Parallel Transportation Systems: Toward IoT-Enabled Smart Urban Traffic Control and Management

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***Abstract*— IoT-driven intelligent transportation systems (ITS) have great potential and capacity to make transportation systems efficient, safe, smart, reliable, and sustainable. The IoT provides the access and driving forces of seamlessly integrating transportation systems from the physical world to the virtual counterparts in the cyber world. In this paper, we present visions and works on integrating the artificial intelligent transportation systems and the real intelligent transportation systems to create and enhance "intelligence" of IoT-enabled ITS. With the increasing ubiquitous and deep sensing capacity of IoT-enabled ITS, we can quickly create artificial transportation systems equivalent to physical transportation systems in computers, and thus have parallel intelligent transportation systems, i.e. the real intelligent transportation systems and artificial intelligent transportation systems. The evolution process of transportation system is studied in the view of the parallel world. We can use a large number of long-term iterative simulation to predict and analyze the expected results of operations. Thus, truly effective and smart ITS can be planned, designed, built, operated and used. The foundation of the parallel intelligent transportation systems is based on the ACP theory, which is composed of artificial societies, computational experiments, and parallel execution. We also present some case studies to demonstrate the effectiveness of parallel transportation systems.**

***Index Terms*— Intelligent transportation systems, parallel transportation systems, cyber physical social systems, computational experiments, parallel execution.**

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I. Introduction

INTELLIGENT transportation systems (ITS) are typical complex systems and they integrate various IT technologies [1], [2]. These technologies include not only traditional IT, such as industry technology and information technology, but also the emerging IT, i.e., intelligence technology. Among these technologies, IoT play an important and fundamental role for data collecting, data analyzing and data management. By connecting ubiquitous devices and facilities with various networks, IoT shows promising future to provides efficient and secure services for all applications, almost anytime and anywhere [3]–[5]. In many situations, IoT is regarded as a new generation of Internet, as it expands the communication from human and human to human and things or things and things [6]. With sensors embedded in such IoT-enabled ITS, physical transportation systems can be monitored in real time, and a vast amount of data is generated. Traffic data that are collected from physical sensors, such as GPS, induction coil, video camera, and so on, have been widely used in transportation management, while brought great convenience to our lives. However, the physical sensors also have some shortcomings, especially for specific applications [7], [8]. For example, the data of floating car is incomplete, due to the taxi in one city is limited and cannot cover each road section simultaneously [9]; the life of one induction coil is usually less than 2 years and there is still much room for the improvement of the reliability of the device; it is difficult to get clear images in adverse weather and low light conditions.

Meanwhile, we have entered the era of "Internet+". In this era, people extensively publish their daily activities and current locations on social network and social media, which have become an inseparable part of our everyday lives [10]. There are tremendous traffic-related information that can be obtained from the social media, such as Twitter, Facebook, Sina microblog, and so on. In some applications, this kind of traffic information can be used more effectively and more convenient than its counterpart that are collected from physical space. Regarding this emerging area, Prof. Wang introduced the term "social transportation" as a new direction for computational transportation study [11].

Accordingly, the usages of IoT are not limited to collect data in physical world. E. Cho et al. use cell phone location data, combined with online location-based social networks, aiming to discover the basic law governing human motion and dynamics [12]. Zheng developed a traffic sensing and analyzing system based on social media data, which can provide traffic information for the transportation department in the area which lack physical traffic detectors, by collecting public opinion, situations, scales and even origins of traffic incidents [7]. Jie et al. used social networks for detection of event-related bursts and further for determination of the time period for each event [13]. All these works have showed tremendous promise in detecting traffic information from social networks.

As IoT-enabled ITS progress in both of physical and network (virtual) world, there is an increasing gap between the two worlds, which inspired an intense demand to combine the technology and solutions of the two worlds into on the smart new one [14]. The concept of Parallel Transportation Systems (PTS) is proposed in this background and has been developed to be new cross-disciplinary science, which involves much from computer science, social science, social computing, computer engineering, and electrical engineering [15], [16].

This paper aims to introduce our work in designing and implementing PTS. The rest of the paper is organized as follows: Section II introduces the architecture of PTS. Section III and Section IV discuss two key steps in building PTS, i.e., data collecting & analyzing and parallel execution, respectively. Section V introduces the field testing and evaluations. Finally, Section V draws the conclusions.

II. The Architecture

IoT is shaping and transforming the way we live and work by connecting human, devices, and services tightly. Currently, we have entered the era of cyber physical social systems (CPSS)—that is, CPS tightly conjoined, coordinated, and integrated with human and social characteristics [17]. In CPSS, the physical world is deeply coupled and interact with the virtual cyber space, which have evolved to be a new normal mode for the operation of modern social organizations. While severe challenges have been put forward, new opportunities have also been provided to manage the complex social systems with innovative methods and in innovative ways. In this era, social media and social networks developed rapidly and influenced our lives notably. Not only the scope of sensing has been expended from physical world to virtual world, but also the speed of sensing has been accelerated greatly. As a result, plenty volumes of social signals have been generated, almost in real time.

