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A MULTI-INTERSECTION MODEL AND SIGNAL TIMING PLAN ALGORITHM FOR URBAN TRAFFIC SIGNAL CONTROL

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Abstract. The urban traffic signal control system is complex, non-linear and non-equilibrium in real conditions. The existing methods could not satisfy the requirement of real-time and dynamic control. In order to solve these difficulties and challenges, this paper proposes a novel Multi-Intersection Model (MIM) based on Cellular Automata (CA) and a Multi-Intersection Signal Timing Plan Algorithm (MISTPA), which can reduce the delay time at each intersection and effectively alleviate the traffic pressure on each intersection in the urban traffic network. Our work is divided into several parts: (1) a multi-intersection model based on CA is defined to build the dynamic urban traffic network; (2) MISTPA is proposed, which truly reflects the real-time demand degree to green time of the traffic flow at each intersection. The MISTPA is composed Single Intersection Volume Algorithm (SIVA), Single-Lane Volume Algorithm (SLVA) and single intersection signal timing plan algorithm (SISTPA). Extensive experiments show that when the saturation is greater than 0.3, the MIM and the MISTPA achieve good performance, and can significantly reduce the vehicle delay time at each intersection. The average delay time of the traffic flow at each intersection can obviously be reduced. Finally, a practical case study demonstrates that the proposed model and the corresponding algorithm are correct and effective.

Keywords: cellular automata; signal timing plan; delay time; multi-intersection model; urban traffic signal control.

Introduction

Nowadays many cities are suffering from severe daily urban traffic congestion, which causes the enormous social and economic problems (Triantis *et al.* 2011). Since changes in the urban area infrastructure are usually not possible, researchers often suppose that an efficient scheduling of traffic signal can help to reduce these problems by improving the flow of vehicles through the cities. Taylor and Heydecker (2014) derives novel approximations for the equilibrium mean and also variance and utilization, using functions linking traffic intensity with green period capacity. With three moments, equilibrium probability distributions can be estimated for which a method based on a doubly nested geometric distribution is described. Christofa *et al.* (2013) presents a person-based traffic responsive signal control system for transit signal priority on conflicting transit routes. He proposed a mixed-integer nonlinear program is formulated, which minimizes the total person delay at an intersection while assigning priority to the transit vehicles based on their passenger occupancy. Nagatani (2008) studied the dynamical behavior of a shuttle bus moving through a traffic signal. The dynamics of the bus is expressed in terms of the nonlinear maps. The bus dynamics is controlled by varying the loading parameter, the cycle time of signal, and the degree of speedup. The typical urban traffic signal control systems are TRANSYT (Wong *et al.* 2002), SCOOT (Robertson, Bretherton 1991) and SCATS (Sims, Dobinson 1980). There are several difficulties and challenges in the previous traffic signal optimization research (Wiering *et al.* 2004; Kerner 2002; McKenney, White 2013):

– many optimization-based methods are based on off-line models, using historical data to optimize traffic signal within the urban road network. However, historical data cannot always accurately reflect the current traffic state (Balaji *et al.* 2010);

– with an expansion of the urban road network, plenty of traffic signal control methods cannot realize real-time control;

– a wide range of traffic signal optimization research may be unable to reflect the real traffic conditions, for these researches typically assume a very simple traffic infrastructure, such as the traffic network consisting of a few intersections.

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In this paper, we propose a novel Multi-Intersection Model (MIM) and a Multi-Intersection Signal Timing Plan Algorithm (MISTPA), which can reduce the vehicle delay time at each intersection and effectively alleviate the traffic pressure at each intersection of the urban traffic network. The main contributions of this paper are described as follows:

- the proposed MIM is to map the urban traffic network to a virtual Cellular Automata (CA) model, which completes the construction of MIM;
- the MISTPA is proposed to calculate the current phase's accurate time of the traffic signal at each intersection.

The rest parts of this paper are organized as follows. Section 1 describes the related works of urban traffic model and typical traffic signal optimization approaches. Section 2 presents the problem description and elaborates the construction of the MIM. Section 3 details MISTPA. Section 4 presents a large number of experiments to validate the proposed model and MISTPA. Final section draws the conclusions and perspectives.

1. Related Works

Regarding the related papers published in the traffic signal control fields, the research works mainly to adopt the deterministic or stochastic approaches, which had achieved great progress in problem description, modeling and solving algorithm. The merit and demerit of the typical models and algorithms for traffic signal fields are concluded in Table 1.

The signal control optimization methods in Table 1 had their own shortcomings. While in addressing problems with complex, non-linear, non-equilibrium, for example, urban traffic signal control, CA was an effective approach. Any system with many discrete elements could use CA to construct model, as urban traffic signal control system could be divided into many components, and each component followed some simple rules. Systems composed of these components could produce very complex behaviors (Mamei *et al.* 2005). Therefore, using cellular automata to establish the urban traffic signal control model was greatly significant. CA models could show a large number of traffic scenarios varying from quite simple ones to the extremely complex ones (Spyropoulou 2007), such as the scene of simulation of traffic lane reduction (Nassab *et al.* 2006), simulation of change behaviors of vehicles by changing lanes (Li *et al.* 2005) and simulation of mixed traffic (Lan, Chang 2003, 2005). In literature (Wei *el al.* 2005), although the CA has been used to investigate urban traffic for several decades, it is mainly applied in microscopic traffic. In a microscopic traffic model, vehicle velocity was used to represent the state variable. The space was discretized into many cells and the one or more vehicles occupied each cell.

