the effective traffic rates of the lanes (i.e., $\lambda(L_{1,2}) + \lambda(L_{2,1})$). Now consider what happens if the direction of $l \in L_{1,2}$ is reversed. By definition, the throughput of the road increases after the reversal of l if and only if:

$$\lambda(L_{1,2})+\lambda(L_{2,1}) < \lambda^*(L_{1,2})+\lambda^*(L_{2,1}) \quad (1)$$

Where,

$$\lambda^*(L_{1,2})=\min\{\beta(I_1),c(L_{1,2})-c(l)\}$$

$$\lambda^*(L_{2,1})=\min\{\beta(I_2),c(L_{2,1})+c(l)\}.$$

In general, lane reversal is beneficial only when one of the directions is oversaturated while the other is undersaturated. Please notice that the if $\lambda(L_{1,2}) + \lambda(L_{2,1}) = \lambda^*(L_{1,2}) + \lambda^*(L_{2,1})$, the lane change action will not take place. Understand the effects of lane reversal on the freeway road sections is helpful to solve the optimization model for corridor level and network level dynamic reversible lane control in the future.

This research task aims to develop the optimization model for network-wide dynamic reversible lane control and routing for mixed CAVs. We model the road network by a directed multigraph denoted by $\phi(\nu, \varepsilon)$, where ν is a set of vertices indicating the road intersections and points of interest, and ε is a set of road segments connecting two vertices. Each road segment $(i, j) \in \varepsilon$ is composed of a number of parallel lanes. Each lane $l \in (i, j)$ is associated with a lane capacity $\mu_{ij,l}$, and travel time $c_{ij,l}$, indicating the corresponding maximum traffic flow rate and estimated travel time, respectively.

It is assumed that all the CAVs running on $\phi(\nu, \varepsilon)$ are managed by a central control center which determines their travel routes and schedules. Each vehicle $k \in \kappa$ is associated with a travel plan modeled by the 4-tuple $(s^k, d^k, \tau_s^k, \tau_d^k)$. $s^k \in \nu$ and $d^k \in \nu$ are the source and destination of vehicle k , respectively. τ_s^k is the earliest time of departure at s^k while τ_d^k is the latest time to arrive at d^k . Thus we can schedule the route of CAV k in the travel time window $[\tau_s^k, \tau_d^k]$, which

gives flexibility for the central control center to determine its travel schedule within the travel time window.

To develop the optimization model, the decision variables are defined as below. Binary variables $x_{ij,l}^{tk}$ are used to indicate which lane segment $l \in (i, j)$ is traversed by CAV k in time t :

$$x_{ij,l}^{tk} = \begin{cases} 1 & \text{if } k \text{ traverses lane } l \text{ from } i \text{ to } j \text{ at time } t, \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

We define binary variable $y_{ij,l}^t$ to indicate the direction of lane l in road segment (i, j) at time t :

$$y_{ij,l}^t = \begin{cases} 1 & \text{if direction of } l \text{ is from } i \text{ to } j \text{ at time } t, \\ -1 & \text{if direction of } l \text{ is from } j \text{ to } i \text{ at time } t. \end{cases} \quad (3)$$

Integer variable Γ_i^k is used to represent the time stamp of CAV k at vertex i . We aim to minimize the total travel time of CAVs. We also set penalty for late arrivals at the destinations. Thus, the objective function for CAVs is given as follows:

$$\sum_{k \in \mathcal{K}} (\Gamma_{d^k}^k - \Gamma_{s^k}^k) + \alpha \sum_{k \in \mathcal{K}} \max(\Gamma_{d^k}^k - \tau_{d^k}^k, 0) \quad (4)$$

Where:

α is the weight of the late arrival penalty.

The non-CAVs are considered in the Stochastic User Equilibrium (SUE) situation, and its optimization and trade-off with the system optimal solution are discussed in the following section.

This research task aims to address the balance between the system optimization and individual optimization. In a mixed traffic scenario, the non-CAVs cannot send requests to the central control center, so they will travel based on their own optimal routing choice and achieve a stochastic user equilibrium. According to Çolak et al. (2016)'s research published on *Nature Communications*, if we consider the travel time on a roadway segment $a \in A$ as cost, i.e., $c_a(x_a) = t_a(x_a)$, where x_a is the throughput on roadway segment a , $t_a(x_a)$ is the travel time (cost)

of the roadway segment when the throughput is x_a , then when x_a changes, the impact on the total travel time of all the vehicles on this roadway segment $x_a t_a(x_a)$ can be regarded as a marginal cost, i.e., $c_a(x_a) = d[x_a t_a(x_a)]/d x_a$. If we give weight $\delta \in [0,1]$ for the marginal cost, and $(1-\delta)$ for the individual travel time (cost), then

$$c_a^\delta(x_a) = (1-\delta)t_a(x_a) + \delta d[x_a t_a(x_a)]/d x_a \quad (5)$$

If we use $c_a^\delta(x_a)$ to replace the $t_a(x_a)$ in the objective function of the user equilibrium model, then the objective function Z could be:

$$\begin{aligned} Z &= \sum_{a \in A} \int_0^{x_a} c_a^\delta(w) dw = \sum_{a \in A} \int_0^{x_a} \{(1-\delta)t_a(x_a) + \delta d[x_a t_a(x_a)]/d x_a\} dw \\ &= (1-\delta) \sum_{a \in A} \int_0^{x_a} t_a(w) dw + \delta \sum_{a \in A} x_a t_a(x_a) \end{aligned} \quad (6)$$

where $\delta=0$ indicates the user equilibrium, and when $\delta=1$, the objective function $Z = \sum_{a \in A} x_a t_a(x_a)$

indicates the total travel time of all the vehicles on the roadway network which is actually the system optimization model. The weigh δ reflects the trade-off between individual optimization and system optimization which is helpful to build the equilibrium strategy-based optimization in this research. According to the theory of Pigovian taxation (Sandmo, 1978), if both directions of a reversible road segment are oversaturated as defined in Section 4.1.1, reversible lane tolling could be useful to mitigate the congestion. A free flow equilibrium will be achieved when the tolling price is high enough. In this way, rich people will pay for the tolling, and the total throughput of the roadway network will be improved. This mechanism could achieve the social equity as well as economic development benefits.

4.2 UPPER LEVEL OPTIMIZATION

This part will introduce the upper level optimization more specifically. We still use the example we proposed in Section 4.1. In the section, we Assume both I_1 and I_2 are sources at which vehicles are generated to travel along road section R at the target traffic rates $\beta(I_1)$ and $\beta(I_2)$ respectively. But the effective traffic rates $\lambda(L_{1,2})$ and $\lambda(L_{2,1})$ at which vehicles actually enter the road are limited by the capacity of the lanes. More precisely, $\lambda(L_{1,2})=\min\{\beta(I_1),c(L_{1,2})\}$ and $\lambda(L_{2,1})=\min\{\beta(I_2),c(L_{2,1})\}$. If $\lambda(L_{1,2})=c(L_{1,2})$, we say $L_{1,2}$ is saturated. If $\beta(I_1) > c(L_{1,2})$, $L_{1,2}$ is oversaturated by an amount of $\beta(I_1)-c(L_{1,2})$. Clearly, if $L_{1,2}$ is oversaturated, $L_{1,2}$ is saturated. $L_{1,2}$ is undersaturated by an amount of $c(L_{1,2})-\beta(I_1)$, if $\beta(I_1) < c(L_{1,2})$. Similarly, the saturation of $L_{2,1}$ can be defined in the same manner.

The throughput of the road R is the sum of the effective traffic rates of the lanes (i.e., $\lambda(L_{1,2})+\lambda(L_{2,1})$). Now consider what happens if the direction of $l \in L_{1,2}$ is reversed. By definition, the throughput of the road increases after the reversal of l if and only if

$$\lambda(L_{1,2})+\lambda(L_{2,1}) < \lambda^*(L_{1,2})+\lambda^*(L_{2,1}) \quad (1)$$

Where,

$$\lambda^*(L_{1,2})=\min\{\beta(I_1),c(L_{1,2})-c(l)\}$$

$$\lambda^*(L_{2,1})=\min\{\beta(I_2),c(L_{2,1})+c(l)\}$$

In general, lane reversal is beneficial only when one of the directions is oversaturated while the other is undersaturated. Understand the effects of lane reversal on a single road is helpful to solve the optimization model for network-wide dynamic reversible lane control.