Accordingly, intelligent transportation systems have been extended from connecting a large number of physical elements, such as connected vehicles, transportation infrastructure, human beings, to involving plenty of social elements, such as economic development, urban planning, emergency management, are involved. All these opened new opportunities for custom-built traffic analytics and control, data-driven intelligent transportation systems (ITS), as well as social transportation [18]. IoT-enabled ITS has greatly expanded the scope of collecting traffic data, besides from physical systems using physical sensor networks, it also can collect traffic data from social systems using social sensor networks. As a consequence, the physical system and the social system are mapping into one integrated system as a whole. Based on this socio-technical infrastructure, parallel transportation systems execute in 3 steps, First, Artificial transportation systems are set up to model and describe the actual transportation system (A). Second, computational experiments are designed and conducted to predict future evolutions and evaluate control plans (C). Finally, the actual and artificial systems are executed in an interactive parallel mode (P) [15]. In parallel execution, instead of guiding the virtual systems to approach to the status of the actual system, as we usually do in transportation simulation, we aim to guide the actual system to approach to the ideal status in the artificial systems. This whole process is called as ACP approach, the main idea of which is to obtain a deeper insight of traffic flow generation and evolution by modeling transportation system using basic rules of individual vehicles and local traffic behavior, and observing the complex phenomena that emerge from interactions between individuals.

The architecture for building a parallel transportation system based on IoT-enabled intelligent transportation systems is shown in Fig.1. Based on IoT-enabled ITS, the parallel transportation system aims to innovate service models and improve traffic service quality. At the bottom of the architecture, IoT provides the infrastructures and driving forces to build a comprehensive transportation system by seamlessly integrating the physical world and the virtual counterparts in the cyber world. In physical world, distributed sensors work in a collaborative mode and multi-node cooperative sensing is achieved. Physical sensor devices, which are installed in cars, along roadside and embedded in mobile devices, communicate with each other and form a distributed sensor network. Through collaboration between the adjacent node devices, local traffic information is synthesized to forming regional traffic information, such as traffic flow, occupancy, average speed, vehicle trajectory, etc. The architecture of the cooperative data collection system is composed of three layers, which are terminal nodes, sink nodes and gateway nodes. In the terminal node layer, radio and video sensors detect and trace vehicles, and communicate with surrounding sink nodes. The sink nodes form a self-organized according to a multi-hop mesh network architecture, through which the collected traffic information can be uploaded to the gateway node. Region traffic data are sent to the control center by gateway nodes for further processing through a proprietary network.

Based on IoT technologies, data sources are extended from the physical space to the social space, and traffic data collection in the social space is implemented based on social sensors and social signals. Social media and social networking platforms such as Facebook, Twitter, Weibo, and WeChat provide ubiquitous chances for people to share ideas, emotion, and information publicly or in specialized communities, generating tremendous volumes of social signals in real-time. Based on the data collected in distribution, artificial traffic scenes are constructed using virtual reality (VR) technology. The artificial scenes possess the characteristics similar to the actual scenes, including static and dynamic objects, weather, illumination, RF signal, video signal, and so on. And then, social traffic perception environment is established to conduct acquisition,

