COMBINED SIGNAL CONTROL AND BOUNDEDLY RATIONAL
TRAFFIC ASSIGNMENT BASED ON CA AND HGA

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Abstract: Signal control and route guidance jointly influence traffic flow in time and space. Firstly, the conceptual structure of combined signal control and route choice (CSCRC) was analyzed. Then, the mathematical models of CSCRC were summarized. Link travel time function and signal control policy have significant influence on solution uniqueness and convergence of CSCRC model. Simulation-based method can allow more complex interactions, therefore win real value than travel time formula. Modified iterative simulation and assignment procedure is built, in which road is discretized by Cellular Automata, traffic flow dynamics is represented by Cell Transmission Model, signal setting is optimized by Hybrid Genetic Algorithm. For toy network, the algorithm converges to stable solution.

Key Words: Combined Signal Control and Route Choice, Cellular Automata, Genetic Algorithm

1. INTRODUCTION

Route choice principle models travellers’ propensity to travel, i.e., how they select their routes, departure times, modes, or destinations. From the perspective of the driver’s decision behavior, route choice principles can be classified into rational traffic assignment principles and boundedly rational traffic assignment principles. Typical rational traffic assignment principles are Wardrop’s (1952) principle, Dynamic User Optimal (DUO) principle, and Stochastic Dynamic User Optimal (SDUO) principle (Ran and Boyce, 1996). Typical boundedly rational traffic assignment principles are Tolerance-based DUO principle (Szeto and Lo 2006), Boundedly Rational User Equilibrium principle (Mahmassani and Chang, 1987, 1986, 1985; Jayakrishnan et al., 1994; Hu and Mahmassani, 1997; Mahmassani and Liu, 1999;), Prospect theory-based Traffic Assignment Principle (Avineri, 2006, 2004; Avineri and Prashker, 2005; Han et al. 2005). Traffic signal control is the readily available flexible means of controlling road traffic in an urban road network. While traffic signal control was first used simply as a means of avoiding collisions and reducing traffic delays at junctions on a very short time scale, it has more subtle long-term pressures on traffic flow pattern. Conventional methods for setting traffic signals assume given flow patterns, whereas demands are assigned to networks assuming fixed signal settings. This method is not fully satisfactory in the normal case in which traffic flow and signal settings are mutually interdependent. Maher and Akcelik (1975) have studied the re-distributional effect of area traffic control policy. Allsop (1974) has suggested that traffic engineers should take explicit account of the long run influence that their signal setting policies have on the pattern of traffic flow, and that this could reasonably be achieved by alternately updating the signal settings for...
fixed flows, and solving the traffic equilibrium problem for fixed signal settings. This procedure has become known as iterative optimization assignment (IOA). Gartner and Stamatiadis (1997) developed an integration framework of dynamic traffic assignment and real-time traffic adaptive control system. Abdelfattah and Mahmassani (1998) presented a formulation and heuristic simulation-based procedure for combined dynamic signal control and dynamic system optimal route guidance. Gartner and Al-Malik (1996) presented a combined model and solution procedure that enables the simultaneous optimization of signal setting and traffic assignment. Lee and Machemehl (1999) compared the algorithm performance between local searches and iterative searches: for small and un-congested network, local search produces better solutions; for large and congested network, iterative search produces better solutions. Chen and Ben-Akiva (1998) formulated combined dynamic traffic control and dynamic traffic assignment as Cournot, Stackelberg, and Monopoly games between a traffic authority and highway users. Claudio Meneguzzo (1997) presented the definition, the circular structure, and practical relevance of Combined Signal Control and Route Choice (CSCRC) problem. Let $\mathbf{f}$ and $\mathbf{g}$ denote respectively a vector of link flows and a vector of signal settings for the network. CSCRC problem is defined to find a pair $(\mathbf{f}^*, \mathbf{g}^*)$ such that $\mathbf{f}^* = \mathbf{f}(\mathbf{g}^*)$ and $\mathbf{g}^* = \mathbf{g}(\mathbf{f}^*)$. The circular structure of the interactions among flow-responsive signal control and user route choice is shown in Figure 1.