This research task aims to develop the optimization model for network-wide dynamic reversible lane control and routing for mixed CAVs. We model the road network by a directed multigraph denoted by $\phi(\nu, \varepsilon)$, where ν is a set of vertices indicating the road intersections and points of interest, and ε is a set of road segments connecting two vertices. Each road segment $(i, j) \in \varepsilon$ is composed of a number of parallel lanes. Each lane $l \in (i, j)$ is associated with a lane capacity $\mu_{ij,l}$, and travel time $c_{ij,l}$ indicating the corresponding maximum traffic flow rate and estimated travel time, respectively.

It is assumed that all the CAVs running on $\phi(\nu, \varepsilon)$ are managed by a central control center which determines their travel routes and schedules. Each vehicle $k \in \mathcal{K}$ is associated with a travel plan modeled by the 4-tuple $(s^k, d^k, \tau_s^k, \tau_d^k)$. $s^k \in \nu$ and $d^k \in \nu$ are the source and destination of vehicle k , respectively. τ_s^k is the earliest time of departure at s^k while τ_d^k is the latest time to arrive at d^k . Thus we can schedule the route of CAV k in the travel time window $[\tau_s^k, \tau_d^k]$, which gives flexibility for the central control center to determine its travel schedule within the travel time window.

To develop the optimization model, the decision variables are defined as below. Binary variables $x_{ij,l}^{tk}$ are used to indicate which lane segment $l \in (i, j)$ is traversed by CAV k in time t :

$$x_{ij,l}^{tk} = \begin{cases} 1 & \text{if } k \text{ traverses lane } l \text{ from } i \text{ to } j \text{ at time } t, \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

We define binary variable $y_{ij,l}^t$ to indicate the direction of lane l in road segment (i, j) at time t :

$$y_{ij,l}^t = \begin{cases} 1 & \text{if direction of } l \text{ is from } i \text{ to } j \text{ at time } t, \\ -1 & \text{if direction of } l \text{ is from } j \text{ to } i \text{ at time } t. \end{cases} \quad (3)$$

Integer variable Γ_i^k is used to represent the time stamp of CAV k at vertex i . We aim to minimize the total travel time of CAVs. We also set penalty for late arrivals at the destinations. Thus, the objective function for CAVs is given as follows:

$$\sum_{k \in \mathcal{K}} (\Gamma_{d^k}^k - \Gamma_{s^k}^k) + \alpha \sum_{k \in \mathcal{K}} \max(\Gamma_{d^k}^k - \tau_d^k, 0) \quad (4)$$

Where,

α is the weight of the late arrival penalty

The previous functions and descriptions are based on the 2 lanes situation. For a more general format, the study summarizes the Upper Level Algorithm in the following part:

- 1) The target of the upper level optimization is for the maximum traffic flow (system equilibrium)
- 2) The lane collection from source 1 to destination 2 is defined as L_{12}
- 3) For the two directions, the lanes in the road segment can be described as:

$$\{l_{12}^1, l_{12}^2, l_{12}^3, \dots, l_{12}^m\} \in L_{12}$$

$$\{l_{21}^1, l_{21}^2, l_{21}^3, \dots, l_{21}^n\} \in L_{21}$$

- 4) Based on the traffic flow prediction model, we select the time interval Δt . The entire algorithm will run once to exam situation of the road segment.
- 5) We assume, the algorithm is running at time t , and the at time $t + \Delta t$, there are k lanes will be changed from L_{12} to L_{21} ($-n < k < m$, $k \in Z$)
- 6) When we change k lanes from L_{12} to L_{21} :

The decrease flow in L_{12} can be represented by the formulation:

$$f_{12} - \min \{f_{12}, c(m - k)\}$$

The decrease flow in L_{12} can be represented by the formulation:

$$f_{12} - \min \{f_{12}, c(m - k)\}$$

Where, $c(x)$ indicates the road capacity when it contains x lanes

7) Therefore, the System Equilibrium can be described as:

Maximize {The total traffic flow in the road section}

8) Based on the present flow, the motivation we change k lanes from L_{12} to L_{21} can be described as:

Increase Flow \geq Decrease Flow

9) Therefore, the Upper Level Optimization can be described as following:

$$\max_k f = [\min\{c(n+k), f_{21}\} - c(n)] - [f_{12} - \min\{f_{12}, c(m-k)\}]$$

Constraints:

$$-n < k < m, k \in Z$$

$$[\min\{c(n+k), f_{21}\} - c(n)] \geq [f_{12} - \min\{f_{12}, c(m-k)\}]$$

4.3 LOWER LEVEL OPTIMIZATION

In the section, we still use the example we used in the previous sections for a more specific explanation. The section will discuss the lower level optimization, the user equilibrium. In the part, we will discuss the mixed CAV situations. In the other word, some vehicles are informed about the system information and some are not. And the systematic information will have impact on the user's choice. Then in the last paragraph in the section will summarize the general situation. To develop the optimization model, the decision variables are defined as below. Binary variables $x_{ij,l}^{tk}$ are used to indicate which lane segment $l \in (i, j)$ is traversed by CAV k in time t :

$$x_{ij,l}^{tk} = \begin{cases} 1 & \text{if } k \text{ traverses lane } l \text{ from } i \text{ to } j \text{ at time } t, \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

We define binary variable $y_{ij,l}^t$ to indicate the direction of lane l in road segment (i, j) at time t :

$$y_{ij,l}^t = \begin{cases} 1 & \text{if direction of } l \text{ is from } i \text{ to } j \text{ at time } t, \\ -1 & \text{if direction of } l \text{ is from } j \text{ to } i \text{ at time } t. \end{cases} \quad (3)$$

Integer variable Γ_i^k is used to represent the time stamp of CAV k at vertex i . We aim to minimize the total travel time of CAVs. We also set penalty for late arrivals at the destinations. Thus, the objective function for CAVs is given as follows:

$$\sum_{k \in \kappa} (\Gamma_{d^k}^k - \Gamma_{s^k}^k) + \alpha \sum_{k \in \kappa} \max(\Gamma_{d^k}^k - \tau_d^k, 0) \quad (4)$$

Where,

α is the weight of the late arrival penalty.

The non-CAVs are considered in the Stochastic User Equilibrium (SUE) situation, and its optimization and trade-off with the system optimal solution are discussed in the following section.

This research task aims to address the balance between the system optimization and individual optimization. In a mixed traffic scenario, the non-CAVs cannot send requests to the central control center, so they will travel based on their own optimal routing choice and achieve a stochastic user equilibrium. According to Çolak et al. (2016)'s research published on *Nature Communications*, if we consider the travel time on a roadway segment $a \in A$ as cost, i.e., $c_a(x_a) = t_a(x_a)$, where x_a is the throughput on roadway segment a , $t_a(x_a)$ is the travel time (cost) of the roadway segment when the throughput is x_a , then when x_a changes, the impact on the total travel time of all the vehicles on this roadway segment $x_a t_a(x_a)$ can be regarded as a marginal cost, i.e., $c_a(x_a) = d[x_a t_a(x_a)]/d x_a$. If we give weight $\delta \in [0, 1]$ for the marginal cost, and $(1-\delta)$ for the individual travel time (cost), then

$$c_a^\delta(x_a) = (1-\delta)t_a(x_a) + \delta d[x_a t_a(x_a)]/d x_a \quad (5)$$

If we use $c_a^\delta(x_a)$ to replace the $t_a(x_a)$ in the objective function of the user equilibrium model, then the objective function Z could be:

$$\begin{aligned} Z &= \sum_{a \in A} \int_0^{x_a} c_a^\delta(w) dw = \sum_{a \in A} \int_0^{x_a} \{(1-\delta)t_a(x_a) + \delta d[x_a t_a(x_a)]/d x_a\} dw \\ &= (1-\delta) \sum_{a \in A} \int_0^{x_a} t_a(w) dw + \delta \sum_{a \in A} x_a t_a(x_a) \end{aligned} \quad (6)$$

$\delta=0$ indicates the all the users in the system cannot get the information about the system.