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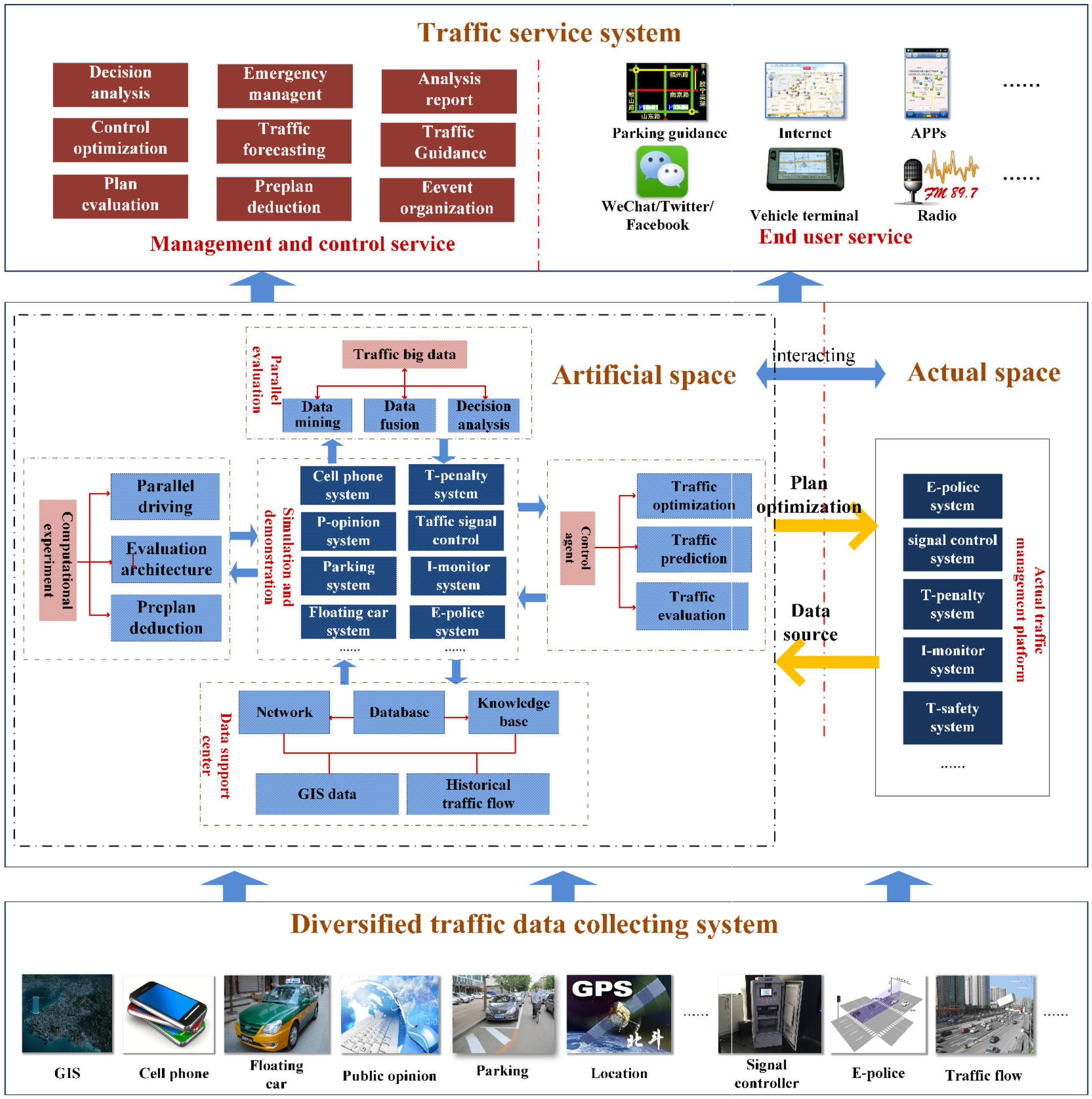

Fig. 1. The architecture of parallel transportation systems based on IoT-enabled intelligent transportation systems.

storage, processing and analysis of traffic situations, continuously and in real-time.

While the ubiquitous and deep sensing capability of real transportation systems is improved by IoT technologies, the emerging theories and applications of big data and artificial intelligence also facilitate the digitalization, virtualization, and modeling of physical transportation scenarios and systems, i.e., creating artificial transportation systems, by providing more and more tools and algorithms. All these forms the foundation of parallel transportation systems.

III. Data Collecting and Analyzing

From ITS to parallel transportation systems, IoT enables the paradigm shift in traffic data collecting and analyzing. In traditional ITS constructions, traffic detectors are usually installed at fixed point, such as at intersections and on some road segments, by traffic management agencies and other stakeholders. The statically agencies centered way to collect data is not only resource-consuming but also coverage-limited, obviously cannot satisfy the demand of traffic management. IoT enables the detector embedded in moving devices, such as vehicles and mobile phones, thus provides a distributed and complete way for traffic data collecting. As fundamental elements of transportation systems, vehicles and individuals are widely distributed over the entire systems, so that the distributed way to collect traffic data by them would cover all the intersections and road segments conveniently and in low cost. Meanwhile, vehicles and individuals are commonly equipped with GPS-based smart devices nowadays, which means that it can acquire traffic-related data, such location, speed, acceleration, and so on, without any extra cost, and it is very economic to utilize these devices to collect traffic data. For traffic data analysis, if the locally collected traffic data are transmitted to the data centers and analyzed in a centered and remote way, which is a traditional method in ITS, extra network load will be brought and corruption and missing data may be inevitable due to communication failures. PTS provides an alternative way that the traffic data could be stored and analyzed locally by edge computing technologies, utilizing the memory and computation resources of the distributed smart devices.

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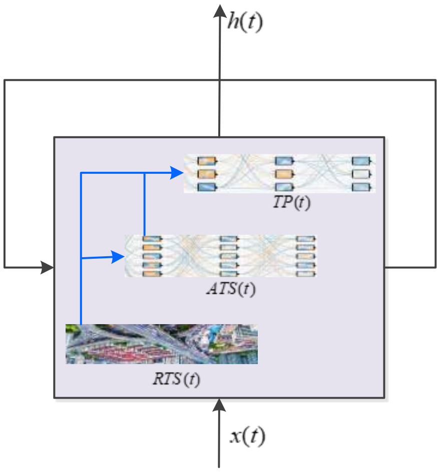

Fig. 2. Traffic prediction based on parallel transportation systems.

