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Collaborative Optimization of Cyber Physical Social Systems for Urban Transportation Based on Knowledge Automation

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Abstract: The integration of signals from physical, social and cyber spaces, known as Cyber-Physical-Social systems (CPSS), is a new research paradigm for urban transportation, where the traffic control and management (C&M) is collaborative optimized among the three sub-systems. Though some technologies and optimization methods have been studied since its proposition, there is a lack of a systemic architecture as well as an overall implementation about how to efficiently exploit the social signals. For this reason, this paper proposes a general framework of CPSS for urban transportation and presents a feasible solution for traffic optimization based on knowledge automation. The specific implementation includes basic modeling of CPSS, knowledge evolution and reasoning, and collaborative optimization of C&P strategies. As a remarkable highlight, the influence of both individual activities and social learning is concerned during knowledge evolution and reasoning part. A case study from the application in the city of Dongguan is also given to validate our proposed framework and methods, showing that they can efficiently improve the average speed of the actual transportation.

Keywords: CPSS, knowledge automation, urban transportation, Collaborative Optimization

1. INTRODUCTION

As a representative of Cyber-Physical-Social systems (CPSS)[Wang, F. Y. 2010] , urban transportation involves three components: the actual traffic system (called the physical system), the human society (called the social system), and the information system (called the cyber system) that bridges the former two [Xiong, G., et al. 2017] . In such a traffic CPSS (T-CPSS), traffic counts, and other traditional signals from the physical system are collected through physical sensor networks. Accidents, travel plans and other implicit traffic knowledge from the social system is detected by the social sensors such as micro blog, etc. By such way, the physical and social systems are equivalently and computationally mapped into the cyber system, which plays as a link to facilitate the interactions between traffic infrastructure and human travellers. Intelligent C&M for the traffic system based on perception, analysis and prediction can be completed via effective algorithms in the cyber system as well [Dong, X. 2019] [Hussein, D., et al. 2015].

The research on T-CPSS is proposed in 2014, when some preliminary studies have been already conducted by a group of pioneers. [Mitrea, O., et al. 2013] proposed to use value-added services to turn the buses into social places for travellers. [Pereira, F. C., et al. 2015] gathered data from traffic IC card, telecom carriers, and hotspots on social media in order to find patterns about people's abnormal behavior and predict the related traffic flow . Though fragmented, these researches have successfully explored how to exploit the social signals for traffic smart C&M. To get the topic focused, [Guo, W. 2015] gave an insightful discussion about the trend of T-CPSS. [Fu, K., et al. 2015] proposed an iterative search algorithm based on relevant rules to mine traffic events. [LI, Y. 2014] [Zhou, T. 2014] [Sang, C. 2014] studied microscopic traffic cognition based on CPS, traffic jam features and suppression methods based on driving behaviors, and multiple traffic flow clustering and evolution based on CPS. [Wang, H., et al. 2015] proposed a layered model for the traffic information physical system.

The existing researches about T-CPSS mainly adopt the technological paradigm of data perception, data analysis and control strategies selection, but for the management of the social system, it still stays at a perceptual level and has no active guidance for the human participants. In 2015, Xiong proposed a new solution which consists of Artificial society, Computational experiments, and Parallel execution (named as the ACP approach), that can analyse the systemic dynamics and test control strategies for the physical system as well as the social system simultaneously [Xiong, G., et al. 2015] [Dong,

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X., et al. 2017] . Objectively, the ACP approach is applicable and feasible for T-CPSS from the perspective of complexity science. However, how to implement the evolution of CPSS to achieve an optimal C&M strategy still remains to be discussed. In this vein, this paper provided three contributions:

1) Propose a framework for T-CPSS analysis and evolution based on knowledge automation;

2) Propose the knowledge evolution framework both activity-based and social-learning-based, and focus on Multi-agent reinforcement learning to improve;

3) Take Dongguan urban transportation as study case, expounding feasibility and management efficiency of T-CPSS based on Knowledge Automation.