In the other word, when $\delta=0$, the objective function $Z = \sum_{a \in A} \int_0^{x_a} t_a(w) dw$ is the user level equilibrium. When $\delta=1$, the objective function $Z = \sum_{a \in A} x_a t_a(x_a)$ indicates the total travel time of

all the vehicles on the roadway network which is actually the system optimization model. The weigh δ reflects the trade-off between individual optimization and system optimization which is helpful to build the equilibrium strategy-based optimization in this research. According to the theory of Pigovian taxation (Sandmo, 1978), if both directions of a reversible road segment are oversaturated as defined in Section 4.1.1, reversible lane tolling could be useful to mitigate the congestion. A free flow equilibrium will be achieved when the tolling price is high enough. In this way, rich people will pay for the tolling, and the total throughput of the roadway network will be improved. This mechanism could achieve the social equity as well as economic development benefits.

Chapter 5. EXPERIMENT AND SIMULATION

5.1 OVERVIEW

To validate the reversible lane control algorithm we proposed in the previous chapters, the study builds up a simulation to test the algorithm. The data we used in the experiment is the real data on the freeway in China. But the experiment builds up a traffic flow generator with poisson distribution to fit the simulation demand. The entire experiment can be summarized as following steps:

1). Traffic flow generation:

Based on the real data we collected, the study builds up the traffic flow generator to generate the traffic flow in the simulated road segment.

2). Traffic flow prediction

Based on the LSTM model we proposed in Chapter 3, we input the historical data (real data), real-time data (simulated data), and attribute data (weather data) into the model to do the traffic flow prediction. By comparing the traffic flow data, the traffic flow prediction result validation process can provide the back propagate feedback for the model to adjust the parameters to get the better result in the future.

3). Determine the time interval

Based on the traffic flow prediction result, we can determine the time interval for the reversible lane to get the best performance.

4). Bi-level Optimization programming

The study sets the predicted traffic flow as the bi-level optimization programming inputs and determines the lane change plan in the following time period.

5). Traffic flow comparison

Based on the reversible lane control algorithm, we can get the total road through output in the test time period. Comparing with the original total through output (the road segment without reversible lane), the results will show the effects of the dynamic reversible lane control algorithm.

The following parts introduces the whole experiment step by step.

5.2 RESEARCH AREA AND DATA



Figure 5.1 Freeway Network in Guangdong Province

Guangdong Province is a coastal province located in southeastern China. It has 21 prefecture-level cities and 119 county-level administrative districts. The expressway network in Guangdong Province is one of the most important transportation network subsystems in South China. The entire road network's main body is composed by nine vertical roads, five horizontal roads and two rings roads, and the total mileage of network is 7673 kilometers (see Figure 5.1). According to the geographical location, the entire network is divided into four sub-areas of the Pearl River Delta

region, the eastern region, the western region and the northern region. Among them, the expressway density in the Pearl River Delta region is at a very high level, second only to New York, USA. It is the first in Asia and the second in the world.