Another paradigm shift in parallel transportation is to artificially generate large scale data rather than collect more data due to the high-cost in collecting real world data based on physical detectors. With the help of IoT, elementary traffic data, such as traffic flow and origin-to-destination census, are firstly collected and then used to build purpose-oriented artificial systems, by which artificial data will be continuously generated. Fig. 2 shows an example of traffic prediction based on parallel transportation systems. The real transportation systems (RTS), the artificial transportation systems (ATS) and the traffic prediction models (TPM) are evolving over time. At the initial phase, the data collected from RTS are low-volume, and the ATS is trained with limited data. Then ATS could generate artificial data that may not completely resemble the data collected from RTS. The artificial data are used to augment the real data. Then the prediction model is trained based on the real data and the synthetic data. As time goes by, there are more data archived in real transportation system so that the artificial transportation system and the traffic prediction model could be incrementally refined. The data generated by TPM would resemble the real data better meanwhile adding diversity to the real dataset by ATS. Resembling and diversity are accomplished by TPM and ATS, respectively. The resembling here means modifying the prediction model to resemble the actual data. Of course, ATS will be adjusted in the process, but it still has its own mechanism to generate data and its main object is to add the diversity to the real data.

To model the randomness and uncertainty of traffic data in PTM, Gaussian mixture model (GMM) [19] is adopted to integrate different data source collected from different sensors. The Gaussian mixture model for traffic data is expressed as follows [20]:

$$\mathrm{P}\left(\mathrm{X}|\Theta\right) = \sum\nolimits_{i=1}^{M} \omega_i \, p_i\left(X|\theta_i\right) \tag{1}$$

The model is composed of M multivariate normal density components, where M is a positive integer. Each component has a d-dimensional mean (d is a positive integer), d-by-d covariance matrix, and a mixing proportion. In the above model, X is the data set,$\Theta = (\omega_1, \ldots, \omega_M, \theta_i, \ldots, \theta_M)$, is the parameter set, ω_i is the mixture weight for the ith variable,

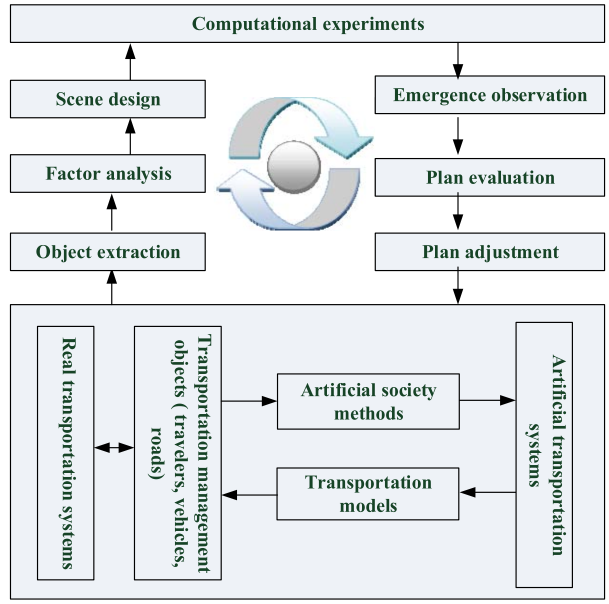

Fig. 3. The workflow of parallel transportation systems.

satisfying $\omega_i > 0$, $\sum_{i=1}^{M} \omega_i = 1$, θ_i is the parameter vector for the ith variable, p_i is the probability density for the ith variable.

Based on the above model, parallel dynamic programming (PDP) [21] is utilized in RTS to estimate the parameters. PDP can model the strong couple nonlinear relations between different data sources. Furthermore, it can predict the missing data based on history data in dealing with incomplete data environment. The evaluation function for PDP is shown in the following:

$$J_i\left(\delta_i, u_i, u_{-i}\right) = \sum\nolimits_{t=0}^{\infty} \gamma^t U_i\left(\delta_i, u_{i,t}, u_{-i,t}\right) \tag{2}$$

where $u_{i,t}$ and $u_{-i,t}$ are the controls between data source i, x_i, and data source j, x_j, δ_i is the error function, $\delta_i = \sum_{j \in N} \rho_{ij} \left(x_{i,t} - x_{j,t}\right)$, ρ_{ij} is the connectivity coefficient between x_i and x_j.

IV. Parallel Execution

Parallel transportation systems study the generation and evolution processes of transportation systems in a dynamic parallel-world perspective. First, to simulate and describe possible situations of complex transportation systems, artificial traffic scenarios are constructed in artificial transportation systems using bottom-up methods efficiently. In this way, virtual "big" traffic data can be generated from the actual "small" traffic data in relatively low cost. In this way, the high costs and the difficulties, if not impossible, in carrying out the experiments in physical world and acquiring the experimental results using physical sensors, can all be solved by the artificial transportation systems and the virtual sensors. Fig. 3 shows the workflow of parallel transportation systems.

The optimization process of the control plans is accomplished through interactive evolution between the artificial systems and the actual system. It is well known that the cost of carrying out transportation experiments is very high, so it is difficult, if not impossible, to quantitatively assess the control plans in real transportation systems. However, the assessment can be conveniently computed in the artificial transportation systems. Thanks to the characteristics of computational experiments on artificial systems, such as designability and repeatability, a variety of experiments on performance quality and reliability can be conducted. Besides normal experiments, specific experiments under special situations, such as accelerated experiments, pressure experiments, boundary experiments, and so on, can also be carried out conveniently. In normal ways, these “experiments” are generally impossible to execute in the actual transportation system.