![Figure 1 Conceptual structure of CSCRC problem](image)

Practical Relevance of CSCRC models has three aspects: CSCRC models can assess the short-term and long-term driver responses to the signal control policy. CSCRC models can provide the higher accuracy of network flow prediction as compared to ordinary assignment models. This may improve the quality of real-time traffic information provided to drivers by route guidance systems. CSCRC models can identify and test system-optimal combinations of signal settings and routing patterns.

2. MATHEMATICAL MODELS FOR CSCRC

CSCRC has been examined extensively in three different ways: the global optimization models, generalized traffic equilibrium formulation, bi-level programming model.

2.1 Global Optimization Models

The global optimization model seeks signal control patterns in which a system performance such as the total travel time is minimized, whereas the driver's route choice behavior is
described with an equilibrium model. Optimization formulations are aimed at finding a pair of vectors (a vector of link flows and a vector of signal settings) that optimize a given network performance under signal setting feasibility constraints and subject to link flow pattern being a user equilibrium. The requirement of user-optimal driver behavior may be expressed in a variety of equivalent forms, either by constraining the objective function with a variational inequality problem, or by embedding a Beckmann-type user equilibrium formulation into the main optimization problem. (Gartner et al. 1980; Fisk, 1981) described the global optimal signal setting problem as a Stackelberg or leader-follower game, in which the upper-level decision maker is able to anticipate the changes in route choices induced by control decisions, while the drivers themselves usually have no knowledge of signal control strategy. (Marcotte, 1983; Sheffic and Powell, 1983; Heydecker and Khoo, 1990) and others proposed heuristic algorithms to solve a small network problem. The main difficulty with the global optimization models is that there are no efficient solution algorithms for calculating optimal settings in general road work while anticipating driver responses in terms of route choice.

2.2 Generalized Traffic Equilibrium Formulation
(Smith, 1981; Smith, 1987) put forward generalized traffic equilibrium formulation. Generalized traffic equilibrium formulation shows that the interaction between equi-saturation and delay minimization control policies and user route choices is likely to yield long-run equilibriums that are not optimal. Smith and colleagues developed some new signal control policies. With these new policies, they obtained a mutually consistent flow-control equilibrium: user choices are such that all routes carrying flow have the same travel time, and all phases receiving green time sustain the same pressure. Properties of this extended assignment problem depend on both the function and the control policy employed.

2.3 Bi-level Programming Model
H.Yang and S.Yagar (1995) developed bi-level programming model for determining traffic assignment and optimizing signal timings in saturated road networks. Both queuing and congestion are explicitly taken into account in predicting equilibrium flows and setting signal split parameters for a fixed pattern of origin-destination trip demand. Delay to traffic at signalized intersections is explicitly divided into signal delay and queuing delay. Queuing delay is due to limited exit capacity and is determined endogenously from network equilibrium conditions rather than predicted by an analytical formula. The lower-level problem represents a network equilibrium model involving queuing explicitly on saturated links, which predicts how drivers will react to any given signal control pattern. The upper-level problem is to determine signal splits to optimize a system objective function, taking account of drivers’ route choice behavior in response to signal split changes. Driver behavior is considered through computing the derivatives of equilibrium link flows and queuing delays with respect to signal splits. These derivatives can be used to predict changes in the link flow pattern and queuing lengths and hence to evaluate driver behavior in response to change in signal split.