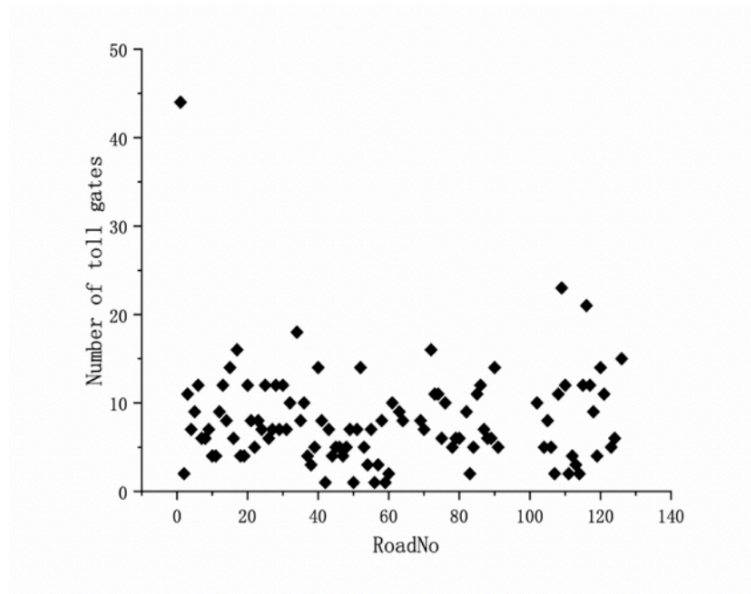


Figure 5.2 Toll Gates Distribution in the Freeway Network

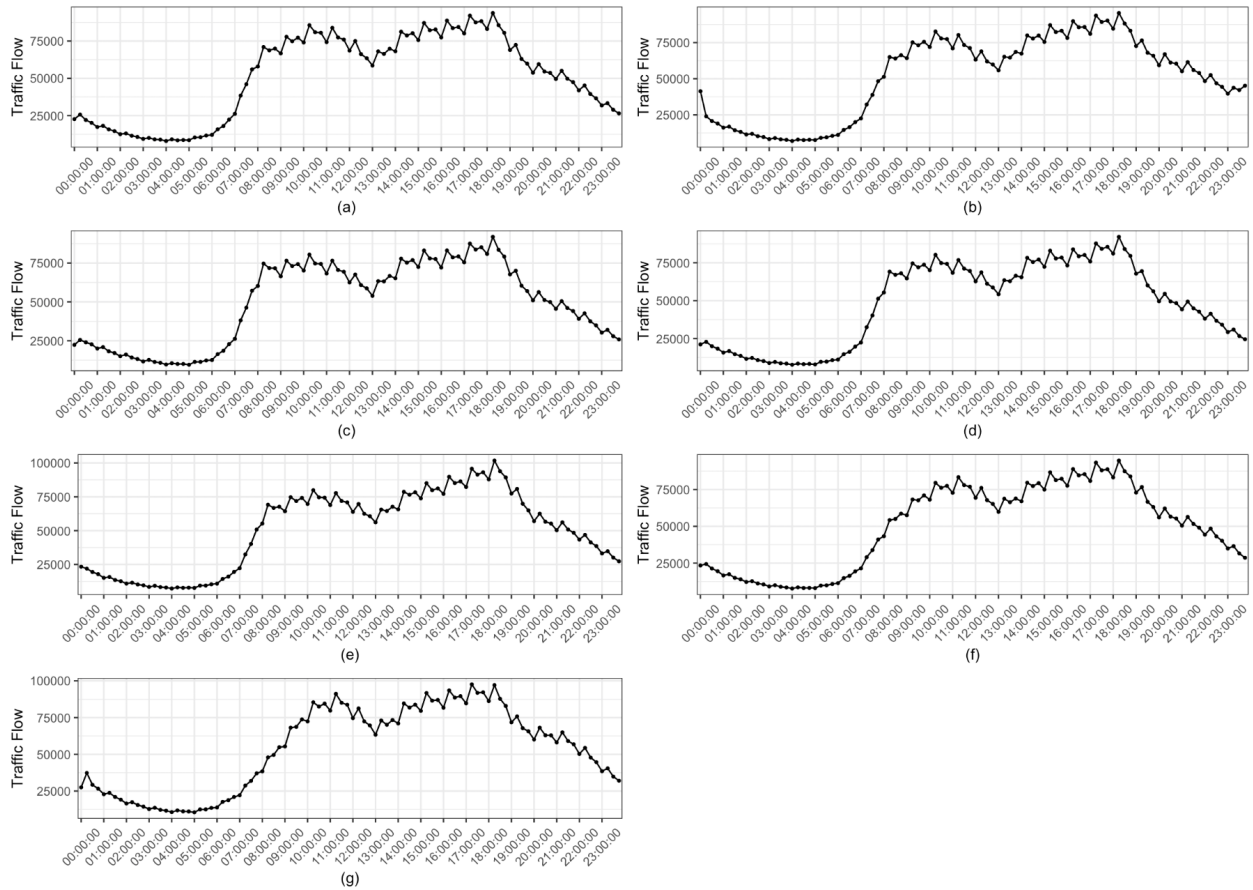


Figure 5.3 Traffic flow – Time Distribution

According to the different construction and management subjects, the entire highway network is divided into 115 sections for charging, with a total of 953 toll gates. Since some toll gates are virtual sites, or separate bridges or tunnel toll gates, and no actual vehicles use these gates to enter or leave the expressway, the actual amount of toll road sections used in this paper are 104, and the total number of toll gates are 844. The distribution of the toll gates in each section is shown in Figure 5.2. The data period is in April 2017, a total of 30 days, the number of traffic toll records of the entire road network is about 3.8 million per day, the distribution of traffic volume over time in the entire network is shown in Figure 5.3. From the figure, we can see in the entire network, the

two peaks (i.e., morning peak and evening peak) are obvious to see. Based on the traffic volume in total, the overall traffic volume is big enough for the reversible lane.

Additionally, we set the toll gate 2 as an example to see the traffic flow in one gate one day. Figure 5.4 shows accumulated percentage of traffic flow is shown in gate 2 in one day. From the figure, we can see that in most cases, the traffic flow per hour is less than 600 veh/hr in the Toll Gate 2. In the study, the traffic volume in one gate in peak hours is a significant factor we need to consider when we choose the test road segment. We will discuss about this in Section 5.3.3.

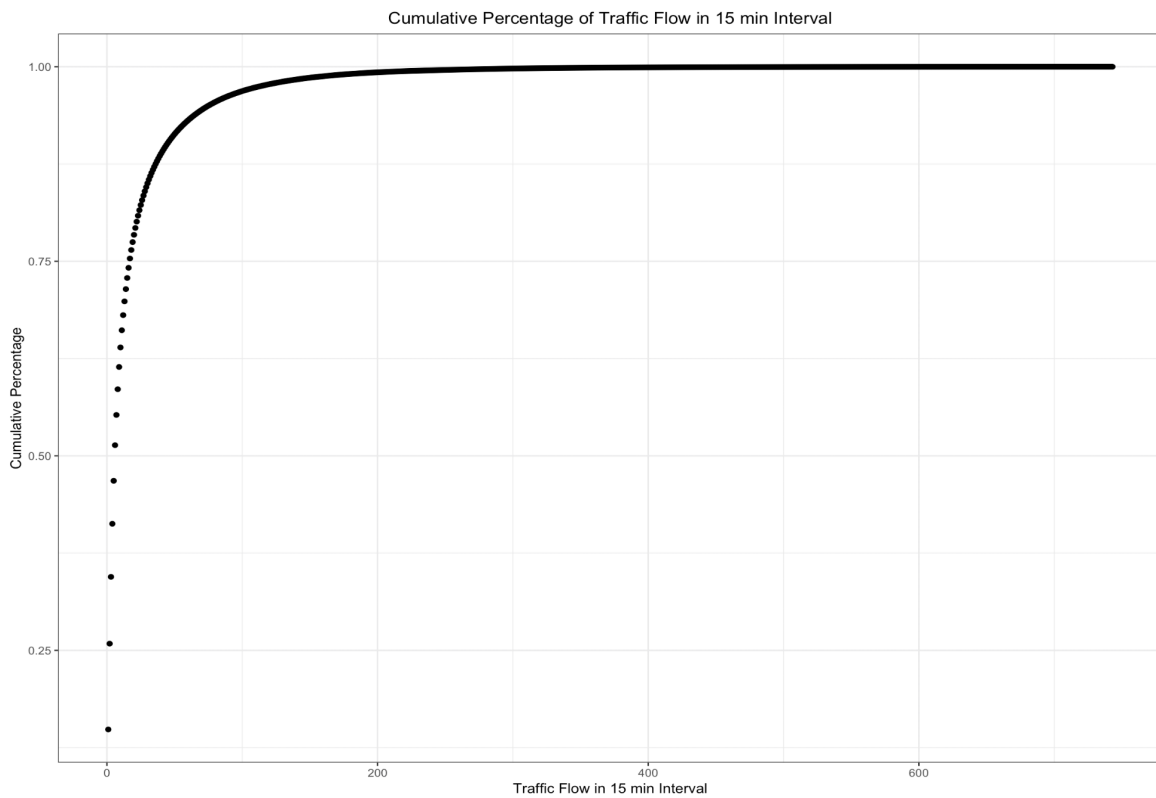


Figure 5.4 Accumulated Percentage Traffic Flow

5.3 TRAFFIC DEMAND FORECASTING

5.3.1 *Traffic Demand Forecasting Method Determination*

In Chapter 3, the study discusses the advantages of Bi-LSTM theoretically. In the case, we select the toll data in some selected gates to test the performance of the common models. The common models we used to compare in the study containing AVG model, Recurrent Neural Network (RNN) model, 1 layer and 2 layer Long Short-Term Memory (LSTM) model, and the Bi-directional LSTM model.

- **AVG:** Simple calculate the average speed of each trip and use the trip mean speed as the predicated cell speed.
- **RNN:** Use basic recurrent neural network (RNN) to predict the traffic flow.
- **1 Layer LSTM and 2 Layer-LSTM:** Use one and two layers Long Short-Term Memory (LSTM) networks to predict the traffic flow. The result shows that a 2-layers LSTM is much better than one-layer [28].
- **Bi-LSTM:** Use bidirectional LSTM (BiLSTM) model with Feature Extraction Module introduced in Chapter 3.

We select three toll gates as the examples to show the performance of the 5 models for the traffic flow prediction. The gates we selected are Gate 02, Gate 06, and Gate 12. And the results comparisons are shown in the Table 5.1, Table 5.2, and Table 5.3.

Gate 02	MAE (veh/30min)	RMSE (veh/30min)	MAPE (%)
AVG	13.40	14.20	104.25%

RNN	9.13	9.44	33.48%
1 Layer-LSTM	7.08	7.85	27.74%
2 Layer-LSTM	4.12	5.16	16.25%
Bi-LSTM	3.67	4.08	14.71%

Table 5.1 Result Comparison in Gate 02

Gate 06	MAE (veh/30min)	RMSE (veh/30min)	MAPE (%)
AVG	16.00	17.10	135.54%
RNN	11.73	12.34	41.69%
1 Layer-LSTM	9.68	10.75	35.95%
2 Layer-LSTM	6.72	8.06	24.46%
Bi-LSTM	6.27	6.98	22.92%

Table 5.2 Result Comparison in Gate 06

Gate 12	MAE (veh/30min)	RMSE (veh/30min)	MAPE (%)
AVG	19.40	21.14	119.98%
RNN	15.13	16.38	45.87%
1 Layer-LSTM	13.08	14.79	40.13%
2 Layer-LSTM	10.12	12.10	28.64%
Bi-LSTM	8.67	9.15	24.08%

Table 5.3 Result Comparison in Gate 13

From the result, it's clear to see that in the three Toll Gates (i.e., Gate 02, Gate 06, and Gate 13) the LSTM network is the most effective method to do the traffic flow prediction. By increasing the layers of LSTM (i.e., the 1 layer and 2 layers LSTM), the accuracy will increase

the about 11% on MAPE. When we apply the Bi-direction LSTM to the scenario, the three indicators are getting better which shows the Bi-direction LSTM is the best LSTM model in the case. Of course the high layer LSTM (e.g., 10 layers LSTM) may have the better performance than Bi-directed LSTM model, but it may take much more computation power and time for the little better results. Therefore, in the case, Bi-directed LSTM is the most efficient model for the traffic flow prediction. And with the assistance of feature extension module, the accuracy is added 2.34% than only use the Bi-LSTM. In many real-world tasks, especially traffic flow prediction, in OD prediction problems, the input of the network is not only related to the input at the current moment, but also related to the output of the past period of time. Such prediction problems often have the length of time series data is generally not fixed, the correlation between adjacent data is very strong, and there is an accumulation effect. Recurrent Neural Network (RNN) is a kind of neural network with short-term memory ability. In a circulating neural network, neurons can not only receive information from other neurons, but also accept their own information to form a network structure with loops.