This paper focuses on the urban traffic signal control under the uncertainty. In order to solve the above problems of existing urban traffic signal control systems, this paper proposes a novel macroscopic MIM based on CA and a MISTPA. In our proposed method, multi-intersections within an urban road network are mapped into a virtual MIM model of CA, which realizes the construction of the MIM. After establishing the model of multi-intersections, the proposed MISTPA can decrease vehicle delay time at each intersection.

Table 1. The merits and demerits of the typical models and algorithms for traffic signal fields

Classification	Models and algorithms	References	Merit and demerit
Deterministic approaches	Partial differential equations	Soh *et al.* 2009	Difficult to solve, suitable for a particular aspect of traffic systems
	Random point process theory	Baras *et al.* 1979	Hard to achieve real-time control
Stochastic approaches	Fuzzy control	Pappis, Mamdani 1977; Wei *et al.* 2001; Niittymäki, Pursula 2000	Effective for small traffic network
	Neural networks	Wei 2001; Wei, Zhang 2002	Had a very simple structure, its neural performance is susceptible to the traffic volumes, so that they had to relearn an effective control approach
	Decision support systems	Almejalli *et al.* 2007	Effectively select the proper strategy, difficult to obtain and maintain historical data and expert knowledge
	Evolutionary computation and swarm algorithm	De Oliveira, Bazzan 2006; García-Nieto *et al.* 2012; Montana, Czerwinski 1996; Sanchez-Medina *et al.* 2010	Requires a great deal of computing resources (a number of simulations). The cost of simulations is high. When traffic network is large enough, real-time control might be impossible
	Reinforced learning	Wiering *et al.* 2004; Bazzan *et al.* 2010	This method was effective, but the performance of these approaches is sensitive to the change of traffic state parameters

2. Problem Description and MIM

2.1. Problem Description

In this paper, the urban traffic adaptive control theory based on CA is adopted to construct the adaptive control model of urban intelligent traffic system. According to the relationship between the local intersection and its neighbors, this paper presents an ideal that urban traffic control is converted into a problem with two-dimensional CA to construct the adaptive control model. In order to meet the requirements of a real-time control of urban traffic signal, the principle of hierarchical progress is used to drive the evolution of urban traffic signal pattern, which can solve some uncertain problems in urban traffic signal control. Modeling of MIM within an urban traffic road network in this paper has three steps as follows:

- discretizing cells;
- explicit of cells information;
- discretizing cells state.

The urban traffic signal control system is discretized into a two-dimensional grid that regards each intersection as a cell. According to the relationship between the local cell and its neighbors, the urban signal control system can be expressed in a virtual CA model, which is shown in Fig. 1. The adaptive evolution processes of all cells run on the virtual CA model based on an attribute matrix. Evolutionary optimization of cell attribute (traffic flow) combined with signal timing plan strategy calculates green wave time of each phase in each traffic signal to achieve the purpose of easing urban traffic pressure.
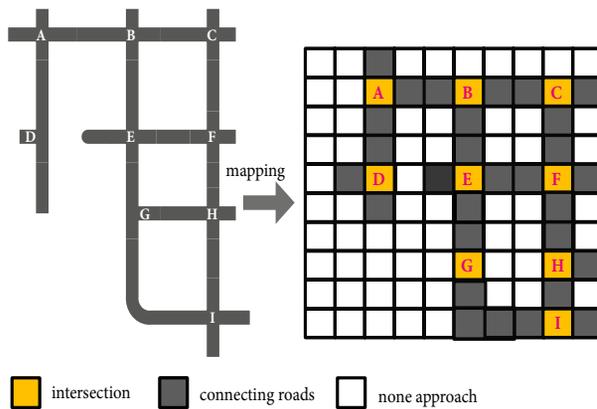

Fig. 1. The mapping between multi-intersections and virtual cell

2.2. Problem Solving Steps

The problem solving steps are described as follows:

- obtaining the structure of urban traffic road network, and setting traffic parameters (including the lands number) of each intersection within the traffic road network. The number of intersections within the traffic road network is defined as *N*, and these intersections are marked with the number of 1 to *N*;

- constructing the urban traffic signal adaptive control system based on CA model, including cell, cell state and CA rule (detailed in Section 2.3);
- obtaining the values of parameters, such as the initial number of vehicles in each intersection, the phase state of traffic signal in each intersection, and converting these parameters into traffic density and traffic velocity of each intersection;
- adding the traffic density and traffic velocity to the corresponding cell, and using CA rules to concurrently evolve each cell at the same time step. After several generations evolutions each cell will get the traffic density and traffic velocity;
- converting the parameters of the evolved traffic density and traffic velocity of each cell into the vehicle flow pressure of each cell;
- calculating traffic signal green wave time of current phase in each intersection (algorithm MISTPA, which is detailed in Section 3).