Various learning techniques, such as predictive learning, integrated learning, and so on, can be utilized in designing computational experiments on the artificial transportation systems. The results of learning processes can recommend the actual transportation system on how to select data sources, and how to install sensors for data acquisition process. The recommend can be regarded as the feedback for the learning process, and the loop of interactions between the actual world and the virtual world goes around and begins again. In this way, a lot of computational experiments are performed, results are analyzed, and future status are predicted. Finally, the optimal actions are returned to the actual space, which guide the actual traffic system to approach the ideal states in artificial systems.

In parallel execution, the adaptive dynamic programming (ADP) is widely used in the optimization of the control plans. The process is shown in the following.

First, the critic function is in ATS defined as follows:

$$V\left(x\left(0\right),u\right)=\sum\nolimits_{k=0}^{\infty}U(x\left(k\right),u(k)) \tag{3}$$

where $x(k)$ and $u(k)$ are input and output of ATS, respectively, and $U \geq 0$ is the specific utility function. Based on the critic function, we try to design the controller with the optimal feedback according to data-based ADP theory, so as to minimize the function in formula (6).

Second, let $\underline{u}_k = \left(u\left(k\right), u\left(k+1\right), u\left(k+2\right), \ldots\right)$ be the control sequence from time k, and $V^*(x(k))$ be the optimal function of performance index which is defined as follows:

$$V^*\left(x\left(k\right)\right)=\min_{\underline{u}_k}V(x\left(k\right),\underline{u}_k)=V(x\left(k\right),\underline{u}_k^*) \tag{4}$$

where $\underline{u}_k^* = \left(u^*\left(k\right), u^*\left(k+1\right), u^*\left(k+2\right), \ldots\right)$ is the optimal control sequence, and u^* is the optimal control function.

Third, according to Bellman dynamic programming theory, we can get the following HJB function:

$$\begin{aligned} V^*\left(x\left(k\right)\right) &= \min_{u(k)}\left\{U\left(x\left(k\right),u\left(k\right)\right)+V^*\left(x\left(k+1\right)\right)\right\} \\ &= U\left(x\left(k\right),u^*\left(k\right)\right)+V^*(x(k+1)) \end{aligned} \tag{5}$$

Finally, a kind of data-based iterative algorithm using value function is utilized to generate the optimal controller in the parallel execution. Let $i = 0, 1, 2, \ldots$ denote the iterative step (also known as the iterative index). The iteration starts from $V^0\left(x\right)=0$, and updates as follows:

$$\begin{cases} u^{(i)}\left(x\left(k\right)\right)=W\left(x\left(k\right),\dfrac{\partial V^{(i)}\left(x\left(k+1\right)\right)}{\partial x\left(k+1\right)}\right) \\ V^{(i+1)}\left(x\left(k\right)\right)=U\left(x\left(k\right),u^{(i)}\left(x\left(k\right)\right)\right)+V^{(i)}(x(k+1)) \end{cases} \tag{6}$$

Usually, $V(x(k))$ is the strongly non-linear function of the status variable $x(k)$ and its solving process depends on the value in the next time, $V(x(k+1))$, thereafter, $V(x(k))$ is normally unknown.

In the parallel execution process, the iteration of the critic function of performance index, $V_i(x(k))$, starts from $V_0(x)$, and its value is updated while $u^{(i)}(x(k))$ is updated in ATS. Non-linear fitting methods, such as neuro network, can be utilized to solve $u^{(i)}(x(k))$ in ATS. And then, the $V^{(i+1)}(x(k))$ in RTS can also be solved. Thereafter, using the iteration of value function in formula (9), the optimal control of parallel execution can be solved.

V. Field Testing and Evaluations

Field testing and evaluations have been carried out in more than 10 cities in China [22], [23] and two typical cases are reported in the following.

A. Binzhou Traffic Signal Control

An application case of Parallel Transportation System, PTS-Binzhou, was carried out in Binzhou, China in 2013 [24]. Binzhou is a representative emerging city in Shandong Province, China. Over the past decade, the economic development of this city far exceeds the surrounding cities, while the car ownership also experiences a rapid increase and serious traffic congestion occured from time to time. As far as the characteristics of the city are concerned, the first is there are many old urban areas, and it is difficult to change the current situation of land use and road network. Other characteristics include many kinds of vehicles, unbalanced road grades, uneven round-trip traffic flow, high degree of correlation between intersections and complex road network. All these are obviously different from those of developed cities. Therefore, it is impossible to directly use the traditional traffic strategies, which had been adopted by foreign cities to optimize urban traffic successfully. This is also a common problem for the developing cities in China, and it has become an urgent problem to develop a specific and effective urban traffic signal control system that adapted to the characteristics of urban traffic in China, especially to the characteristics of road network and motor vehicles in small and medium-sized cities.