3. INFLUENCE OF TRAVEL TIME FUNCTION AND SIGNAL CONTROL POLICY ON CSCRC
Solution uniqueness and convergence behavior of the solution algorithm are important not only from the standpoint of theoretical consistency, but also in view of their potential impact upon the relevance and reliability of the model as a tool for policy assessment. Route choice
principle can be formulated as either a nonlinear complementarity problem, variational inequality problem, or fixed-point problem. It is established that the existence of solutions requires the mapping function of the problem to be continuous (Theorem 1.4 in Nagurney, 1993) whereas the uniqueness of solution further requires the mapping function to be strictly monotonic (Theorem 1.8 in Nagurney, 1993). Therefore, solution existence (uniqueness) requires route travel times to be continuous (strictly monotone) with respect to route flows. Szeto (2006) compared the properties of Traffic Assignment Model with point queues versus those with physical queues. One important finding is that with the more accurate physical queue paradigm, solutions for dynamical user optimal route choice principle do not exist. So He put forward tolerance-based dynamic user optimal principle. Signal control policy and route travel time function have important influence on uniqueness and convergence. Smith and Van Vuren (1993) showed that the same control policy considered under different link travel time assumptions may possess completely different theoretical properties and thus may be expected to give rise to completely different practical performance results.

Van Vuren and Van Vliet (1992) had tested the performance of various control policies under BPR travel time function and Webster’s travel time function. A very important consequence of this influence of travel time functions is the credibility and usefulness of calculated green times and related flow. The influence of the travel time functions on the results is best illustrated by a comparison of resulting green splits and total network travel times per policy after application of the iterative assignment control procedure. Computations have shown that the differences between resulting green times with different travel time functions may be greater than the differences arising from the use of different control policies. This in particular supports application of IOA procedure. Its greatest advantage is that such a decomposed method allows realistic network representation and travel time calculations. The test results showed that, although theoretical properties with respect to convergence can’t be established, the resulting green splits and associated flow may be expected to have at least some reality value.

4. SIMULATION-BASED IOA SOLUTION ALGORITHM

It is hard to capture the complex phenomenon of delays at signalized intersections in BPR or Webster travel time function. Capturing physical queue and traffic dynamics has become the research trend. This emphasizes the need for realistic travel time calculations in the procedure. The determination of realistic travel time function, particularly in a congested urban context, has been a subject of research for a considerable number of years. (Allsop, 1972; Hutchinson, 1972) have reviewed travel time function. Simulation-based method can allow more complex interactions, and therefore win real value. One of the most successful model is SATURN (Van, 1982), which uses the concept of cyclic flow profiles (Robertson, 1969). The tests (Van Vuren and Van Vliet, 1992) on the three real-life networks showed that IOA procedure converged well. The actual value of the calculated green splits depends heavily on the realism of cyclic flow profiles in network simulation and delay calculations. On the link, platoon has dispersion phenomenon. D.I.Robertson adopted Geometric distribution to describe this phenomenon, which has been used in TRANSYT. With platoon dispersion function, flow profile of different position can be predicted. Platoon dispersion coefficient of this function is determined by experience, so there is prediction inaccuracy.

Cellular Automata is discrete in space, time, and state. Traffic flow is also essentially discrete.
So traffic flow description with cellular automata has advantage. Since NS (Kai, 1992) model, traffic model based on cellular automata has been research emphasis. Based on Cellular Automata, Daganzo puts forward Cell Transmission Model (Daganzo, 1994), which is discrete analog of LWR (Lighthill and Witham, 1955) model and can capture shockwave. So, the complex side calculations required by LWR model to keep track of shockwaves are eliminated. (Lo, 2001) transformed CTM to a set of mixed-integer constraints and subsequently cast the dynamic signal control problem to a mixed-integer linear program, and formulated a cell-based traffic control formulation. Based on CTM and cell-based traffic control formulation, we can simulate traffic flow and optimize signal control with cellular automata.

IOA is to update alternatively the signal setting for fixed flows and solve the traffic equilibrium problem for fixed signal settings until the solutions of the two problems are considered to be mutually consistent. This approach has the advantages that traffic assignment and signal setting techniques can be employed to solve the problem and can be applied to large networks. (Van Vuren and Van Vliet, 1992) put forward streamlined version of iterative simulation and assignment procedure, which is shown in Figure 2.