2.3. MIM based on CA

2.3.1. Definitions

Assumptions and definitions are defined as follows:

- Cycle Length (CL). CL is the total traffic signal time of all phases in the intersection. In this paper, CL is a fixed value;
- Traffic signal control time step (t_{step}). t_{step} is evolutionary time step of cells, which is set as 5 s in this paper;
- Evolutionary Generations of the Cell (EGC). EGC is the needed generation times for cell evolution, which usually ranges from 8 to 10;
- Phase switching. Considering the reality of the urban traffic situation, this paper adopts four kinds of phases of traffic signal within the urban traffic road network. These phases are shown in Fig. 2. The four kinds of traffic signal phase in cycles alternately change.

2.3.2. Cell

In this paper, each intersection within an urban traffic road network is regarded as a cell. The relationship of cells uses the relative position of geographic topology in the urban traffic road network to describe. So a Virtual Adjacency Matrix (VAM) can be used to express the neighborhood relationship of intersections within the urban traffic road network. The VAM is shown in Equation (1):

$$VAM = \begin{bmatrix} b_{11}, b_{12}, b_{13}, b_{14} \\ b_{21}, b_{22}, b_{23}, b_{24} \\ \dots\dots\dots\dots\dots \\ b_{n1}, b_{n2}, b_{n3}, b_{n4} \end{bmatrix}, \quad (1)$$

where: *n* is the number of intersections in the urban traffic road network; *b* is an intersection in an urban traffic road network, which is regarded as a cell in VAM. For example, b_{12} is an intersection of *road*1 and *road*2.
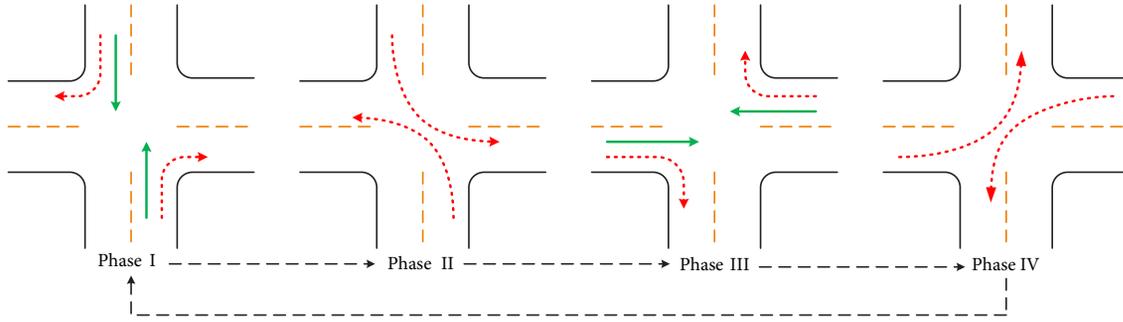
Fig. 2. Four kinds of traffic signal phase

2.3.3. Cell State

By analyzing a large number of parameters in the traffic flow information, this paper defines a Vehicle Flow Pressure (*vfp*) of each road in the intersection as the state of the cell. *vfp* reflects the demand degree to green light of traffic flow at each road of the intersections, and it is closely related to the queue length at each road of the intersections. *vfp* is shown in Equation (2):

$$vfp = \sum_{k=1}^{K} STotalVolume_k, \qquad (2)$$

where: *K* represents the number of lanes at road *j* of intersection *i*; $STotalVolume_k$ represents traffic flow of lane *k* at road *j* of intersection *i*. The unit of traffic flow is vehicle number per one hour [veh/h].

The vector variable S_i represents the state of cell, which is shown in Equation (3) and represents a set *vfp* of all the roads in the intersection. If the road *j* of the intersection *i* does not exist, set $vfp_j = -1$.

$$S_i = \left\{ vfp_j \middle| j = 1-4 \right\}. \qquad (3)$$

2.3.4. CA Rule

The paper adopts Von Neumann neighborhood, and evolutionary rule of CA based on Von Neumann neighborhood, shown in Equation (4):

$$S_i^{k+1}(t) = F\left(S_i^k(t), S_{i1}^k(t), S_{i2}^k(t), S_{i3}^k(t), S_{i4}^k(t) \right), \quad (4)$$