2.COLLABORATIVE OPTIMIZATION OF CPSS FOR URBAN TRANSPORTATION BASED ON KNOWLEDGE AUTOMATION

As mentioned before, the ultimate objective of T-CPSS is to optimize the C&M strategies for the actual urban traffic system. Achieving such a goal, however, needs to investigate the potential evolutionary trajectories of the actual system in the near future, given its current state. Here we propose to use knowledge automation to complete this process in the cyber space by considering both physical and social signals. As is shown in Fig.1, the whole process can be divided into three steps: basic modeling of T-CPSS, knowledge evolution, and collaborative decision optimization.

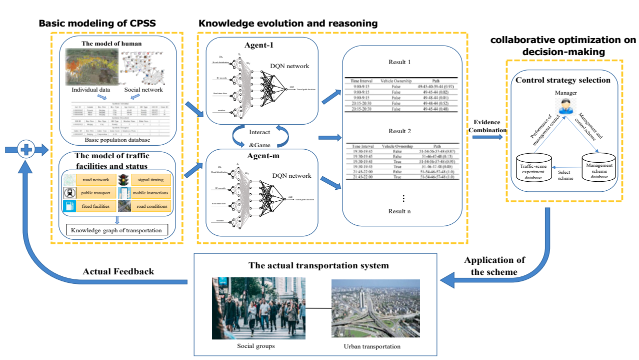

Fig. 1. Framework of CPSS for urban transportation

2.1 Basic Modelling of CPSS

The basic modelling of CPSS is to acquire corresponding computational models of urban population and traffic infrastructure. Its objective is to provide the participant elements as well as their initial states for the knowledge automation evolution.

The modelling of human travellers in benchmark years usually uses multi-agent method. This method synthesizes a basic population database containing various individual attributes such as age, gender, and car ownership by using the data from census, travel surveys and urban geographic information, etc. [McElreath, R., et al. 2005]. In general, common synthetic methods include discrete copulas [Ye, P. Wang, X. 2018], combinatorial optimization approach [Voas, D., Williamson, P. 2000], synthesis and reconstruction [Wilson, A. G., Pownall, C. E. 1976] , etc.. In discrete copulas, the input data can be categorized into two types. The first one is from census and urban statistical yearbooks, used to estimate the optimal core tensor. The second type is a small proportion of individual samples, called the disaggregate samples. In this dataset, each record represents an individual with all the attribute values given. These are utilized to estimate factor matrixes.

A few of dynamic evolution rules should be added to deduce the population state in target year after synthesizing in base year, such as:

- The sum of the proportion of each age group equals 1.
- The age of each agent increases by 1 at each time step.
- The gender of agents is divided into male and female.

A feasible way to model the traffic infrastructure in T-CPSS is to use knowledge graphs to realize the universal knowledge representation from multiple data sources. Generally, we use three item tuples to encode the basic knowledge of urban transportation, which will be explained more clearly in Part 3.1. The knowledge graph is composed as follows. First, based on open source database and online encyclopedia API, we collect the infrastructure data and traffic states from physical and social sensory networks. The raw data is structured to be further processed as well. Then, according to the online encyclopedias and expert knowledge databases, concepts, entities and relations are extracted from the structured input data to build primitive knowledge graphs. Finally, the primitive knowledge graphs from each data source are correlated and merged to generate a final universal consistent knowledge graph. The fusion of primitive knowledge graphs is based on the semantic matching where each property of the entities is investigated. The more similar entities it covers, and the more probable that the corresponding graphs merged. Property correlation is expressed as:

$$Simi = \frac{\sum_{a,b}|\{e|e(A)=a,e(B)=b\}|}{\sqrt{\sum_{a}|\{e|e(A)=a\}|}\cdot\sqrt{\sum_{b}|\{e|e(B)=b\}|}} \quad (1)$$

Where a, b are specific values of attribute A, B respectively, and $|\{e|*\}|$ represents the number of instances satisfying the condition $*$.

