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Heuristic Ant Algorithm for Road Network Traffic Coordination Control

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Abstract. The defects in macro traffic model research are pointed out firstly. In order to remedy these defects, traffic movements at the grid intersection were analyzed, and with the basic framework of the traffic transmission model, the new macro traffic model used in the paper for control simulation and evaluation has been proposed. Secondly, the bi-level optimization control model is proposed, using minimal delay and maximal throughput as its upper objectives, and optimal traffic coordination on both sides as the lower objective. A corresponding heuristic ant algorithm is subsequently designed to solve the control model. Finally, the proposed method is tested at a suppositional road network, under three different demand scenarios, compared with Transyt-7F. The results show that the proposed method has better performance, especially under high demand scenarios.

Keywords. Macro Traffic Model, Intersection Macro Model, Heuristic Ant Algorithm, Signal Timing, Optimization Control.

2010 Mathematics Subject Classification. 90B20.

1 Introduction

Reasonable signal timing is important for traffic flow stable running at road network. The effective method of seeking for signal timing is one of the key research contents in traffic control. Many scholars presented lots of theories and methods, such as using fuzzy control [5], Markov decision making [13], multi-agents coordination [7], hybrid Petri net optimization [4], and mathematical modeling [1–3, 9, 10, 12] to seek for reasonable timing. However, with the expansion of the urban traffic network and the increasing traffic volume, traffic optimal control becomes more and more complicated, and these methods also meet lots of challenges. Rapid expansion of the optimization space is hard to handle for the methods based on mathematical programming, such as Markov decision making and mathematical modeling. On the other side, the requirement of taking account

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of all system factors, the rules used in hybrid Petri optimization or fuzzy control are hard to design as well, for the complexity of large-scale network traffic flow.

Macroscopic traffic model describes the global status of traffic in the road network, with its basic characteristics of integrity and continuity. Compared with micro models, they have lower workload, and they are more suitable for large-scale traffic simulation. For the reasons above, more and more scholars have paid attentions to them. The earliest research was done in the 1960s, the method of counting the throughput capacity of road network builds the connections among the throughput capacity, the area of road networks, and the proportion of roads to the whole area. The second level theory was introduced later. But both were too brief and hard to be applied to traffic optimal control. Abu and Benekohal [2], Liu and Chang [9] and others proposed their macro models for traffic control from different considerations, both are based on the traffic transmission model. However, these models still have defects. They did not take the dynamic process of oversaturated traffic from queuing to overflow and finally getting well into consideration. Without the well description of this process, the evaluation of control schemes will not be accurate, and effective signal timing can not be found either.

In order to solving these problems, traffic behaviors at intersections were analyzed. With the method of gridding the intersection, the new macroscopic traffic model used for evaluating control schemes has been established. The control model for traffic coordination control is constructed to the form of bi-level programming: upper model with aims of fewest travel time and maximal throughput, and lower one with the aim of fewest coordination delay among neighboring intersections. Then a corresponding heuristic ant algorithm is proposed to solve the control model. Finally, this proposed method is tested at a suppositional road network, under three different demand scenarios, and compared with Transyt-7F. The results show that the proposed method has better performance, especially under high demand scenarios.

2 Traffic Simulation Model

Macro traffic models describe the global status of traffic flow in the road network. Compared with micro models, they have lower workload, and they are more suitable for large-scale traffic simulation. For these reasons, the macro traffic model is chosen for schemes evaluation in the paper. Since existing models have many defects mentioned above, the first thing to do is to propose our specialized macro model. The proposed macro model pays attention to research on traffic behavior at intersections, which are gridding for analysis.