where: S_i^{k+1} expresses the state of cell *i* after evolution of the *k*+1 times generation; $S_{ij}^k (j = 1,2,3,4)$ represents state of cells which is related to cell *i*; *F* is nonlinear state updated function; *t* is the absolute time at the beginning of time step t_{step}; *k* is evolutionary generations, and if *k* is zero, S_i expresses the detected actual traffic data. Evolutionary computation of each intersection within the urban traffic road network is in parallel, and after several generation evolutions, we can get a set of stable and global coordinated *vfp*, which is shown in Fig. 3, where t_{step} is detailed in Section 2.3.1, and t_{step} is equally divided into *k* segments; $t_i (i = 1,2,3,\cdots,k)$ is a segment time; GT_{start} is the beginning time of green phase of traffic signal; min *GT* represents minimum time of each
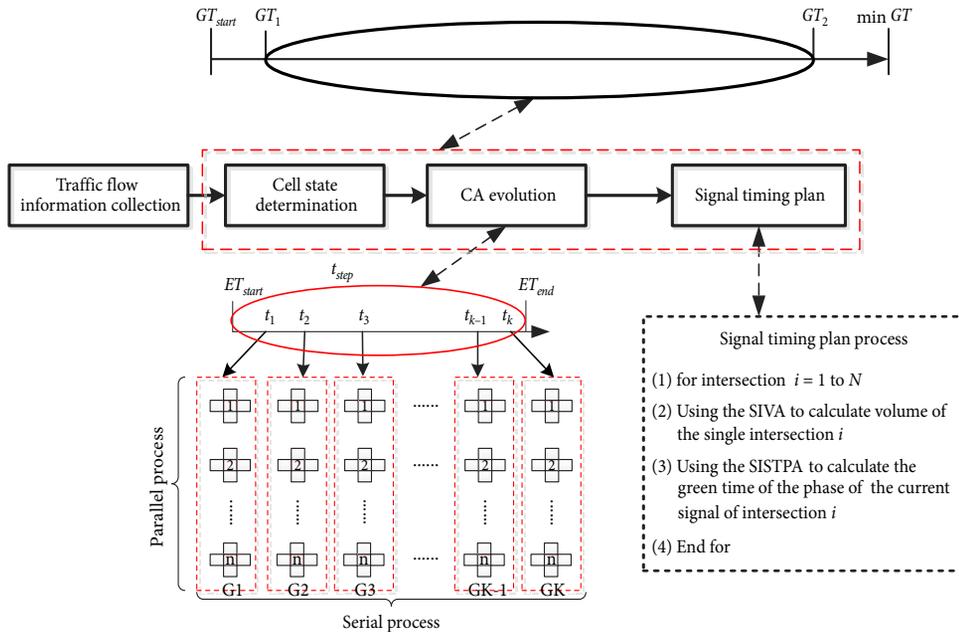

Fig. 3. The process of urban traffic signal adaptive control

phase of each traffic signal during a cycle; ET_{start} and ET_{end} express the beginning and the end evolutionary time of cell state; GT_1 and GT_2 denote the beginning and the end of the procedure of cell state determination, CA evolution and signal timing plan; G_i represents the ith ($i = 1, 2, 3, L, k$) generation evolution of cell. During t_{step}, cell collects traffic flow information of intersection, and then converts the information into the state of cell. After several generation evolutions of cell state, the evolutionary result provides the necessary decision support for signal timing plan of the current phase.

There are some similarities between the ordinary fluid and the urban traffic flow (Pipes 1953), so this paper introduces Navier–Stokes equation of the ordinary fluid into the urban traffic flow. The Navier–Stokes equation is shown in Equation (5):

$$\rho \cdot \frac{du_i}{dt} = \rho \cdot f_i - \frac{\partial p}{\partial x_i} + \frac{\partial}{\partial x_j}\left(\mu \cdot \left(\frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i}\right)\right), \quad (5)$$

where: ρ is the fluid density; f_i represents the mass force; u_i and u_j denote i direction and j direction of the fluid velocity; p expresses the intensity of pressure. By mathematical reconstruction of the Equation (5), it can get the simplified Navier–Stokes equation that can be applied to the urban traffic flow. The simplified Navier–Stokes equation is shown in Equation (6):

$$\frac{du}{dt} = -\frac{1}{\rho} \cdot \nabla p + \tilde{\mu} \cdot \nabla^2 u, \quad (6)$$

where: u is the traffic velocity [m/s or km/h]; ∇p represents the pressure gradient force; $\tilde{\mu}$ expresses the viscosity coefficient; ρ denotes the traffic density; t is the time.

Using the finite difference method to decompose the Equation (6) (Kita, Toyoda 2000), we can get the local evolution of CA rule, which is shown in Equation (7):

$$u_{j,k}^{n+1} = \left(1 - 2 \cdot \lambda_1\right) \cdot u_{j,k}^n + \lambda_1 \cdot u_{j+1,k}^n + \lambda_1 \cdot u_{j-1,k}^n + \lambda_2 \cdot \tilde{p}, \quad (7)$$

where:

$$\lambda_1 = \frac{\tilde{\mu}}{\left(\Delta x\right)^2} \cdot \Delta t;$$

$$\lambda_2 = \Delta t;$$

$$\tilde{p} = -\frac{1}{\rho} \cdot \nabla p.$$

3. MISTPA

3.1. Step Workflow of MISTPA

MISTPA is composed of a Single Intersection Volume Algorithm (SIVA) and a Single Intersection Single Timing Plan Algorithm (SISTPA). The average vehicle volume of intersection i at current signal phase and the total average vehicle volume of interaction i are computed by algorithm SIVA. $TotalVolume_i$ represents the total average vehicle volume of interaction i; $volumeofsignal_i$ represents the average vehicle volume of intersection i. The signal green time of intersection i at current signal phase is the ratio of $volumeofsignal_i$ and $TotalVolume_i$. The steps of MISTPA are detailed in ***Algorithm MISTPA***:

Algorithm MISTPA
Input: the vehicle flow pressure of each intersection at current signal phase (rules are detailed in Section 2.3.4)
Output: the signal green time of each intersection
1: FOR i=1 to N
2: Computing $volumeofsignal_i$ and $TotalVolume_i$ by SIVA (SIVA is detailed in Section 3.2)
3: Computing signal green time of each intersection at current signal phase by SISTPA (SISTPA is detailed in Section 3.3)
4: END FOR

3.2. SIVA

SIVA is composed by two parts:
- computing $volumeofsignal_i$;
- computing $TotalVolume_i$.

The symbols in SIVA are defined in Table 2. The steps of SIVA are detailed in ***Algorithm SIVA***.

3.3. SISTPA

The $volumeofsignal_i$ and $TotalVolume_i$ of each intersection are computed by algorithm SIVA. The signal green time $GreeT_i$ of each intersection is computed by Equation (8):

$$GreeT_i = \frac{CL \cdot volumeofsignal_i}{TotalVolume_i}. \quad (8)$$

The symbols of algorithm SISTPA are defined in Table 3. If $GreeT_i$ is smaller than $MinT$, set $MinT = GreeT_i$, and if $GreeT_i$ is bigger than $MaxT$, set $MaxT = GreeT_i$, otherwise $GreeT_i$ remains unchanged. The steps of SISTPA are detailed in ***Algorithm SISTPA***.

4. Performance Evaluation and Comparison

This section is devoted to the performance evaluation of the proposed model MIM and the algorithm MISTPA. The adopted experiments data and parameters setting will be described in Section 4.1. Section 4.2 details the comparison results of performance of the proposed algorithm under different saturations. Section 4.3 presents a real case study in City of Wuhan, China.

4.1. Experiment Setup

In the traffic simulation system, the constraints/conditions are defined as follows (the parameters setting is shown in Table 4):
- the local traffic network of the experiment is a 5×5 structure, which is shown in Fig. 4. The intersections are all crossroads and are all numbered from left to right, from up to down in turn. The lanes and lengths of the roads are set as the real conditions;
- the local traffic network is an open region. Traffic flow enters the local traffic network from the boundaries, so the traffic capacity of horizontal and vertical roads should be set. In this experiment, the traffic capacity of horizontal roads is 2000 veh/h, and the traffic capacity of vertical roads is 1400 veh/h;

Table 2. Symbol definition of SIVA

Symbols	Descriptions
i	Intersection (cell number)
k	The road number not in passing state of intersection i at current signal phase
$edge\_count_k$	The average volume of road k of intersection i at current signal phase
num_lanes	Lanes number of road
M_k	The actual lanes of road k of intersection i at current signal phase
avg_cars_k	The average volume of road k of intersection i at current signal phase
$distance1$	The distance of $road1$ in passing state of intersection i at current signal phase
$distance2$	The distance of $road2$ in passing state of intersection i at current signal phase
$cars\_num1$	The variable of vehicle
$cars\_num2$	The variable of vehicle
β_s	The vehicle going straight ratio of connecting roads in intersection
β_{left}	The vehicle going left ratio of connecting roads in intersection
β_{right}	The vehicle going right ratio of connecting roads in intersection

Algorithm SIVA

Input: the vehicle flow pressure value of cell i, which is two-way, and is defined as vfp_i1 and vfp_i2
Output: $volumeofsignal_i$ and $TotalVolume_i$
1: Initializing the values of $volumeofsignal_i$ and $TotalVolume_i$ as zero
2: FOR $k = 1$ to 2
3: Initializing the values of $edge\_count_k$ and $volumeofsignal_k$ as zero
4: FOR $num\_lanes = 1$ to M_k
5: $TotalVolume_k$ is the summation of the vehicle number of lane num_lanes and $TotalVolume_k$
6: $volumeofsignal_k = \dfrac{TotalVolume_k}{M_k}$ (details in a Single-Lane Volume Algorithm – SLVA)
7: $edge\_count_k = \dfrac{volumeofsignal_k + edge\_count_k}{2}$
8: END FOR
9: $TotalVolume_i = edge\_count_k + TotalVolume_i$
10: $cars\_num1 = vfp_i1 + distance1$
11: $cars\_num2 = vfp_i2 + distance2$
12: END FOR
13: IF the current signal phase of intersection i is phase I or phase III
14: $cars\_num1 = \dfrac{cars\_num1 \cdot \left(\beta_s + \beta_{right} \right)}{lane\_phase1}$, where: β_s and β_{right} are the ratio of $road1$; $lane\_phase1$ is the total lane number
　　　of going straight lane and going right lane in $road1$
15: $cars\_num2 = \dfrac{cars\_num2 \cdot \left(\beta_s + \beta_{right} \right)}{lane\_phase2}$, where: β_s and β_{right} are the ratio of $road2$; $lane\_phase2$ is the total lane number
　　　of going straight lane and going right lane in $road2$
16: END IF
17: IF the current signal phase of intersection i is phase II or phase IV
18: $cars\_num1 = \dfrac{cars\_num1 \cdot \beta_{left}}{lane\_phase3}$, where: β_{left} is the ratio of $road1$; $lane\_phase3$ is the total lane number of going left lane
　　　in $road1$
19: $cars\_num2 = \dfrac{cars\_num2 \cdot \beta_{left}}{lane\_phase4}$, where: β_{left} is the ratio of $road2$; $lane\_phase4$ is the total lane number of going left lane
　　　in $road1$
20: END IF
20: $volumeofsignal_i = cars\_num1 + cars\_num2$
21: $TotalVolume_i = TotalVolume_i + volumeofsignal_i$