2.2 Knowledge Evolution and Reasoning of T-CPSS

For knowledge evolution and reasoning, agents' travel behavior rules are to exact. On one hand, the travel behavior model should be able to describe the generative process of travel activities. In each travel activity, the agent will complete three selection procedure: travel start time, travel mode and travel route. The activity-based travel modelling method is to establish the activity plan of each type of synthetic population, and then objectively reflect the generation process of behavior based on individual travel needs. On the other hand, considering the sociality of the agent, social learning is proposed to T-CPSS to supplement travel behavior modelling.

(1) Activity-based travel behavior modelling

Firstly, travel start time is closely related to agents' activity types, which can be divided into 11 types, including staying at home, working, attending school, shopping, official activities, physical fitness, eating outside, cultural entertainment, visiting friends, sending children and receiving children. Among them:

- Life activities--Occur with a certain probability, and start time is not strictly limited within allowable range.
- Non-life activities--Official activities occur with a certain probability within working hours; Going for work, school, sending and receiving children have strict time limits.

Except for the occasional time, the classification results listed above basically cover common travel purpose, and have a good corresponding relationship with travel start time.

Secondly, travel mode selection depends drastically on travellers' psychological demands. Safety, punctuality and economy are the most basic requirements of travellers. Furthermore, travellers will extend many higher requirements, such as convenience, comfort. Therefore, different factors can be considered to build a rule database of travel mode, e.g.:

- Travel distance has a decisive influence on whether to choose motor vehicle.
- The relationship between travel cost of car and public transport, $C =$ {Much higher, higher, nearly, lower}.

Thirdly, the essential factors affecting driver's willingness to choose travel route contain: travel time, familiarity, the number of intersections need to pass and so on. Agents tend to choose the action that gain the highest cumulative revenue. We propose a route selection decision-making process based on Deep Reinforcement Learning (DRL) [Bloembergen, D., et al., 2015]. Let S_t denote all information that can be utilized to decide at time t. This mainly consists of its perception of the external environment, based on the current incomplete information acquired, and its internal attributes, including long-term knowledge, path preference, energy and so on. Based on the current state $\mathrm{S_t}$, agent selects the optimal travel path A_t for purpose of reaching destination safely and fast. Strategy $\pi(a|s)$: $s \rightarrow a$ is the mapping of the current state to behavior. And the routine cognitive-decision model is equal to the learning of the optimal strategy π^* . Fig 2 takes typical traffic data (e.g. weather data, real-time flow data and road distribution data) as input, and the optimal routine as the output of deep neural network.

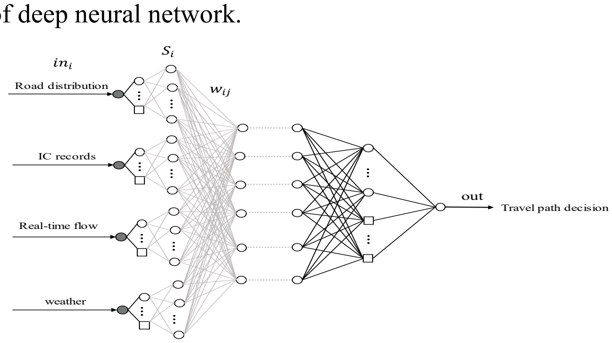

Fig. 2. Evolution diagram of single agent's travel decision

(2) Sociality -based travel behavior modelling

Activity-based model is individual-based, without considering the social relationship between individuals. In practice, social interaction induces social learning through the exchange of information, and then influences their own travel behaviors. Therefore, here, social-learning theory is introduced into T-CPSS, so as to consummate the knowledge evolution process.