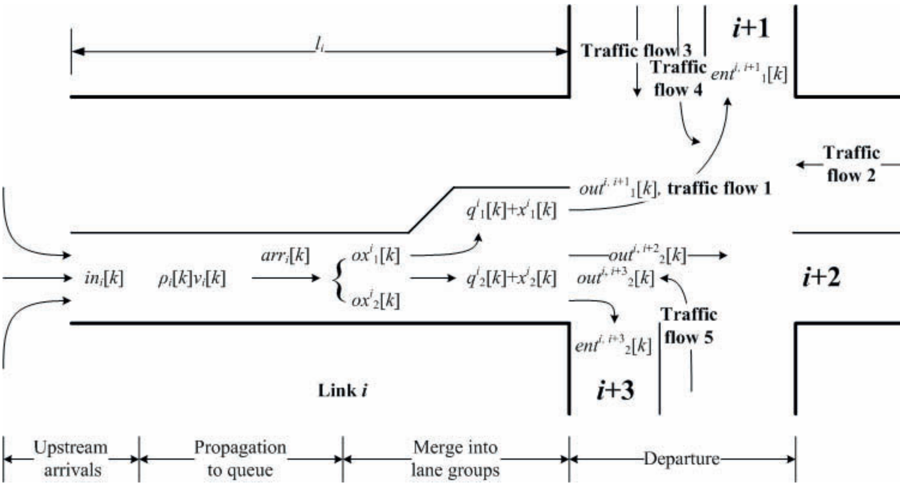

Figure 1. Dynamic traffic flow along a link i. All the movements (including upstream arrivals, propagation to queue, merge into lane groups and departure) of traffic flow are shown in this figure.

Completed macro models should be constructed based on characteristics analysis of traffic flow at road network. These characteristics include traffic generation, sections of arrival, dynamic queuing, departing from stop line and entering a next section, as shown in Figure 1, and variables' meaning are given in Table 1. Through the whole process analysis, the new macroscopic traffic simulation model will be established.

2.1 Demand Entries

Arterial demand entries are modeled as follows:

$$\mathrm{in}_s[k] = \min\left\{d_s[k] + \frac{w_s[k]}{\Delta t}, s_i, \frac{r_i[k]}{\Delta t}\right\}, \tag{1}$$

$$w_s[k+1] = \min\{0, w_s[k] + (d_s[k] - \mathrm{in}_s[k])\Delta t\}, \tag{2}$$

Equation (1) indicates that the flow entering downstream link i from demand entry s depends on the demand distribution and existing flows queuing at s, discharge capacity of link i, and the available space in link i. Equation (2) updates the queue waiting at the demand entry during each time step k.

Variables	Meaning
k	Time step index
l_i	Length of link i (in meters)
$\mathrm{in}_s[k]$	Flow rate entering the link from demand entry s at step k (in vph)
$\mathrm{arr}_i[k]$	Number of vehicles arriving at end of queue of link i at step k (in vehs)
$\mathrm{ox}^i_m[k]$	Number of arrival vehicles with destination to lane group m queued outside the approach lanes due to blockage at step k (in vehs)
$x^i_m[k]$	Number of vehicles join the queue of lane group m at step k (in vehs)
$q_i[k]$	Number of vehicles in queue at link i at step k (in vehs)
$\mathrm{out}^{ij}_m[k]$	Number of vehicles depart from lane group m of link i to link j at step k (in vehs)
$\mathrm{ent}^{ij}_m[k]$	Number of vehicles entering link j from lane group m of link i (in vehs)
$d_s[k]$	Flow rate generated at demand entry s at step k (in vph)
$w_s[k]$	Queue waiting on the entry s at step k (in vehs)
$r_i[k]$	Available space of link i at step k (in vehs)
h^i_m	Capacity of lane group m of link i (in vehs)
$q^i_m[k]$	Number of vehicles in queue at lane group m of link i (in vehs)
$x^{i,\mathrm{pot}}_m[k]$	Number of vehicles potentially to merge into lane group m of link i at step k (in vehs)
δ^{ij}_m	Binary, indicating whether traffic from link i to link j uses lane group m
$\gamma_{ij}[k]$	Turning fraction of traffic flow from link i to link j at step k
$\omega^i_{m'm}[k]$	Blockage parameter between lane group m and m' at step k
$\lambda^{ij}_m[k]$	Percentage of movement from link i to j in lane group m
$g^i_m[k]$	Binary, indicating whether signal of lane group m at link i is green at step k

Table 1. List of key variables used in the model.