Algorithm SLVA

Input: the vehicle volume of each lane, the weight of the vehicle volume. The Observed Frequency is defined as OF
Output: the vehicle volume of single-lane
1: Initializing the value of vehicle volume of single-lane as zero
2: FOR $i=1$ to OF
3: The value of vehicle volume of single-lane = the value of vehicle volume of single-lane + the product of the ith observed
　　vehicle volume and the weight of the ith observed data
4: END FOR

Table 3. Symbol definition of SISTPA

Symbols	Descriptions
proportion	The ratio of *volumeofsignal$_i$* and *TotalVolume$_i$*
MinT	The minimum signal green time (constant)
MaxT	The maximum signal green time (constant)
Offsettime	The offset value of signal green time

Algorithm SISTPA

Input: *volumeofsignal$_i$* and *TotalVolume$_i$* of each intersection
Output: the value of *GreeT$_i$*

1: $propotrion_i = \dfrac{volumeofsignal_i}{TotalVolume_i}$

2: $GreeT_i = \dfrac{CL \cdot volumeofsignal_i}{TotalVolume_i} + Offsettime$

3: IF *GreeT$_i$* < *MinT*
4: *MinT*= *GreeT$_i$*
5: END IF
6: IF *GreeT$_i$* > *MaxT*
7: *MaxT*= *GreeT$_i$*
8: END IF
9: Return the value of *GreeT$_i$*

Table 4. The parameters setting in the experiment

| Parameters	Distribution	Default	Variable
Detecting distance	–	–	Y
Simulation step	–	100	Y
t_{step}	–	5 s	N
MinGT	–	15 s	Y
MaxGT	–	60 s	Y
CL	–	120 s	Y
Vehicle length	–	4 m	Y
The evolution algebra	–	10	Y
β_{left}	–	–	Y
β_{s}	–	–	Y
β_{right}	–	–	Y
Vehicle density	–	–	Y
Vehicle speed	–	–	Y
Vehicle arrival rate	Poisson distribution	–	Y
Delay time	–	–	Y
Average delay time	–	–	Y
Vehicle number	Random distribution	–	Y
Vehicle saturation	–	–	Y
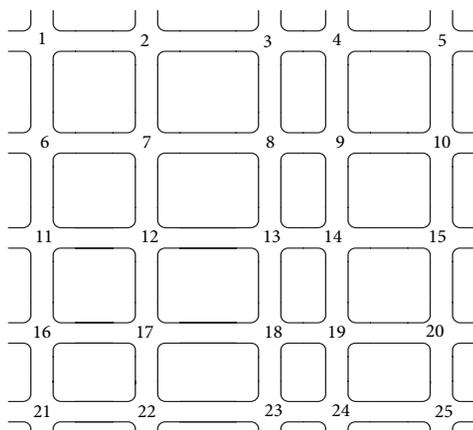
Fig. 4. Local traffic network structures

– the vehicle arrival rate of the boundary intersection admits a Poisson distribution;
– the initialized conditions of experiments under different saturations are the same;
– three strategies are introduced to the experiment to compare the delay time of vehicles. Three strategies are detailed in Table 5.

Table 5. The description of three strategies

Strategy name	Abbreviation	Comments
Signal Timing Strategy Based on CA Model	STSBNCAM	Using CA model to map the real road network and using signal time planning algorithm
Signal Timing Strategy Without CA Model	STSWCAM	Only using signal time planning algorithm
Signal Timing Strategy Based on the Fixed Green Time	STSBFGWT	Without CA model and signal time planning algorithm

### 4.2. Experimental Results and Analysis

4.2.1. Simulation under Different Signal Timing Plan Strategies

The delay time is introduced to be an evolution index of the experiment. The experiments are conducted under different saturations by three different signal time planning strategies in Table 5. The experiment parameters are set as Table 4. Saturation is the rate of road or intersection traffic flows and traffic capacity of road or intersection, which is normalized as from 0 to 1. The saturations of this experiment are set ranging from 0.1 to 1. Fig. 5 is the performance of the average delay time under different saturations. On the basis of these results in Fig. 5, we can draw the following conclusions:

– when the saturation is small (less than 0.3), the three strategies have the similar performance on vehicle delay time because the neighbor intersections have less effect on the local intersection;
– when the saturation is moderate (0.5), SISBNCAM presents a better performance than STSWCAM and STSBFGWT. SISBNCAM can dramatically reduce the average delay time;
– when the saturation is big (more than 0.7), SISBNCAM has a better performance than STSWCAM and STSBFGWT. SISBNCAM optimizes the green time of current phase by prediction and can dramatically reduce the average delay time.