The coverage and the architecture of PTS-Binzhou is shown in Fig. 4. There are 212 intersections in this area, which is south to the Yellow River 1st road, north to the Yellow River 13th road, east to the Bohai 2nd road, and west to the Bohai 12th road, as shown in Fig. 4(a). The structure of Binzhou's road network is like a chessboard. The north-south roads from east to west are sequentially from Bohai 1st Road to Bohai 30th road. Among them, Bohai 2nd Road, Bohai 5th Road, Xinli River West Road, Bohai 18th Road, Bohai 21th Road and Bohai 24th Road are the arterial roads from north to south.

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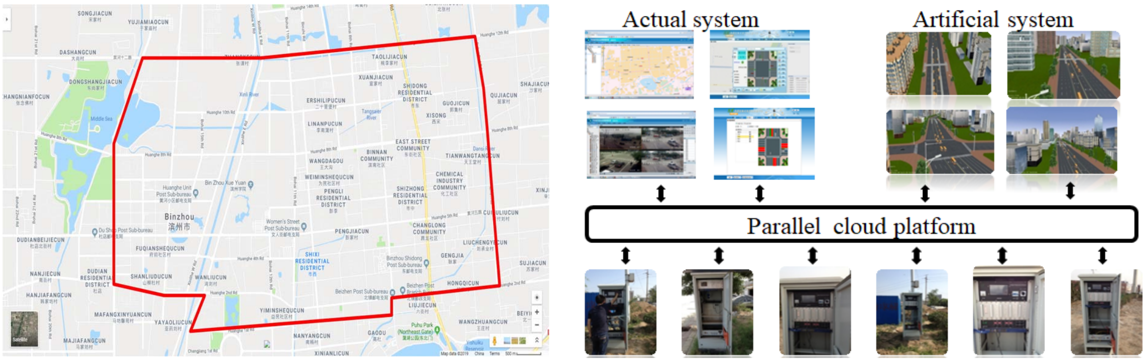


(a) The coverage of PTS-Binzhou (b) The architecture of PTS-Binzhou

Fig. 4. PTS-Binzhou.

The east-west road from the south to the north are sequentially from the Yellow River 1st Road to the North Outer Ring Road. Among them, the Yellow River 2nd Road, the Yellow River 5th Road, the Yellow River 8th Road, the Yellow River 12th Road and the North Outer Ring Road are the arterial roads. Binzhou City is divided into the east part and the west part by Bohai 11th Road. In the east part, most area is covered by old town, and the road network is relatively dense. Most roads are very narrow, the intensity of land development is high, and the proportion of land use in road construction is low, all these lead to serious traffic congestions in the old city. Most of the western urban area is new developing area, and most roads were constructed with high grade, most of which are two-way six-lane or eight-lane. The density of the road network is relatively sparse (except the road network around the municipal government). Because the land use intensity and population density of the new urban area are lower than those of the old urban area, the current road traffic condition of the new urban area is good and the saturation degree is low.

On the basis of completing the construction of the actual transportation system, we have also constructed the artificial transportation system in Binzhou, in which the scale of the artificial population is 845,000. After the implementation of parallel traffic system, we evaluated the effect of the system by analyzing traffic flow data. Here, we use the intersection of Huanghe 8 Road and Bohai 15 Road as an example. Fig. 5 shows the comparison of the traffic flows from west to east at this intersection between before and after the construction. The top shows the traffic flows of one week (from Jul. 15 to Jul. 21) before the construction, while the bottom shows the traffic flows of another week (from Aug. 19 to Aug. 25) after the construction. From this figure, we can see that the traffic flows of the two weeks are very similar and there is no significant difference between them. Queue length is used as one index to evaluation the effect of Binzhou-PTS. Fig. 6 shows the accumulated queue length at this intersection for the traffic flow from west to east. We can see that all the queue lengths decrease for the whole week, especially for the 6^{th} day of this week.

B. Qingdao City-Wide Traffic Management and Control

From 2013 to 2014, parallel transportation systems for Qingdao, PTS-Qingdao, was constructed to improve the traffic environment in Qingdao, China [21]. This project was the first-time large-city-wide application of the parallel transportation system. The application area covers Shinan District, Shibei District, Licang District and part of Laoshan District and includes more than 4 million residents. Both the coverage and complexity reached record level and they put forward great challenges to construction. The implementation of the project started on March 1st, 2013 and ended on October 1st, 2014. More than 200 people participated in the project and they came from 7 agencies, all are leading ITS R&D institutes, companies, or operators. Among them, the Institute of Automation, Chinese Academy of Sciences and Tsinghua University lead the ITS research in China. The planning and preparation of the project took almost 10 years. During this period, more than 50 PhD students in ITS, two national ITS standards, 30 patents, over 100 publications in journal and conference, have been produced.