![Figure 2 A streamlined version of iterative simulation and assignment procedure](image)

Vuren and Vliet (1992) used Cyclic Flow Profiles to simulate and calculate travel time. In this paper, we used CTM and Cell-based traffic control function to calculate travel time and optimize signal setting. Boundedly rational traffic assignment principle can be considered as a relaxation of rational traffic assignment principle with the rational traffic assignment principle as a special case (Szeto, 2006). So the paper chooses tolerance-based traffic assignment principle to describe the travelers’ route choice behavior. Tolerance-based dynamic user optimal (DUO) principle can be expressed as:

For fixed demands, it is to find a route flow vector \( \overrightarrow{f} \) such that:

\[
\begin{align*}
 f^r_p (t) \cdot \varepsilon(\eta^r_p (t) - \pi^r (t), \varepsilon_{\text{max}}) &= 0, \forall rs, p, t \quad \text{(1)} \\
 \varepsilon(\eta^r_p (t) - \pi^r (t), \varepsilon_{\text{max}}) &\geq 0, \forall rs, p, t \quad \text{(2)} \\
 \sum_p f^r_p (t) &= q^r (t), \forall rs, t \quad \text{(3)} \\
 \eta^r_p (t) &= \Phi^r_p (\overrightarrow{f}), \forall rs, p, t \quad \text{(4)} \\
 \overrightarrow{f} &\geq 0 \quad \text{(5)}
\end{align*}
\]

Where \( \varepsilon(\cdot) \) is the transformation function, \( \varepsilon(y, u) = \begin{cases} 0 & \text{if } 0 \leq y \leq u \\ y & \text{if } y > u \end{cases} \), \( u \) and \( y \) are independent non-negative variables; \( q^r (t) \) is the demand of OD pair \( rs \) at time \( t \); \( \Phi^r_p (\cdot) \) is a unique mapping yielding route travel time for a given route flow vector \( \overrightarrow{f} \).

Equations (1)-(2) express the tolerance-based DUO principle. Equations (3) and (5) are flow conservation and non-negativity conditions. Equation (4) considers the traffic flow...
component as a unique functional mapping yielding route travel time for given route flows. In this paper, we adopt CTM as the underlying traffic flow model to capture the effect of realistic physical queuing, such as queue formation and dissipation, and queue spillback.

The Revised Simulation-based IOA procedure is as follows:

**Step 1:** Initialization
\[ n = 1 \]
\[ \vec{f}^{(n)} = \vec{0}, \vec{f} \] is flow vector for all links.
For all links set travel time to free flow travel time, and carry out a all-or-nothing traffic assignment.

**Step 2:** Simulation and Signal Control
For current flow, use Hybrid Genetic Algorithm to optimize signal setting, which is subject to delay minimization policy. Based on Cellular Automata, use CTM to simulate traffic flow dynamics and calculate travel time.

**Step 3:** Tolerance-based Traffic Assignment
Modified route-swapping algorithm (Sezto, 2003) is adopted to solve tolerance-based traffic assignment. The detailed algorithmic steps are the following:

1. **Step (1):** Set the iteration counter \( \tau = 1 \). Initial route flow \( f_{rs}^\tau(t) \) is flow obtained by step 2.
2. **Step (2):** Determine the route travel time \( \eta_r^\tau(t) \) through CTM and find \( \pi_r^\tau(t) = \min(\eta_r^\tau(t), \forall p) \).
3. **Step (3):** Update the route flow as below:
\[ f_{rs}^{\tau+1}(t) = \max\{0, f_{rs}^\tau(t) - \rho f_r^\tau(t), [\eta_{rs}^\tau(t) - \pi_r^\tau(t)], p \in P_{rs}, p \notin P_{rs}^{\tau} \} \]
\[ f_{rs}^{\tau+1}(t) = f_{rs}^\tau(t) + \frac{\psi_{rs}^\tau(t)}{P_{rs}^{\tau}}, p \in P_{rs}^{\tau}, \]
where \( \psi_{rs}^\tau(t) = \sum_{p \in P_{rs}^{\tau}} \{ f_{rs}^\tau(t) - f_{rs}^\tau(t), \pi_r^\tau(t) \} \), \( P_{rs}^{\tau} = \{ p : \eta_{rs}^\tau(t) - \pi_r^\tau(t), \leq \varepsilon_{\text{max}} \} \)
4. **Step (4):** Stop if \( H(f) \leq \varepsilon_{\text{max}} \) or \( \tau = \tau_{\text{max}} \). Where \( H(f) = \max\{\delta_r^\tau(t), (\eta_r^\tau(t) - \pi_r^\tau(t)), \forall rs, p, t \} \), \( \delta_r^\tau(t) \) equals 1 if the flow on route \( p \) between OD pair \( rs \) is nonzero, and equals zero otherwise. \( \tau_{\text{max}} \) is the maximum number of iterations. Otherwise, set \( \tau = \tau + 1 \) and return to step (2).

If outer loop converges, algorithm converges. Otherwise, go to step 2.

### 4.1 Cell Transmission Model

Cell Transmission model (CTM) replicates kinematic waves, queue formation, and dissipation in an explicit manner. This capability makes it a suitable platform for modeling dynamic traffic. CTM is a convergent numerical approximation to the hydrodynamic model. Road is represented as a collection of equal length cells. The length of each cell is equal to the distance that a single vehicle traverses in one time step at the free-flow speed. When there is no congestion, vehicle can move from one cell to another at each time step. Figure 3 shows the basic CTM building block.
vehicles ready to enter it, $y_i$. The inflow into cell $i+1$ at time $t$ is governed by the following equation:

$$y_{i+1}(t) = \min\left\{n_i(t), Q_{i+1}, \delta \left[ N_{i+1} - n_i(t) \right] \right\}$$  \hspace{1cm} (6)

Where $n_i(t) =$ number of vehicles waiting to enter cell $i+1$; $Q_{i+1} =$ maximum number of vehicles that can enter cell $i+1$ in a given time step; $N_{i+1} - n_i(t) =$ available space in cell $i+1$; and $\delta =$ ratio of shockwave speed to free flow speed. This formulation automatically covers both the congested and uncongested regions. In situations where there is little demand, the first term constrains flow; while in congested conditions, the last term constrains flow. In the case of a bottleneck between the two cells, the middle term serves as the applicable constraint. The network can be easily updated with the following conservation equation:

$$n_i(t+1) = n_i(t) + y_i(t) - y_{i+1}(t)$$  \hspace{1cm} (7)

The equation (7) states that the number of vehicles in a cell is equal to the number of vehicles that was in that cell before plus the number of vehicles that entered and minus the number of vehicles that left. Equation (6) and (7) provide a procedure of simulating traffic. Equation (6) determines the flow between cells in each time step, whereas equation (7) determines the time-variant traffic in each cell based on the conservation condition. Despite the simplicity of this approach, the fundamental diagram is well captured by these two equations.

### 4.2 Cell-based Traffic Control Formulation

In congested situations, frequent stop-and-go movements generate traffic dynamics in the form of shockwave. Without fundamental diagram, it is difficult to describe queue dynamics accurately, which is needed to generate good timing plans for oversaturated traffic. (Lo, 2001) developed a cell-based dynamic signal control formulation, which considers the entire range of the fundamental diagram by encapsulating CTM. Lo transformed CTM to a set of mixed-integer linear program. Lo showed that the model could be applied to signalized street networks by formulating $Q_{i+1}(t)$ as a binary variable that fluctuates between null and saturation flow $Q_{\text{max}}$ to simulate the effects of a traffic signal.

$$Q_{i+1}(t) = \begin{cases} Q_{\text{max}} & \text{if } t \text{ green phase} \\ 0 & \text{if } t \text{ red phase} \end{cases}$$  \hspace{1cm} (8)

$i+1 \in \text{signalized cell}$

This can be solved formally with mathematical programming techniques. For large size network, heuristic solution approach is used.