Observation is the basis of imitation. First, the observation mechanism of agent travel should be established. Suppose that the frequency of a certain travel behavior determines the observed probability. Let $N(\mathrm{s}, \Delta t)$ denote the total number of choices made by the artificial population in the state s during the latest Δt interval, and $X(s, d, \Delta t)$ denote the number of choosing behavior d, then the observed probability of d is:

$$p_0(s,d) = \frac{X(s,d,\Delta t)}{N(\mathrm{s},\Delta t)} \tag{2}$$

Second, based on linear imitation model(LIM) [McElreath, R., et al. 2005], we assume that the total number of decisions the agent i observed in state s during the latest Δt interval is $N_i(\mathrm{s}, \Delta t)$, and the number that observed to select behavior d is $X_i(\mathrm{s}, \mathrm{d}, \Delta t)$. The probability that agent i selects d in state s corresponds to:

$$p_i^n(s,d) = (1-\beta)L_i^n(s,d) + \beta\frac{X_i(\mathrm{s,d},\Delta t)}{N_i(\mathrm{s},\Delta t)} \tag{3}$$

Where β is the rate of the social learning, $L_i^n(s,d)$ is the probability involving only individual activity plan.

Additionally, Multi-agent Deep Reinforcement Learning (MDRL) is applicable for routine planning [Bloembergen, D., Tuyls, K., et al. 2015]. The cumulative return of each agent also related to others due to mutual game and cooperative communication. It is proposed to take typical data sets of transportation as input of deep neural network to deduce the whole state S of current transportation system and then explore the optimal joint action. In T-CPSS, n indicates the number of agents; A_i indicates action space of the i_{th} traffic agent; $A = A_1 \times A_2 \times \cdots \times A_n$ indicates the joint action space; $T = S \times A_1 \times \cdots \times A_n \times S \rightarrow [0,1]$ denotes the system's transition probability function; R represents reward function; $R_i(s, a_1, \cdots, a_n, s')$ represents the immediate reward of the i_{th} agent if the whole system determine the joint action $(a_1, \cdots, a_n)$ at sate s, and then transmit to state s'. To simplify model, we define $-i = n\{i\}$ as all agents except the i_{th} agent. State value function when the i_{th} agent performs strategy π can be expressed as:

$$V_{i,\pi}(s) = \sum_{a\epsilon A}\pi(s,a) \cdot$$
$$\sum_{s'\epsilon S} T(s,a_i,a_{-i},s')\left[R_i(s,a_i,a_{-i}) + \gamma V_{i,\pi}(s')\right] \tag{4}$$

The optimal strategy of the i_{th} agent also has something with others' strategies:

$$\pi_i^*(s,a_i,\pi_{-i}) = \arg\max_{\pi_i}\sum_{a\in A}\pi_i(s,a_i)\pi_{-i}(s,a_{-i}) \cdot$$
$$T(s,a_i,a_{-i},s')\left[R_i(s,a_i,a_{-i}) + \gamma V_{i,\pi,\pi_{-i}}(s')\right] \tag{5}$$

2.3 Collaborative optimization on decision-making

The third step is to select the optimal decision scheme from various evolutionary control paths. We propose an optimal decision-making method based on the Evidence Theory (ET). Assume that knowledge evolution has been carried out N times, the distribution frequency of each result after clustering is $\{r_1: n_1, r_2: n_2, \cdots, r_m: n_m\}$, where $n_1 + \cdots + n_m = N$. Further assume that $n_1 \geq \cdots \geq n_m$, without loss of generality. Actually, in evolution experiments, a considerable part of the evolutionary results has very low frequency. To eliminate the effect of noise, it is proposed to set threshold η, and suppose that $n_1 \geq \cdots \geq n_k \geq \eta \geq n_{k+1} \geq \cdots \geq n_m$. Then, the identification frame can be expressed as:

$$\{r_1: \frac{n_1}{N}, r_2: \frac{n_2}{N}, \cdots, r_k: \frac{n_k}{N}, (r_1, r_2, \cdots, r_k): 1 - \frac{n_1 + \cdots + n_k}{N}\}$$

Next, according to ET:

$$b(r_i) = \frac{1}{K} \sum_{\alpha_1 \cap \cdots \cap \alpha_n = r_i} b(\alpha_1) \cdot b(\alpha_2) \cdot \cdots \cdot b(\alpha_n)$$
$$= \frac{1}{K} \cdot \frac{n_i}{N} \cdot \left(1 - \frac{n_1 + \cdots + n_k}{N}\right) \tag{6}$$

$$K = 1 - \sum_{\alpha_1 \cap \cdots \cap \alpha_n = \phi} b(\alpha_1) \cdot b(\alpha_2) \cdot \cdots \cdot b(\alpha_n)$$
$$= 1 - \frac{1}{N^k} \prod_{i=1}^{k} n_i \tag{7}$$