4.2.2. Comparison Experiment

We compare the proposed algorithm with three other state-of-the-art algorithms mentioned in Section 1, including SIA-PSO (Swarm Intelligent Approach-Particle Swarm Optimization) (García-Nieto *et al.* 2012), SOCA (Self-Organizing Control Approach) (Wei *et al.* 2005) and GA+CC (Genetic Algorithm and Cluster Computing) (Sanchez-Medina *et al.* 2010).
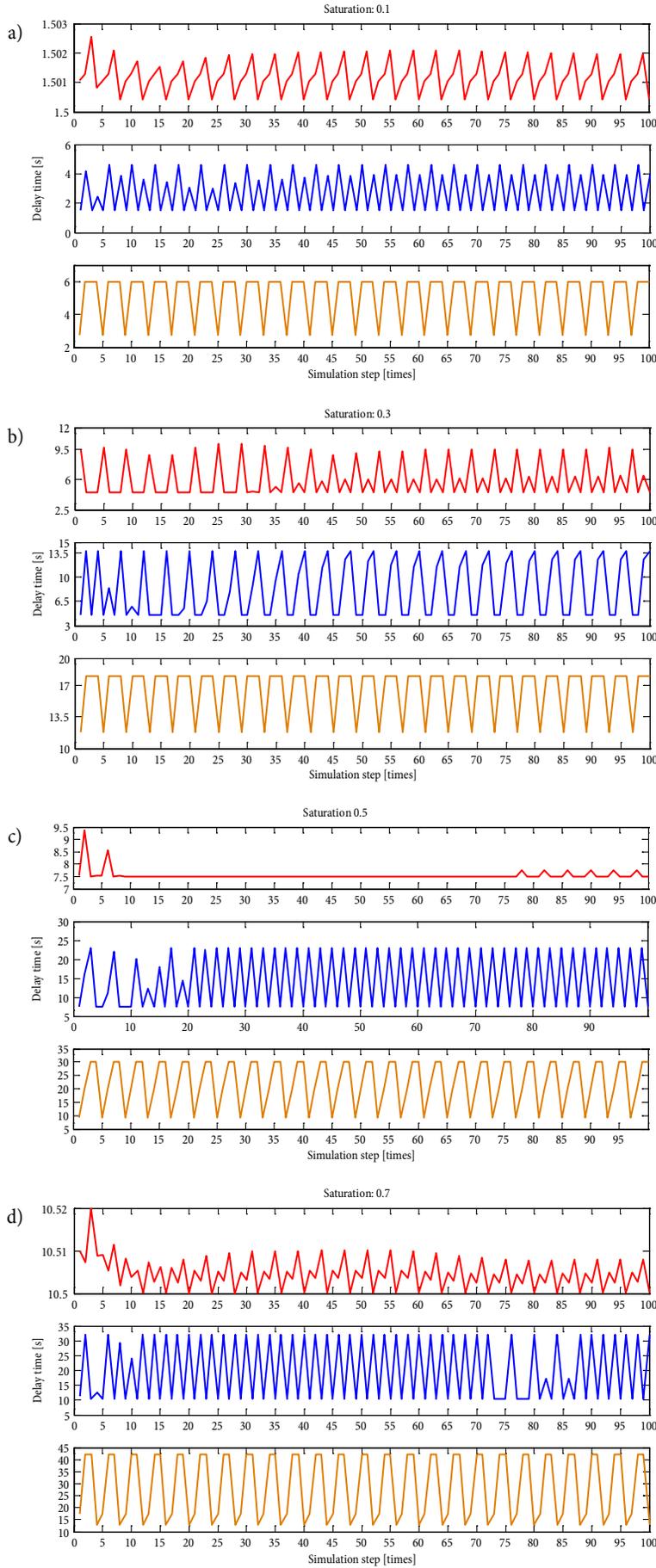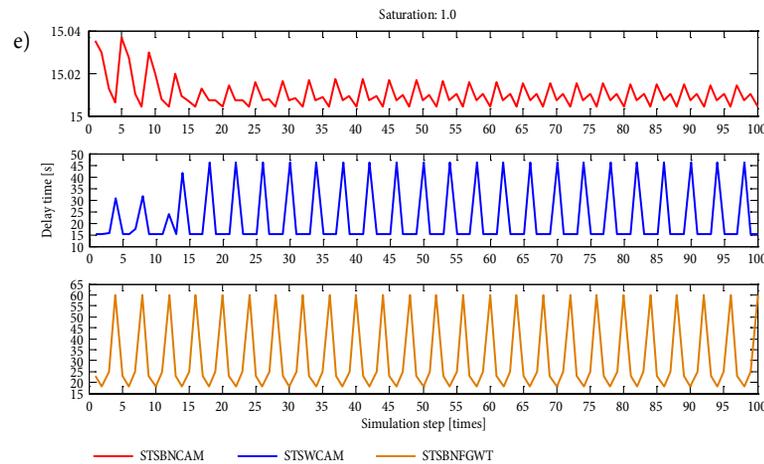
To be continued

e) Saturation: 1.0

Fig. 5. The average delay time under different saturations: a – saturation = 0.1; b – saturation = 0.3;
c – saturation = 0.5; d – saturation = 0.7; e – saturation = 1.0