Bidirectional LSTM (BiLSTM) is a novel improved version of LSTM network. The reason why the Bi-LSTM has the best performance In BiLSTM, two LSTM layers pass the data sequence on two opposite directions, one forward direction and another backward direction. The output is concatenated both layers into a long vector including both direction time dependency features. Both former step input and later step input information are combined. Six unique weights are used repeatedly here, which are correspond to: input to the forward and backward hidden layers (w_i, w_m), and hidden layers to the hidden layer itself (w_j, w_n), forward and backward hidden layer to output layer (w_k, w_o).

In summary, the Bi-direction LSTM model is the best model in the case no matter in theoretical analysis (the discussion in Chapter 3) and practical results (Table 5.1, Table 5.2, and Table 5.3). In the following content, all the LSTM model we used on the data indicates the Bi-direction LSTM model.

5.3.2 Time Interval Determination

In dynamic reversible lane control, determining the lane direction reverse frequency is significant for the system performance. Still, the study sets Gate 02, Gate 06, and Gate 13 as examples to show the Bi-direction LSTM model performance. Additionally, considering the target application is the heavy traffic scenario, we only select the traffic flow data in morning peak (8:00AM~11:00AM) to do the tests. Based on Bi-directional LSTM model, we do the traffic flow prediction in 15 min, 30 min, 45 min, and 60 min. Table 5.4, Table 5.5, and Table 5.6 show the results in various prediction time periods in Gate 02, Gate 06, and Gate 13 respectively.

Prediction Time	MAE	RMSE	MAPE
15min	2.76	3.13	12.67%
30min	2.27	2.69	11.42%
45min	2.44	2.72	12.01%
60min	2.91	3.31	13.24%

Table 5.4 Gate 02 Traffic flow prediction performance in various prediction time periods

Prediction Time	MAE	RMSE	MAPE
15min	3.10	3.54	15.87%
30min	2.61	3.10	14.62%

45min	2.78	3.13	15.21%
60min	3.25	3.72	16.44%

Table 5.5 Gate 06 Traffic flow prediction performance in various prediction time periods

Prediction Time	MAE	RMSE	MAPE
15min	3.21	3.62	18.17%
30min	2.72	3.18	16.92%
45min	2.89	3.21	17.51%
60min	3.36	3.80	18.74%

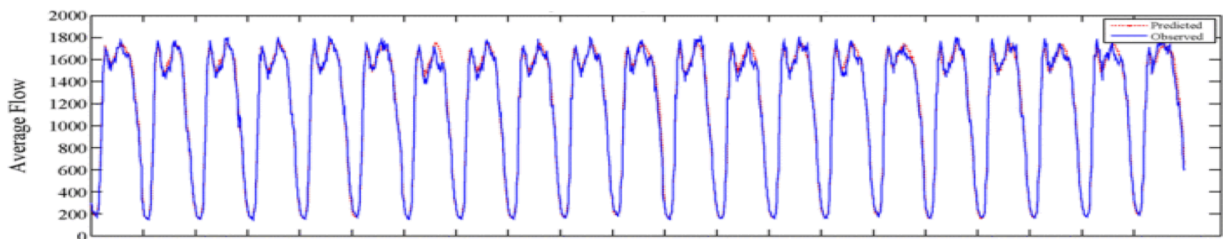
Table 5.6 Gate 13 Traffic flow prediction performance in various prediction time periods

From the results, it is obvious that in all three indicators, the 30 min time period is the best among all the sample toll gates. Therefore, the following contents will set 30 min as the traffic flow prediction time period.

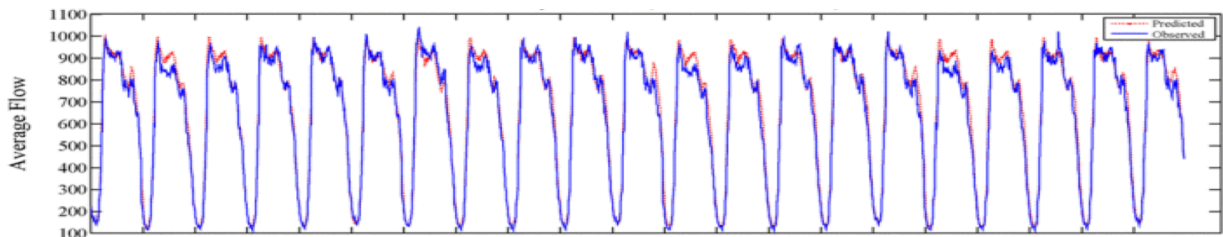
5.3.3 *Road Segment Determination*

In dynamic reversible lane control, after determining the prediction time period, another important thing is determining the road segments which have the highest demand to the reversible lane control algorithm. In most cases, the answer is the road segments with the highest traffic demands. As discussed in Chapter 3, Bi-direction LSTM is a novel improved version of LSTM network. In Bi-direction LSTM, two LSTM layers pass the data sequence on two opposite directions, one forward direction and another backward direction. The output is concatenated both layers into a long vector including both direction time dependency features. Both former step input and later step input information are combined. Therefore, in theoretically, the Bi-direction LSTM can fit the heavy traffic flow best. To validate this, we still set Gate 02, Gate 06,

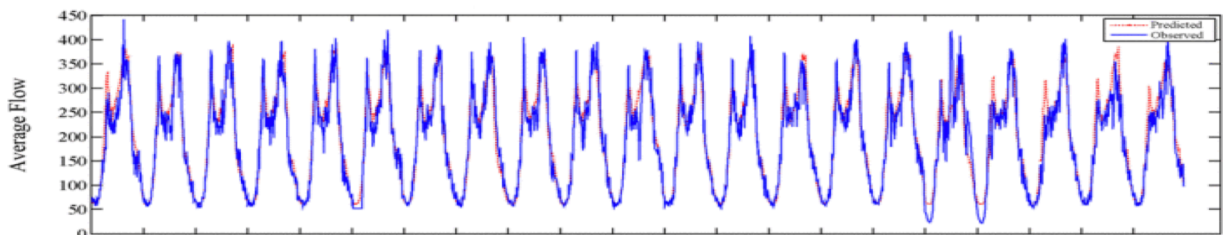
and Gate 13 as three examples. The three toll gates can represent the heavy traffic flow, median traffic flow, and light traffic flow. The 30 min traffic flow prediction results of the three toll gates are shown in Table 5.1, Table 5.2, and Table 5.3. And Figure 5.5 shows difference between the predicted traffic flow and real traffic flow in the three situations (i.e., heavy traffic flow, median traffic flow, and light traffic flow)



(a) Road segment with heavy traffic flow



(b) Road segment with median traffic flow



(c) Road segment with light traffic flow

Figure 5.5 Comparison between predicted traffic flow and real traffic flow

From the results, as our expectation, the Bi-direction LSTM model works best in the heavy traffic flow scenarios. Additionally, the target of the study is to improve the maximum

traffic flow in the peak hours by reversible lane. Therefore, we select road segment between Toll Gate 02 and Toll Gate 03 for the study area.

The road segment between Toll Gate 02 and Toll Gate 03 is the road segment with the heaviest traffic flow in the network. Therefore, the road segment is chosen as the target in the experiment. The road segment between Toll Gate 02 to Toll Gate 03 is the freeway between Guangzhou and Foshan, the two biggest cities in Guangdong Province. The road segment contains 8 lanes in the two directions and each direction has 4 lanes. Figure 5.6 shows the road segment on the google map.