The result with the largest distribution probability b can be expressed as the expected evolution result of CPSS:

$$r^* = \underset{r_i}{\operatorname{argmax}}\, b(r_i) \tag{8}$$

Finally, managers can formulate the optimal control strategy and feedback it to the actual system. This guides the actual system to approach the expected target state, and optimizes the management scheme.

3. CASE STUDY IN DONGGUAN CITY

To illustrate the rationality and feasibility of knowledge automation to realize the transportation CPSS, this part takes the transportation system of Dongguan City as an example. We construct the corresponding T-CPSS prototype system, and parallel computational experiments we set up covers the inner area of Dongguan Huancheng road, essentially covering the central area of Dongguan. The experiment area is about 150 square kilometers, including 163 residential areas, 86 workplaces, 59 schools, 19 shopping centers, 21 hospitals, 37 hotels, and 13 entertainment places((Fig.3.).

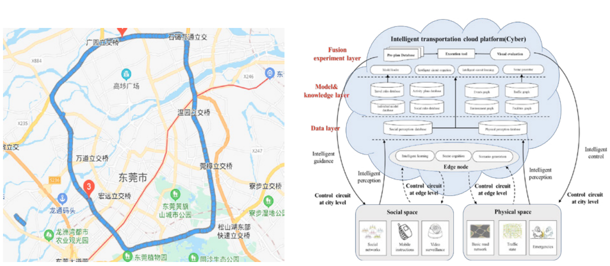

Fig.3. Experimental area and system structure of Dongguan T-CPSS

3.1 Basic modelling of Dongguan T-CPSS

The overall census data and micro samples (tax records, real estate registration in Dongguan, etc.) in 2010 can be acquired. First, we utilize Discrete Copulas for population synthesis in 2010, with a population scale of 200,000. Then, based on the evolution rules such as growth rules, we deduce the population status of 200,000 people in 2020.

The infrastructure modelling employs the actual road network and the information of schools, shopping centers and other places of activity in the research area, and uses the multi-source knowledge graph in the form of triple. Table 1 is a knowledge graph segment of urban traffic infrastructure. The entities include roads, intersections and subway stations. Accordingly, the tuples are represented as <Station, Sation_id, varchar>, <road, Road_id, varchar>, et al.

Table 1. DATA STRUCTURE OF SUBWAY STATION

Data id	Explanation	Type
Station_id	ID of station	varchar
Road_id	The road ID where station entrance is located	varchar
Start_id	The start intersection ID of the road where the station entrance is located	varchar
End_id	The end intersection ID of the road where the station entrance is located	varchar

3.2 Knowledge evolution of Dongguan T-CPSS

The type of the activity plan has a great corresponding relationship with travel start time. For non-life activities, assume the time attributes obey normal distribution $N(\mu, \sigma^2)$, the value range is specified as $\mu \pm 3\sigma$ to ensure validity. For life activities, let d_1, d_2, d_3, d_4, d_5 denote 5 varieties of life activities, the probability of occurrence is $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$. Then generate a random number r from 0-1 uniform distribution. If $r > \sum_{i=1}^{5} \alpha_i$, all life activities are planned; else, randomly choose an activity d_k. If $\sum_{i=1}^{k-1} \alpha_i < r \leq \sum_{i=1}^{k} \alpha_i$ where S^- denotes the set of existed life activities, d_k will be joined to the new set of planned activity plan. Finally, according to the distribution function of duration time of d_k, determine duration time. Table 2 gives an example of individual's activity plan.