The parallel transportation systems of the interactive operation and evolution between the actual transportation and the artificial transportation systems, is constructed and is used to resolve the problems in transportation management and control, such as operation objectives are too complex, experiments can't be carried out duo to time, economic or legal constraints, and so on. The specific artificial transportation system of Qingdao, ATS-Qingdao, includes 1020 sites which are directly related to traffic flow generation: 263 residential communities, 186 office buildings, 109 schools, 87 restaurants and hotels, 71 hospitals, 69 shopping malls, 63 recreational parks, and 60 sport facilities. Traffic elements include 424 signal-control intersections, 1500 detectors, 350 traffic signs, 20 VMS, 50 speed-limit road and 50 flyovers. Figure 2(a) shows one area in ATS-Qingdao.

By connecting the actual transportation system and ATS-Qingdao, computational experiments can be carried on the artificial transportation systems and the optimization and evaluation can be implemented much easily. The ATS-Qingdao provides the hardware-in-the-loop mechanism and general external interfaces, which enable the interactions between the actual devices and the artificial software modules. The following computational experiments have been carried out:

1) Setting the morning and evening peak periods, evaluating the influence of the adjustment of working time.

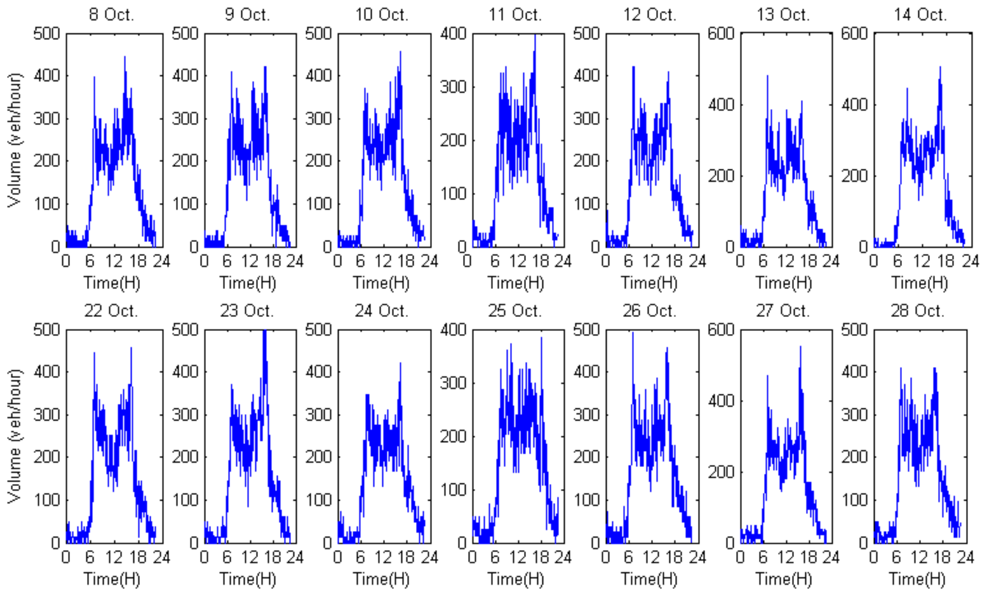


Fig. 5. The comparison of traffic flow (veh/hour) between before (Jul. 15–21) and after (Aug. 19–25).

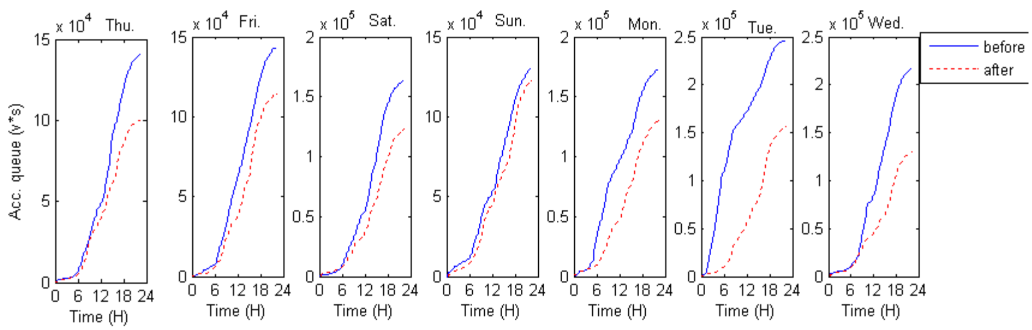


Fig. 6. The comparison of space density between before (Jul. 15–21) and after (Aug. 19–25).

2) Setting the position and capacity of the parking lots, evaluating the parking pressure when holding large events in the specific area;

3) Setting the time and participants, predicting the traffic pressure when holding large events and optimizing the distribution of the policemen;

4) Setting the position and impact range of traffic accident, analyzing its impact on the traffic;

5) Setting the bus evacuation routs, analyzing the evacuation process;

6) Setting specific traffic control measures, such as banning vehicles on specific days, one way street, analyzing the their impact on the traffic;

7) Setting bus priority, analyzing the public transport service capacity and its impact on social transportation;