Figure 5.6 The road segment between Toll Gate 02 and 03

The chosen road segment is part of Guangfo Express Road whose ends are Guangzhou and Foshan, the two big cities in Guangdong Province. The distance between the two cities is only 60 miles. Therefore, the communication between the two cities is very close. A lot of people travel between the two cities for various purposes like commute purpose, business purpose, or visiting purpose. Guangfo Express Road is the key connector between the two cities.

Therefore, it is one of the busiest freeways in Guangdong Province. The traffic congestion is happened everyday even weekends and holidays even it contains 8 lanes in two directions totally. the Figure 5.7 shows the satellite view of the freeway.



Figure 5.7 Satellite View of Guangfo Express Road



Figure 5.8 Directional Congestion on Guangfo Express Road⁵

⁵ Figure Resource: <http://www.fsonline.com.cn/p/246541.html>

Guangfo Express Road is the most congested road segment in Guangdong Province from 2017 to present. And because of the travel purpose (i.e., travel to Guangzhou in the morning peak, and travel back Foshan in the evening peak), the directional congestion scenes are common in Guangfo Express Road (See Figure 5.8).

5.3.4 *Summary*

Based on the analysis in the previous sections, the study has determined the prediction model (modified Bi-directional LSTM model), prediction time (30 min), and target road segment between Toll Gate 02 and Toll Gate 03 (heavy traffic flow scenario). After determining the all the factors, we can apply the data into the Advanced Bidirectional LSTM for 30 min traffic flow prediction. And the prediction results will be work as the input in the Bi-level Programming Algorithms.

5.4 BI-LEVEL PROGRAMMING ALGORITHM

5.4.1 *Upper Level Programming*

Based on the discussion in Chapter 4, we will apply the selected road segment information and the predicted traffic flow data to the Upper level Optimization formulations. In the Chapter 4, the Upper Level Optimization formulas can be described as:

Objective Function:

$$\max_k f = [\min\{c(n+k), f_{21}\} - c(n)] - [f_{12} - \min\{f_{12}, c(m-k)\}]$$

Constraints:

$$-n < k < m, k \in Z$$

$$\min\{c(n+k), f_{21}\} > \min\{f_{12}, c(m-k)\}$$

Where,

f : The total through output of the road during the time periods in both directions

f_{12} : The traffic flow from source 1 to destination 2 in the time period

f_{21} : The traffic flow from source 2 to target 1 in the time period

$c(x)$: The capacity of the road with x lanes

k : k lanes will change from direction 12 to direction 21 in the next time period

n : there are n lanes in direction 12 originally

m : there are m lanes in direction 21 originally

In the road segment between Toll Gate 02 and Toll Gate 03, there are 8 lanes in the two directions in total. Therefore, in the formula, $m = n = \frac{6}{2} = 3$ lanes in each direction. Therefore, the range of k can be defined as $[-3, 3]$. Based on the standard formula in “Highway Performance Monitoring System” (HPMS) , we can regard the road capacity is proportional to the lanes $c(x) \propto x$. The study cites the calculation process provided in the document. The specific formula can be described as:

$$c(x) = \frac{2,200 + 10 \times (\min(70, FFS) - 50)}{1 + \%HV/100} \times lanes$$

Where,

FFS = Free Flow Speed

$\%HV$ = percent of heavy vehicles (decimal), with heavy vehicles consisting of trucks

with more than four tires, buses, and recreational vehicles Multilane Highways

Based on HPMS, the free flow speed can be calculated by the following formula:

$$FFS = 75.4 - f_{LW} - f_{RLC}$$

Where,

$f_{LW} = \text{adjustment for lane width} .$

$f_{RLC} = \text{adjustment for right side lateral clearance} .$

Based on the document about the GuangFo Express Road, the Level of Service is the highest level which indicates the lane width is 12 feet and the right-side lateral clearance is 6 feet. Therefore, based on the freeway level of service (LOS) indicator, the two parameters f_{LW} and f_{RLC} will affect the free flow speed a lot. According to the information above, the free flow speed is about 65 mph on the Guangfo Express Road.

Based on “The fourth Traffic investigation in Gunagdong province Report”, the percent of heavy vehicles is around 4%. Guangdong is a coastal province. Therefore, the oversea cargos will be transferred from Guangdong to the other regions all over China. Therefore, the percentage of heavy vehicles is a little higher than other cities.

Until now, all the parameters in the Upper Level Programming has been determined, and the High-Level Programming formula will be solved by the solution proposed by .

1. Set iteration $j=1$. Set maximum iteration j_{max} . Randomly generate m feasible solutions $k_{i(j)}$ and compute the corresponding objective function values.
2. Find the optimal feasible solution by sorting m objective function values in descending order. Set this best objective function value as $Z_{(j)}^u$.
3. According to the probability distribution of the first n feasible solutions in descending order, generate $m - n$ feasible solutions $k_{i(j+1)}$. The new feasible solution set is composed of $m - n$ feasible solutions $k_{i(j+1)}$ and the n feasible solutions $k_{i(j)}$.
4. Find the best objective function value $Z_{(j+1)}^u$ from the new feasible solution. If the objective function value difference between 2 iterations is less than the convergence precision ε (i.e., $Z_{(j)}^u - Z_{(j+1)}^u < \varepsilon$), then the iteration procedure will be stopped;

otherwise, set $j = j + 1$ and check whether the iteration count reaches j_{max} . If $j < j_{max}$, go to Step 3; otherwise, the iteration procedure will be stopped.

5.4.2 Lower Level Programming

Based on the introduction in Section 4.3, the lower level optimization formula can be described as:

$$\begin{aligned} Z &= \sum_{a \in A} \int_0^{x_a} c_a^\delta(w) dw = \sum_{a \in A} \int_0^{x_a} \{(1-\delta)t_a(x_a) + \delta d[x_a t_a(x_a)]/d x_a\} dw \\ &= (1-\delta) \sum_{a \in A} \int_0^{x_a} t_a(w) dw + \delta \sum_{a \in A} x_a t_a(x_a) \end{aligned} \quad (6)$$

To simplify the process of calculation, we regard the situation that there is no CAV on the road.

The weigh δ reflects the trade-off between individual optimization and system optimization which is helpful to build the equilibrium strategy-based optimization in this research. A free flow equilibrium will be achieved when the tolling price is high enough. In this way, rich people will pay for the tolling, and the total throughput of the roadway network will be improved. This mechanism could achieve the social equity as well as economic development benefits. Therefore, in the case, $\delta = 0$. The objective function can be rewrite as :

$$Min Z = \int_0^{f_{12} \cdot \Delta t} t(w, m - k) dw + \int_0^{f_{21} \cdot \Delta t} t(w, n + k) dw \quad (7)$$

In the formula, the relationship among travel time, number of lanes, and traffic flow is significant for the users' cost calculation. Before applying the reversible lane system on the Guangfo Express Road, there are 4 lanes for each direction. We assume the traffic flow will distribute on the 4 lanes evenly in every direction. Based on the toll data, we can estimate the average traffic flow on each lane. Additionally, the toll data can tell us the time when the vehicle

drive in and out. Based on the enter time and exit time, we can calculate the travel time of the vehicle in the road segment. The three element of traffic flow theory are travel speed, traffic flow and traffic density. Therefore, we calculate the travel average speed based on the travel time in the road segment. Figure 5.9 shows the relationship between the average travel speed and average traffic flow in each lane.