Table 2. AN EXAMPLE OF ACTIVITY PLAN

Order	Activity	Start time	End time	locale
1	at home	00:00	06:10	habitation
2	send children	06:50	07:10	kindergarten
3	go to work	08:30	16:20	workplace
…	…	…	…	…

The attributes of travellers are different, the intensity of different travel modes is also different, the rule database of travel mode selection is established as follow(Fig.4).

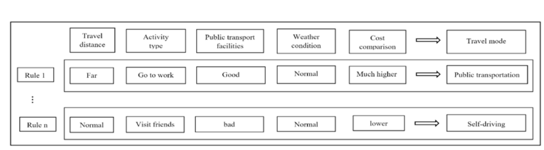

Fig.4. Rule database of travel mode selection

The perception of external environment and inference of internal attributes of agents are ingredients for state inference. Let O_t be perception of external environment at time t, which contains the observation of others' travel destination, traffic network and real-time traffic flow, etc. Due to the subjectivity of these attributes, we grade the internal attributes by experts' scoring. For example, agent's energy can be expressed by 1-10, in which 1 represents extremely tired and 10 vigorously well. Combine the inferred state with the goal of maximizing the cumulative return of RL, the optimal path can be output.

Based on the preliminary activity-based agent travel rule, social learning is integrated to perfect the evolution rule. Social learning rate is set as 0.3 in Linear-Imitation. Moreover, the cooperation and game are further regarded, and the optimized joint action of multi-agents can be obtained through MDRL framework. Taking route planning of one agent within the study area an instance, where travel origin is Dongguan Science and Technology Museum and destination is Dongguan No.2 senior high school and this agent chooses self-driving (Fig.5.). Table 3 lists three possible paths and some related information.

Table 3. INFORMATION OF THREE PATHS

	Path 1	Path 2	Path 3
Path length(km)	4.8	5.3	5.0
Number of traffic lights	4	4	5
Current traffic volume	heavy	light	light
Historical congestion	Frequently	sometimes	rarely

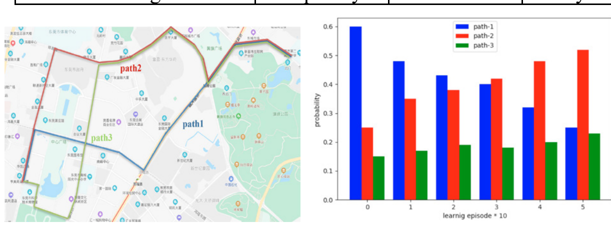

Fig.5. Changes in probability distribution of route selection

Figure 5 demonstrates the probability distribution curve of selecting these three paths when adding sociality in the process of continuous learning. Time-0 represents the probability considering only its activity plan. With the increasing number of learning times, agent prefers to path 2, rather than path 1 in the initial stage. In other words, this agent pays more attention to the congestion situation and traffic volume of the route from communication, rather than its own activity preference.

3.3 *Collaborative optimization of Dongguan T-CPSS*

After N times of knowledge evolution, the most likely travel rules of 200,000 synthetic population are obtained through ET, so as to generate specific traffic scenarios. To obtain effective management and control strategy, Dongguan T-CPSS platform is constructed, where parallel experiments are conducted. DongGuan T-CPSS is deployed on the cloud platform in the way of cloud-edge integration and has three layers (Fig.3). The bottom layer is data perception layer, which is mainly used to collect two categories of information: social perception data (2010 census data, etc.), and physical perception data (road network information, etc.). These two types of information will be perceived, extracted, associated and fused both in physical space and in social space, then are saved in the middle layer–the model &knowledge layer in the form of various knowledge graphs. Further, taking these knowledge graphs as input, the generation and evolution of various situations are completed through activity-based and sociality-based evolution model. The fusion experiment layer can provide visual display of the results to traffic managers based on ET, and extract the corresponding optimal management plan for actual traffic system. The optimization results of parallel experiments at a single intersection and global urban traffic conditions are shown as follows:

(1) Optimal control of traffic signal at a single intersection

Taking the intersection of Dongcheng East Road and Dongzong Road as an example, Table 4 lists the release time comparison between the original scheme and the optimization scheme. The start time of optimal control scheme is April 15, 2020. We select the traffic flow data the day before--April 14 and the day after--April 21 for comparison, due to the same weekday and the traffic flow has certain similarity. Evaluation metric is the average speed of vehicles.