These three algorithms mentioned above are the most representative ones of the swarm intelligent approach, reinforced learning and CA approach and the hybrid approach described in Section 1. In the comparison experiments, we implement these algorithms since the corresponding references detail the algorithm steps.

The performance of MISTPA and other state-of-the-art algorithms are given in Table 6. Based on these results of Table 6, we can draw the following conclusions on the performance on average delay time:

– it is apparent from the results that MISTPA has better performance than SIA-PSO, SOCA and GA+CC. In most cases, MISTPA provides a lower average vehicle delay time than other state-of-the-art algorithms;

– with the increment of saturation, the advantage of MISTPA is more obvious, which shows that MISTPA is more efficient than other state-of-the-art algorithms in solving problems under bigger saturation conditions.

4.3. Case Study

A real local traffic network of Hongshan District, Wuhan City, China, is shown in Fig. 6. There is no road name in Fig. 6 in order that the relation between intersections can be distinctly identified. In this real case study, the following constraints/conditions are defined. The constraints/conditions and parameters are set according to Table 4 in Section 4.1.
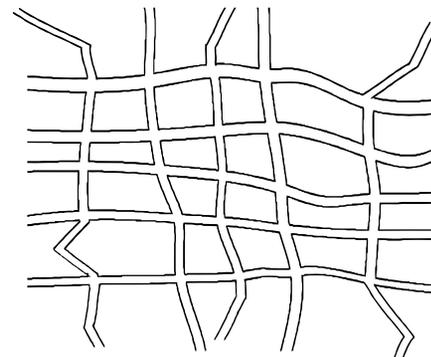

Fig. 6. Local traffic networks

We simulate the traffic system under the different conditions (from under saturated to saturated). The average delay time and results from a set of simulation experiments are shown in Table 7. Based on the simulation results, we can draw the following conclusions:

– The simulation results show that the STSBNCAM provides a lower average vehicle delay time than STSWCAM and STSBFGWT;

– In addition, Table 7 shows that the effects of the three strategies are almost identical in low saturation, because the neighbors' flow pressures almost have no effect on the local intersection when the traffic demands are low. With the increment of saturation, STSBNCAM is obviously superior. When traffic demand is large, through

Table 6. Simulation data and comparison with other state-of-the-art algorithms

Cases	Saturation	MISTPA Average delay time [s]	SIA-PSO Average delay time [s]	SOCA Average delay time [s]	GA+CC Average delay time [s]
1	0.1	1.487	1.522	1.432	1.421
2	0.3	6.091	6.871	6.111	6.132
3	0.5	7.432	7.912	7.621	7.591
4	0.7	10.499	11.233	10.985	10.796
5	1.0	15.129	17.912	15.654	15.642

the perception to neighbors' states, the signals can be coordinated in traffic network to reduce the unnecessary delay time of forthcoming flow at a leisure intersection. Thus, from the simulative results, the STSBNCAM based on the proposed model and algorithm is effective in urban traffic signal planning.

Table 7. Simulation data and comparisons

Cases	Saturation	Average delay time [s]		
		STSBNCAM	STSWCAM	STSBFGWT
1	0.1	1.502	2.312	5.184
2	0.3	5.938	8.238	16.445
3	0.5	7.516	14.213	22.172
4	0.7	10.515	19.771	28.507
5	1.0	15.012	27.413	31.430

Conclusions and Future Work

Urban traffic signal planning is a complex real control problem; the main difficulty includes the modeling complication and difficulty in real controlling. This paper proposes a multi-intersection model based on CA and a novel multi-intersection signal timing plan algorithm to solve the problem.

Extensive experiments are conducted to evaluate the proposed model and corresponding algorithm, which show that they can dramatically reduce the vehicle delay time and ease the pressure of urban traffic network:

- MISTPA can compute the green time of current signal phase according to the real time traffic flow, which reduces the delay time of vehicle in each intersection;
- STSBNCAM can predict the neighbors' states by CA evolution rules and can use MISTPA to compute the green time. Because of the discreteness and parallelism of CA, the real-time processing of traffic signal planning can be assured;
- the real case study shows that STSBNCAM provides a lower average vehicle delay time than the other strategies, which proves that the proposed model and algorithm are efficient and can direct practical application well.

Despite the above progress in our proposed method, further research is still needed. Because the MISTPA takes traffic flow as the research object, it does not consider the factors of microcosmic traffic. So how to express the behaviors of microcosmic traffic is the main research direction of MISTPA, which can extend the application of MISTPA and satisfy the real condition of urban traffic signal planning.

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