### 4.3 Measuring Delay On Link

Within this cell-based network representation, delay at the cell level is

$$d_i(t) = n_i(t) - y_{i+1}(t)$$  \hspace{1cm} (9)

Once the delay has been determined at the cell level, it can easily be determined at the link level by adding the delay of the component cells. The objective is to minimize total system delay, determined as

$$\min \sum_i \sum_i d_i(t)$$  \hspace{1cm} (10)

The average delay can be calculated by dividing the total delay by the number of affected vehicles.

### 4.4 Hybrid Genetic Algorithm Parameters
Genetic Algorithm (GA) is a global optimization and search technique based on the principles of genetics and natural selection. GA allows a population composed of many individuals to evolve under specified selection rules to a state that maximizes the fitness. GA does not depend on derivatives of the objective function and hence can work with noisy and discontinuous functions. This procedure has been successfully used in DISCO (Lo et al. 2004). Coupling GA with simulation is becoming a more popular way to do searches (Randy and Sue, 2004). Hybrid GA combines the power of the GA with the speed of a local optimizer. The GA finds the region of the optimum, and then the local optimizer takes over to find the minimum.

In this paper, the total system delay minimization [Equation (10)] is determined by combining Hybrid GA with cellular automata simulation. Genetic Algorithm first optimizes globally, then basing this result as starting point, Patternsearch function optimizes locally. GA uses three operators in creating the following generation: reproduction, crossover, and mutation. The population size in each generation is set to be 800. The fitness is determined by taking the total delay(TD) of each chromosome into account. The fitness of chromosome \( i \) (FIT\(_i\)) is defined as

\[
FIT_i = \sum A_i
\]

\[
A_i = \exp[\frac{TD_i - TD_{\text{min}}}{TD_{\text{max}} - TD_{\text{min}}} \cdot p]
\]

Where \( TD_i \) = total delay of chromosome \( i \), \( TD_{\text{max}} \) and \( TD_{\text{min}} \) = maximum and minimum total delay within the generation, respectively. The parameter \( p \) is used to magnify the differences among the performances of the chromosomes, which is set to 5. Reproduction operation adopts roulette method. Crossover operation adopts single point crossover and crossover probability is 0.01. Mutation operation adopts Gaussian mutation, and the mutation rate is set to be 0.005.

Number of generation is set to 20. After the GA operations, each member of the new population is evaluated and the processes of reproduction-crossover-mutation repeat. If there is no further improvement for 5 generations, GA terminates. Decision variables are Cycle, Phase duration, Offset. Each decision variable is coded as a seven-bit binary string, allowing for a total of 127(= 2\(^7\) ) distinctive values. For traffic signal control, phase durations are typically defined in the unit of seconds and not longer than 120 s. Therefore, seven-bit binary strings are sufficient for practical applications.

### 4.5 Vehicle Agent

Suppose every vehicle has the same characteristic, it can receive route information and comply with guidance which is calculated by modified simulation-based IOA procedure. Generally, vehicle agent can be described in two-layered agent architecture (Wahle et al. 1999) to model the individual driver, which is illustrated in Figure 4.
The basic layer is the tactical layer which describes the task of driving, i.e., accelerates, brakes, or changes the lane. The strategic layer collects information and route recommendation which result in his route choice behavior. In this paper, traffic flow model is CTM, which is a macroscopic traffic flow model through microscopic description. So, we emphasize the strategic layer of vehicle agent. Driver route choice behavior can be described by BDI (Beliefs, Desires, Intentions) formalism, which is well known in the field of multi-agent systems. Advanced Traveler Information Systems (ATIS), for example in-vehicle route guidance system, are an integral part of Intelligent Transportation Systems (ITS). They provide traffic information to the drivers in order to rearrange spatial distribution of traffic pattern and alleviate traffic congestion and utilize the capacity more efficiently. In this paper, for simplicity, we assume that all the drivers have the same tolerance and they fully comply with route guidance information which is calculated by combined signal control and boundedly rational traffic assignment model and provided by in-vehicle route guidance system.