Table 4. COMPARISON OF RELEASE TIME

Release order				
Original	Peak-time	40s	10s	20s
	Non-peak-time	35s	10s	15s
Optimized	Peak-time	[40s,50s]	[10s,30s]	[20s,30s]
	Non-peak-time	[35s,50s]	[10s,30s]	[15s,30s]

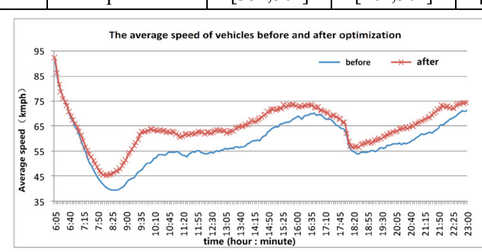

Fig.6. Comparison of average speed after optimizing

Fig.6 demonstrates that the average speed of vehicles has increased significantly: the average speed has increased from 58.5kmph to 64.3kmph, with an increase of 11%.

(2) Traffic conditions in Dongguan improve significantly

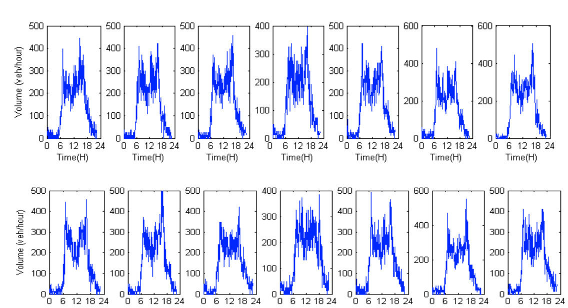

Fig.7. Traffic flow on April 7-13 and April 21-27

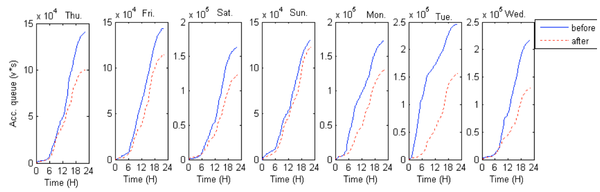

Fig.8. Comparison of queue length before and after

The travel time of trunk road in Dongguan is reduced by 20% on average, and the number of parking is reduced by 45%. Through the implementation of traffic optimization scheme for core roads, the congestion mileage is reduced by approximately 30%, the traffic time is reduced by 25%, and the traffic efficiency is increased by 43.39%. For traffic flow from south direction to north direction at the intersection of Dongguan Avenue and Hongfu road, Fig.7 shows the comparison of traffic flow in the week before--April 7 to April 13 and the week after--April 21 to April 27. Fig.8 exhibits the comparison of queue length, indicating that the traffic situation has been significantly improved by implementing the T-CPSS system though the traffic demand has not been reduced.

4. CONCLUSIONS

Knowledge automation has promoted the most aspects of knowledge generation, acquisition and application. While, though the research of T-CPSS based on ACP approach is consistent with the paradigm of complexity sciences, how to implement the evolution of CPSS in order to achieve an optimal C&M strategy still remains to be explored. Therefore, we combine knowledge automation with T-CPSS, and propose a framework for T-CPSS analysis and evolution based on knowledge automation system.

T-CPSS focuses on three sequential tasks: basic modelling of CPSS, knowledge evolution and reasoning and the optimal C&M strategy from the cyber artificial systems to the actual physical systems. In knowledge evolution and reasoning, to the best of our knowledge, it is the first time to introduce both activity processive model and sociality-based model to T-CPSS. Case study results in Dongguan by establishing Dongguan T-CPSS platform demonstrates this T-CPSS based on knowledge automation is effective to provide the optimal C&M strategy for mangers, and can improve the control of both single traffic signal and the traffic conditions of the whole city significantly.

ACKNOWLEDGEMENTS

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