2.2 Upstream Arrivals

For internal links, inflows to link i can be stated as the sum of the flows departing from its entire upstream links and finally entering link i:

$$\mathrm{in}_i[k] = \sum_{j \in \mathrm{upstream}(i)} \mathrm{ent}_{ji}[k],$$

For source links, inflows can be stated as

$$\mathrm{in}_i[k] = \mathrm{in}_s[k] \cdot \Delta t.$$

2.3 Propagation to the End of Queue

Assume $v_i[k]$ is the average approaching speed of traffic flow to the end of queue at link i at step k. It can be stated as

$$v_i[k] = \begin{cases} v_i^{\mathrm{free}} & \text{if } \rho_i[k] < \rho^{\min}, \\ v^{\min} + (v_i^{\mathrm{free}} - v^{\min}) \cdot \left[1 - \left(\frac{\rho_i[k] - \rho^{\min}}{\rho^{\mathrm{jam}} - \rho^{\min}}\right)^{\alpha}\right]^{\beta} & \text{if } \rho^{\min} < \rho_i[k] < \rho^{\mathrm{jam}}, \\ v^{\min} & \text{if } \rho_i[k] > \rho^{\mathrm{jam}}, \end{cases}$$

where $\rho_i[k]$ is the density, $\rho^{\min}$ is the minimum critical density below which traffic at link i moves at the free speed v_i^{free}, and oppositely, ρ^{jam} is the jam critical density upon which traffic at link i moves at the minimum speed $v^{\min}$. α, β are constant model parameters to be calibrated.

$\rho_i[k]$ can be stated as

$$\rho_i[k] = \frac{h_i[k] - q_i[k]}{n_i(l_i - \frac{q_i[k]}{n_i \cdot \rho^{\mathrm{jam}}})},$$

where $(h_i[k] - q_i[k])$ represents the number of vehicles moving at the segment between link i upstream and the end of queue, and $(l_i - q_i[k]/n_i \cdot \rho^{\mathrm{jam}})$ represents the length of that segment over time. Then vehicles arriving at the end of queue at link i can be dynamically updated as

$$\mathrm{arr}_i[k] = \min\{\rho_i[k] \cdot v_i[k] \cdot n_i \cdot \Delta t, h_i[k] - q_i[k]\}.$$

2.4 Merging into Lane Groups

Obviously, the number of vehicles which may successfully merge into lane group m is depending on the available space of lane group m at step k:

$$\max\{h_m^i - q_m^i[k], 0\}. \tag{3}$$

Further, vehicles arriving at the end of queue and queued outside the approach lanes due to blockage at step k also need to be considered:

$$x_m^{i,\mathrm{pot}}[k] = ox_m^i[k] + \sum_{j \in \mathrm{downstream}(i)} \mathrm{arr}_i[k] \cdot \gamma_{ij}[k] \cdot \delta_m^{ij}.$$

Besides, considering the impact of lane group blocking, the number of vehicles that potentially merge into the lane group m may be stated as

$$x_m^{i,\mathrm{exp}}[k] = \max\left\{x_m^{i,\mathrm{pot}}[k] \cdot \left[1 - \sum_{m' \in S_i^M} \omega_{m'm}^i[k]\right], 0\right\}. \tag{4}$$

(More details can be found in [9].) Finally, the number of vehicles allowed to merge into lane group m at step k should be the lower value of equation (3) and (4):

$$x_m^i[k] = \min\left\{\max\left\{h_m^i - q_m^i[k], 0\right\}, x_m^{i,\mathrm{exp}}[k]\right\}.$$

2.5 Departure Process

The number of vehicles potentially departing from lane group m of link i to link j at step k is given by

$$\mathrm{ent}_m^{ij,\mathrm{pot}}[k] = \min\left\{q_m^i[k] + x_m^i[k], s_m^i \cdot g_m^i[k]\right\} \cdot \lambda_m^{ij}[k],$$

$$\lambda_m^{ij}[k] = \frac{\delta_m^{ij} \cdot \gamma_m^{ij}[k]}{\sum_{j \in \mathrm{downstream}(i)} \delta_m^{ij} \cdot \gamma_m^{ij}[k]}.$$

Note that actual departure of traffic from link i also depends on the blocking situation of the joint intersection downstream, and the available space of downstream links. As shown in Figure 1, if downstream link $i + 1$ does not have sufficient available space for flow 1, overflow will happen at link $i + 1$, and flow 2, 3, 4 and 5 may be blocked. This blocking may even result in completely deadlock of the intersection, and in high demand scenarios blocking may easily spread to the whole road networks. Unfortunately, most of the present models ignore this process. The following is the analysis of traffic behavior at gridding intersections (see Figure 2).

2.5.1 The Path of Traffic Flow

As shown in Figure 2, the path is presented by the series of grids following which traffic flow will go through one by one.