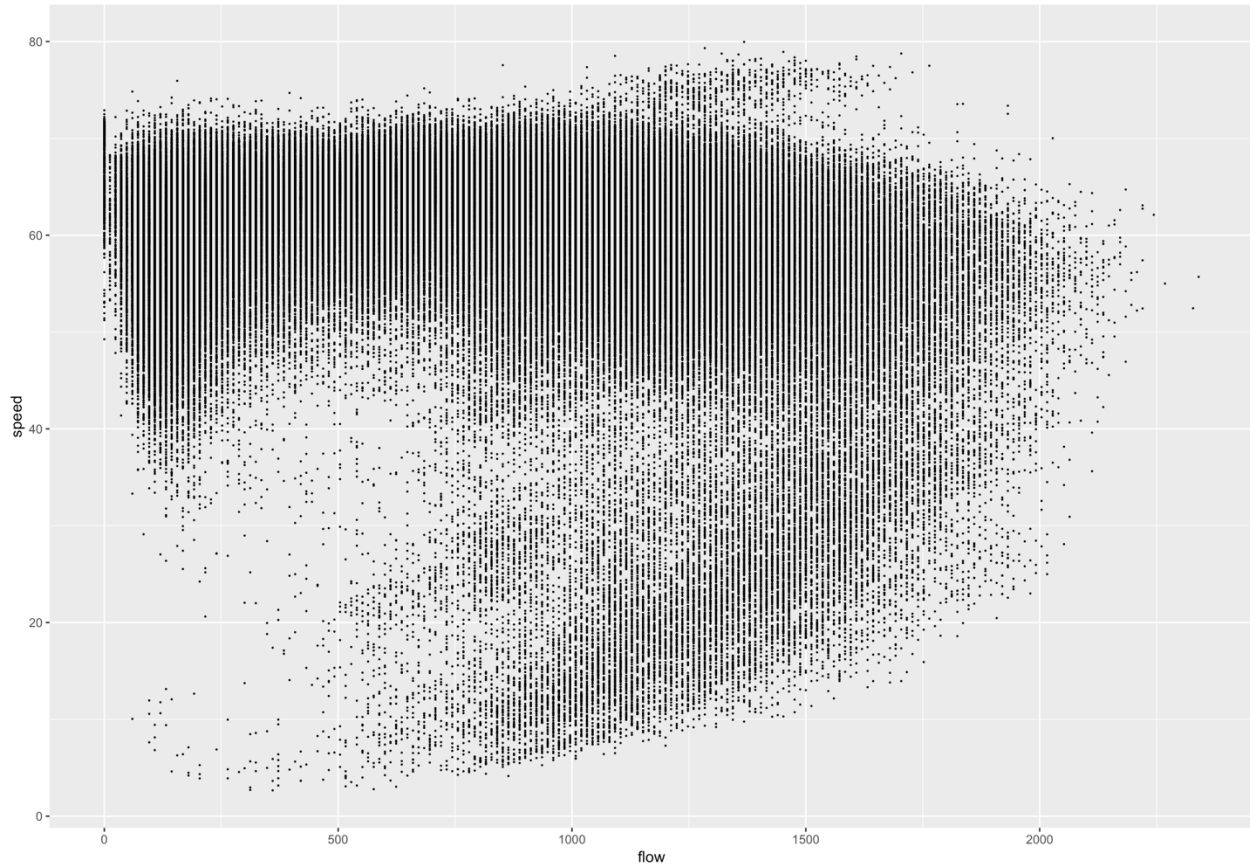


Figure 5.10 The relationship between traffic flow and travel speed

To figure out the relationship between average travel speed and average traffic flow in each lane, the study proposes the formula:

$$flow = a + b * speed + c * speed^2 + d * speed^3$$

The fitting results are shown in Table 5.7.

Coefficients	Estimated Value	Standard Error	T value	P value
<i>Intercept</i>	72.02278	1.994×10^1	3.612	0.000304
<i>Speed</i>	109.35358	1.641×10^0	66.642	$< 2 \times 10^{-16}$
<i>Speed</i> ²	-2.85634	3.962×10^{-2}	-72.090	$< 2 \times 10^{-16}$
<i>Speed</i> ³	0.02036	2.937×10^{-4}	69.315	$< 2 \times 10^{-16}$

Table 5.7 Relationship between traffic flow and average travel speed

From Table 5.7, we can see that the coefficient of *Speed*³ is much less than the other parameters, which can be omitted from the formula. Therefore, the relationship between the traffic flow in each lane and the average travel speed can be described as:

$$flow = 72.02 + 109.35 * speed - 2.86 * speed^2$$

Because the travel time can be calculated as:

$$t = l/speed$$

Where, $l = 16km$

The relationship between travel time and flow can be described as $t(q)$:

$$q_{12} = (72.02 + 109.35 * l/t - 2.86 * \left(\frac{l}{t}\right)^2) \times n$$

After determining the relationship between travel time and traffic flow, the lower level optimization solved by the Method of Successive Averages (MSA) based on road section flow. The MSA procedure starts with a preset iteration step sequence $\{\kappa_n\}$ where the iteration count $n = 1, 2, \dots$. To guarantee the convergence of MSA, the iteration step sequence must follow the condition $\sum_1^{n=+\infty} \kappa_n = \infty$, $\sum_1^{n=+\infty} (\kappa_n)^2 < \infty$, and the solution search direction is descent.

Sheffi [] proved that the descent expectation direction is adequate for guaranteeing the convergence of MSA even though the search direction is stochastic in each iteration [33], [44]. If the iteration step sequence $\kappa_n = \{\frac{1}{n}\}$, MSA procedure is described as follows:

1. Set the iteration count $n=1$. Initialize $t_a^{(1)}$. Randomly load route flows (based on defined distribution) onto the road network and obtain the initial road section flow $q_a^{(1)}$.
2. Set iteration count $n=n+1$. According to road section flow $q_a^{(n)}$, update impedance of the road segment $c_a^{(n)} = c_a(q_a^{(n)})$.
3. According to impedance $c_a^{(n)} = c_a(q_a^{(n)})$, assign OD demands to route and obtain the additional road section flow $q_a^{(n)}$. Set the search direction as the direction of $q^{(n)} - q^{(n-1)}$.
4. The new road section flow $q_a^{(n+1)} = q_a^{(n)} + (q_a^{(n)} - q_a^{(n-1)})/(n - 1)$.
5. If the change rate of road section flows between 2 iterations is less than the convergence precision(i.e., $\sqrt{\sum_{a \in A} (q_a^{(n)} - q_a^{(n-1)})^2} / \sum_{a \in A} q_a^{(n-1)} < \epsilon$, then the iteration procedure will be stopped and the traffic flow assignment will be output; otherwise, go to Step 3.

5.5 EXPERIMENT RESULT

This section will do the calculation job based on the parameters determined by the previous process and present the results. Finally, a brief analysis will be done for the control algorithm validation.

The traffic flow in the road segment is calculated by the toll data in the two toll gates located in the two ends of the freeway. Figure 5.11 shows the traffic flow in the road segment. The two peaks (i.e., morning peak and evening peak) are obvious to be observed in the figure. It

is clear that in the morning peak, the east direction (i.e., from Foshan to Guangdong) has the higher traffic flow. And in the evening peak, the west direction (i.e., from Guangdong to Foshan) has the higher traffic flow. Therefore, in the morning peak and evening peak, the directional congestion is easy to observe. In the morning peak, a lot of people travel from Foshan to Guangdong for business purpose, and in the evening peak, the people travel home from Guangdong to Foshan.