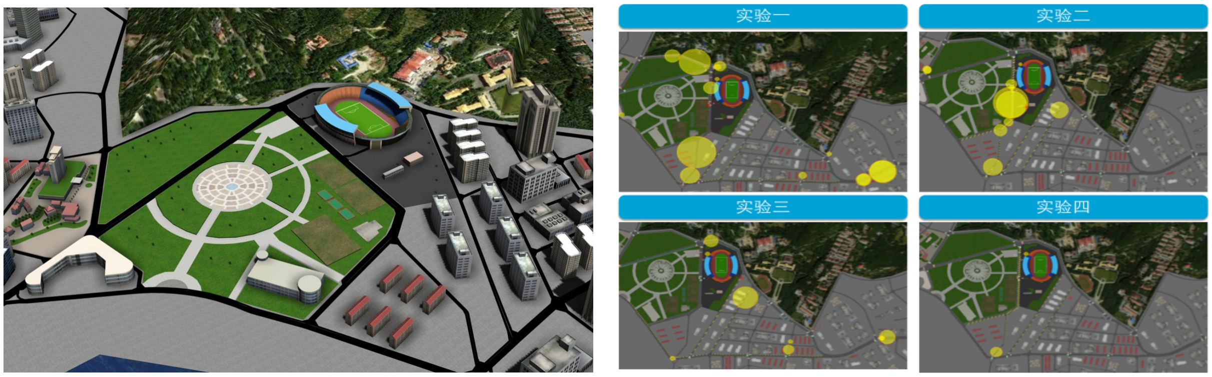
8) Simulating the traffic status in adverse weather, predicting its impact on transportation;

9) Simulating different traffic signal plans in specific intersections, evaluating the effect of different plans;

10) Optimizing and evaluating other traffic management measures.

Figure 7(b) shows some snapshots of the computational experiments which are in running. Computational experiments are carried out based on the interactions between the actual transportation system and the artificial transportation system. Computational experiments can be seen as a higher level of simulation software, and they differ from other optimization methods based on traditional traffic simulation or mathematics models at least in the following 3 aspects: a) The focus of simulation software is to generate the traffic phenomena while the focus of computational experiments is to explore deep insight on the mechanisms of the transportation, such as the generation and evolution process of traffic congestions. b) The object of simulation software is to generate current traffic status, while the object of computational experiments not only include current status, but also include the status that is not happened currently, but possible to happen in the future. c) The strategies in simulation software are usually passive, i.e., they try to adapt to the traffic flow, while the strategies in computational experiments are more active, i.e., they try to guide the traffic flow.

After the construction of PTS-Qingdao has been finished, Qingdao government spent about 3 months to evaluate the effects of the system and drew the conclusion that significant improvements have been achieved. Some main effects are listed in the following:



(a) Artificial transportation system for Qingdao

(b) Computational experiments GUI

Fig. 7. PTS-Qingdao.

(1) Traffic status has been improved significantly.

After 6 months of the implementation of PTS-Qingdao, arterial travel time and the number of vehicles' stops on arterial streets are reduced by 20% and 45%, respectively. Congestion miles of major key roads is reduced by 30%, travel time is reduced by 25%, and the travel efficiency is improved by 43.39%.

(2) The accuracy of real-time road traffic information has been improved.

Traffic information is the foundation for formulating management plan and providing services for travelers. Up to now, the accuracy of real-time road traffic information disseminated is more than 90% and the accuracy is more than 20% higher than using floating car. Besides traffic congestion status, the disseminated information of PTS-Qingdao includes point-point travel time, traffic regulation, traffic accidents, traffic maintenance, etc., which is more comprehensive and more practical than any other systems in China that have been built.

(3) Individual traffic information has been collected from social network and personalized travel service has been developed on social media.

Smartphone App for real-time traffic condition is developed in PTS-Qingdao, which has been downloaded more than 15,000 times. The app can disseminate traffic status and traffic accident in real time, and have dynamic navigation function. PTS-Qingdao can also disseminate traffic information on Wechat. The information includes traffic video screenshot and GIS-based traffic status. Up to now, the registered users, the access times, the registers vehicles and the vehicle violation messages have broken 8,500, 440 million, 5,8000, and 20,000, respectively. As social networks and connected societies become normal of our life, we should speed up our work in transportation games for social transportation, and make our ITS real smart, in human's terms.

VI. Conclusion

We have stepped into the era of cyber physical social system, where IoT enabled us to easy access to sensing, communications, and control in physical world, as well as in virtual worlds. Based on IoT, Parallel transportation systems are built up in 3 steps. First, Artificial transportation systems are set up to model and describe the actual transportation system. Second, computational experiments are designed and conducted to predict future evolutions and evaluate control plans. Finally, the actual and artificial systems are executed in an interactive parallel mode. In parallel execution, instead of guiding the virtual systems to approach to the status of the actual system, as we usually do in transportation simulation, we aim to guide the actual system to approach to the ideal status in the artificial systems. Accordingly, there are also three functions in PTS, descriptive analytics, predictive analytics and prescriptive analytics. Besides helping to improve transportation systems, PTS also has a promising future in building smart cities. Current, the building of PTS is still in its initial stage, future works include verifying the reliability of the data collected using social sensors, horizontal optimization based on computational experiments, parallel learning algorithms based on actual data and virtual data [34], and so on.

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