5. TEST ROAD NETWORK AND EXPERIMENT

The paper studies interaction and integration between signal control and traffic assignment, so test network should have two characteristics. The first feature is two or more alternative routes. The second feature is signal setting and physical queue are specially considered. Test road network is illustrated as Figure 5.

Simulation setup is as following: Traffic demand from O to D is 3000veh/hr. Route a is major road, which has three lanes. The length of route a is 13 cells. Free flow speed of route a is 40km/hr. Saturation flow rate per lane is 1800veh/hr. There are three signal control intersections. Three local streets which intersect with route a are single lane. Route a and three local streets are network 1. Free flow speed of local street is 30km/hr, and flow is
360veh/hr. Route \( b \) is minor road, which has two lanes. The length of route \( b \) is 19 cells. Free flow speed of route \( b \) is 30km/hr. Saturation flow rate per lane is 1800veh/hr. There are two signal control intersections. Two local streets which intersect with route \( b \) are single lane. Route \( b \) and two local streets are network 2. Free flow speed of local street is 30km/hr, and flow is 300veh/hr. The drivers’ tolerance is 5 seconds, and swapping rate is 0.001. Solution process results of modified IOA algorithm are shown in Table 1 and Figure 6.

### Table 1 Solution process results of modified IOA algorithm

<table>
<thead>
<tr>
<th>Iteration number</th>
<th>Inflow of route a</th>
<th>Travel time of route a</th>
<th>Total time of network 1</th>
<th>Inflow of route b</th>
<th>Travel time of route b</th>
<th>Swapping flow</th>
<th>Total time of network 2</th>
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</tr>
</tbody>
</table>

![Figure 6 Equilibrium solution convergence of combined signal control and boundedly rational traffic assignment model](image)

When modified IOA algorithm converges, inflow rate of route \( a \) is 1359, optimized signal plans are as following: Intersection 1: Offset is 6(s); Cycle is 116(s); Stage durations are respectively 52(s), 3(s), 58(s), 3(s). Intersection 2: Offset is 12(s); Cycle is 116(s); Stage durations are respectively 58(s), 3(s), 52(s), 3(s). Intersection3: Offset is 23(s); Cycle is 116(s); Stage durations are respectively 57(s), 3(s), 53(s), 3(s). Inflow rate of route \( b \) is 1642, optimized signal plans are as following: Intersection 1: Offset is 0(s); Cycle is 105(s); Stage durations are respectively 27(s), 3(s), 72(s), 3(s). Intersection 2: Offset is 4(s); Cycle is 105(s); Stage durations are respectively 26(s), 3(s), 73(s), 3(s).

### 6. CONCLUSION

In this paper, we build computational platform of modified iterative optimization and assignment algorithm for solution to combined signal control and boundedly rational traffic assignment model. In this computational platform, traffic flow dynamics is described by
CTM, and signal setting is optimized by hybrid genetic algorithm. For toy network, we compute the combined signal control and boundedly rational traffic assignment. The algorithm can converge to stable point. From computational results, we can see that travel time of route a and route b can be in tolerable domain through route guidance information provided by in-vehicle route guidance system. But travel time of local streets which intersect with route a and route b change because of inflow rate change and optimized signal setting. Though we only care traffic assignment of inflow rate of route a and route b, if travel time of local streets is more than those drivers’ tolerance, they will change the route. If this case occurs, traffic assignment calculated previous will be invalid because local street drivers change their route. So one sight is that we must consider the influence of signal control on route choice behavior, and traffic assignment model must consider signal control, i.e., combined signal control and traffic assignment has more practical value.

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