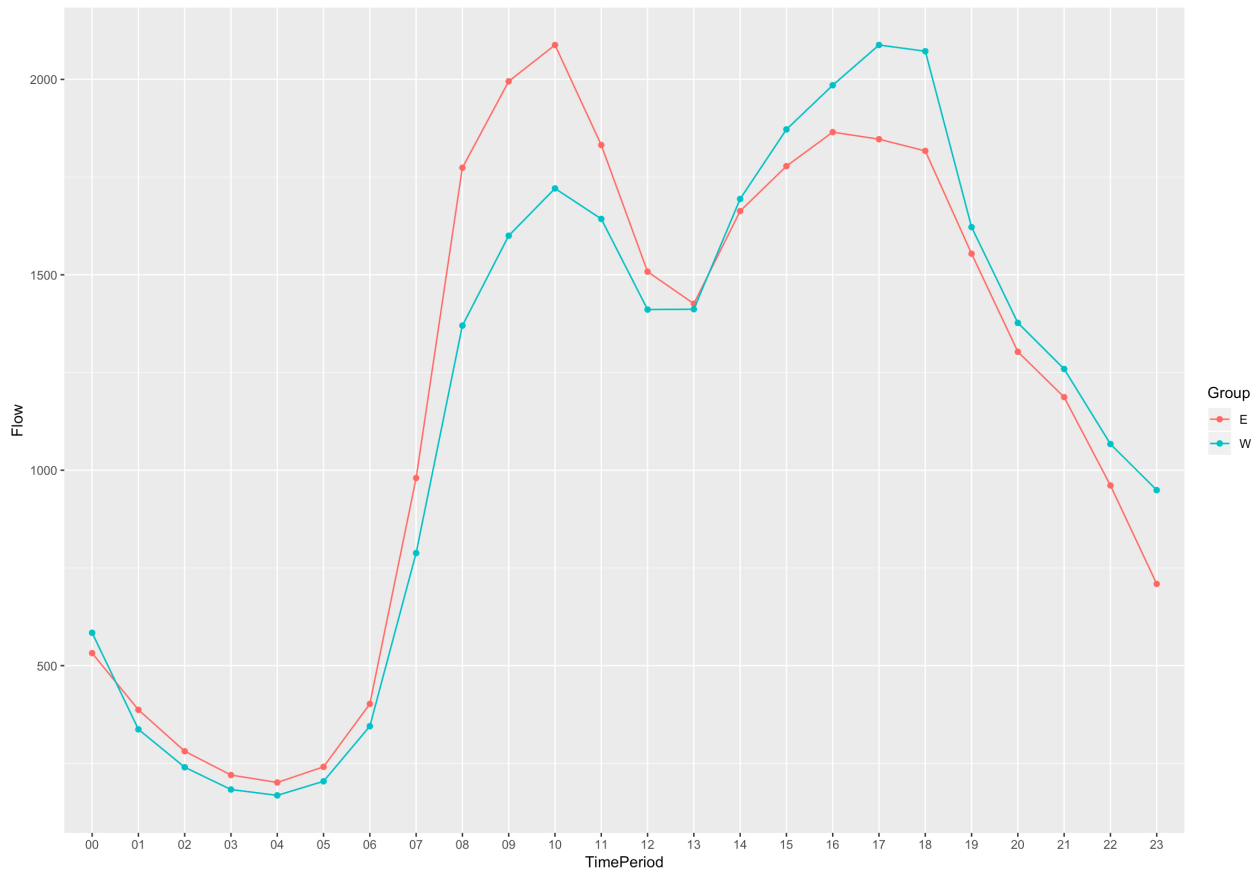


Figure 5.11 Original traffic flow in the road segment between Toll Gate 02 and 03

Based on the process we proposed in the previous chapters, we run the simulation in the road segment. The following tables describe the performance of the algorithm in various time periods.

Time	Direction	Before Reversal (veh/hr)	After Reversal (veh/hr)	Change
00:00~01:00	02-03	532	532	0.00%
	03-02	584	584	0.00%
01:00~02:00	02-03	387	387	0.00%
	03-02	337	337	0.00%
02:00~03:00	02-03	281	281	0.00%
	03-02	240	240	0.00%
03:00~04:00	02-03	220	220	0.00%
	03-02	183	183	0.00%
04:00~05:00	02-03	201	201	0.00%
	03-02	168	168	0.00%
05:00~06:00	02-03	241	241	0.00%
	03-02	204	204	0.00%
06:00~07:00	02-03	402	402	0.00%
	03-02	345	345	0.00%
07:00~08:00	02-03	980	980	0.00%
	03-02	788	788	0.00%
08:00~09:00	02-03	1774	2014	13.52%
	03-02	1370	1241	-9.39%
09:00~10:00	02-03	1995	2339	17.23%
	03-02	1600	1410	-11.87%
10:00~11:00	02-03	2088	2464	18.03%

	03-02	1721	1495	-13.12%
11:00~12:00	02-03	1832	2131	16.33%
	03-02	1643	1479	-10.00%
12:00~13:00	02-03	1508	1508	0.00%
	03-02	1411	1411	0.00%
13:00~14:00	02-03	1426	1426	0.00%
	03-02	1412	1412	0.00%
14:00~15:00	02-03	1663	1663	0.00%
	03-02	1694	1694	0.00%
15:00~16:00	02-03	1778	1778	0.00%
	03-02	1872	1872	0.00%
16:00~17:00	02-03	1865	1865	0.00%
	03-02	1985	1985	0.00%
17:00~18:00	02-03	1847	1573	-14.81%
	03-02	2088	2464	18.03%
18:00~19:00	02-03	1817	1561	-14.11%
	03-02	2072	2441	17.82%
19:00~20:00	02-03	1554	1554	0.00%
	03-02	1622	1622	0.00%
20:00~21:00	02-03	1303	1303	0.00%
	03-02	1377	1377	0.00%
21:00~22:00	02-03	1187	1187	0.00%

	03-02	1259	1259	0.00%
22:00~23:00	02-03	961	961	0.00%
	03-02	1067	1067	0.00%
23:00~24:00	02-03	709	709	0.00%
	03-02	949	949	0.00%

Table 5.8 Traffic flow improvement after reversible lane

From Table 5.8, it is clear that except the morning peak hours and evening peak hours, the lane direction will not change for traffic flow improvement because the travel demand is lower than the road capacity during the periods. Therefore, in most off-peak hours, the traffic flow change is 0. In the morning peak, the gap between the travel demands of the two directions are large enough for the lane change actions. Therefore, in the time periods, we can see that the direction with more lanes will contain more traffic flow than before, however, the ability of the direction with less lanes is decreasing. Comparing with the traffic flow change in the two directions, the increasing traffic flow is larger than the decreasing traffic flow, which can increase the total through output of the road segment. In the most cases, the through output change is about 5%~6%. Therefore, we can see the reversible lane algorithm proposed in the study can improve the total traffic flow in the busy hours.

Chapter 6. CONCLUSION

The study introduces a bi-level method based on short-term traffic flow prediction for the dynamic reversible lane control. The work improves the traditional traffic management method, reversible lane control, from static control to dynamic real-time traffic management. The study can be separated into three parts: traffic flow prediction, bi-level programming optimization, and validation. In the study, for the first part, the Long Short-term Memory (LSTM) model will be employed for the real-time short-term traffic flow prediction. To increase the prediction accuracy, the study embeds the environment factors as a matrix into the model. For the second part, based on the predicted travel demand, the study maximizes the total traffic flow in both directions which determine the lane deployment. Also, the study considers the user costs in the lower level optimization formula. Finally, the validation part, the study builds up a simulation to test the effect of the dynamic reversible lane control algorithm.

The algorithm proposed in the paper can provide a solution for the traffic congestion scenario with unbalanced traffic flow, which can improve the traffic capacity of the road. In the work, the contribution of the study can be summarized as three points. The first contribution is the traditional LSTM model improvement for the accurate traffic flow prediction. The advanced Bi-directional LSTM model is proposed in the study for the traffic flow forecasting. Comparing with the traditional traffic flow prediction models, the performance of our model is much better, especially in the heavy traffic flow conditions. Secondly, the bi-level programming optimization for reversible lane control based on the predicted traffic flow. In the algorithm, the upper level is the system level equilibrium and the lower level is the user equilibrium. Not only the present traffic flow but also the predicted traffic flow in the future are the inputs of the algorithm, which make the system is more sightseeing and invisible. Finally, the study has proposed a completed algorithm

for the reversible lane control instead of a theoretical algorithm. The algorithm can be applied to any road segment after initial the parameters in the system. It can address the traffic congestion in the peak hours in the real world.

From the simulation results, the control algorithm has some impacts on the road capacity improvement. In the all the peak hours, the reversible lane control can increase the through output 10% totally. And for the direction with heavy traffic flow, the increasing can reach 20%. The results validate the effect of the algorithm.

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