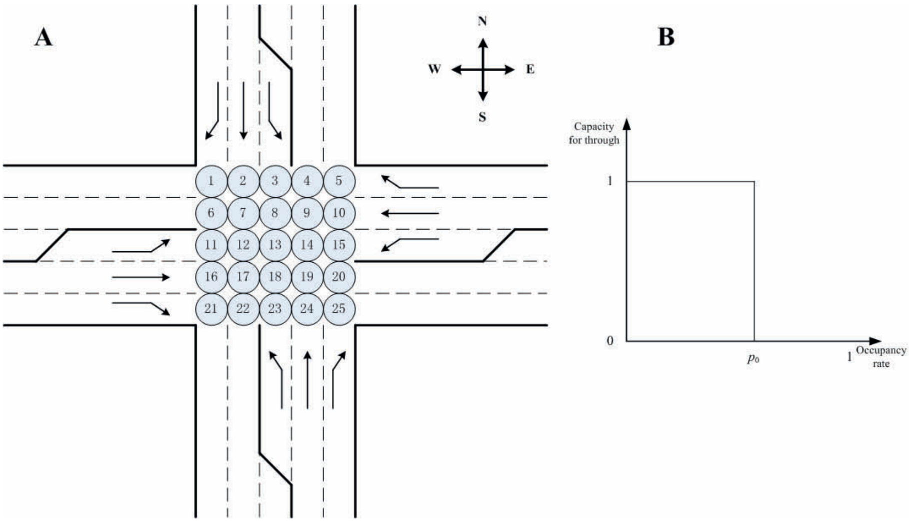

Figure 2. The gridding intersection and its characteristic. A, resolve the intersection using grids; B, the through capacity of the grid depending on its occupancy rate.

(1) Path of straight traffic flow. From north to south: 2-7-12-17-22, and the opposite: 24-19-14-9-4; from west to east: 16-17-18-19-20, and the opposite: 10-9-8-7-6.

(2) Path of left-turn traffic flow. From north to east: 3-8-14-20, and from west to north: 11-12-8-4; from south to west: 23-18-12-6, and from east to south: 15-14-18-22.

(3) Path of right-turn traffic flow. From north to west: 1, and from west to south: 21; from south to east: 25, and from east to north: 5.

2.5.2 Traffic Characteristics of the Grid

Assume $\mathrm{st}_i[k]$ $(i = 1, 2, \ldots, n)$ is the space occupancy rate of grid i at step k, and sp_i is its available space. In actual networks, the width of lane is normal between 3.25 and 3.5 meters, considering the width of vehicles is 2.7 meters; there exists a critical occupancy rate p_0. When the space occupancy rate is bigger than p_0, the grid is forbidden to go through, and if the rate is lower, the grid is allowed to go through (as shown in Figure 2).

Obviously, the flow which causes blockage has different effects on different flow:

(1) The effect on the same flow. As shown in Figure 2, take the flow from north to east as an example. If it blocks grid 14 at step $k-1$, and has not dissipated at step k, $\mathrm{st}_{14}[k] \geq p_0$, then the successive flow is blocked, but it can use the residual space of grid 14 at step k.

(2) The effect on different flow. Still use the flow from north to east as an example. It blocks the flow from south to north at step k. That flow can arrive to grid 19, but cannot enter grid 14.

2.5.3 Departure

Assume $\mathrm{obs}_i[k]$ $(i = 1, 2, \ldots, lg)$ is the number of vehicles that are detained in the intersection, it is the difference between the number of vehicles that departed from upstream and entered downstream:

$$\mathrm{out}_i[k] = \mathrm{obs}_i[k] + \mathrm{ent}_i[k].$$

Considering actual networks, the number of vehicles depart from upstream is concerned with the available space of downstream at step k. (Road_i is the grids series of flow i.)

(1) If $\forall\, \mathrm{st}_j[k] = 0,\ j \in \mathrm{Road}_i$, the departing number is

$$\mathrm{out}_i[k] = \min\left\{\mathrm{out}_i^{\mathrm{pot}}[k], r_l[k] + \sum_{j \in \mathrm{Road}_i} \mathrm{sp}_j\right\},$$

where $\mathrm{out}_i^{\mathrm{pot}}[k]$ is the potential departing number of flow i at step k, and the entering downstream number is

$$\mathrm{ent}_{il}[k] = \min\left\{\mathrm{out}_i^{\mathrm{pot}}[k], r_l[k]\right\},$$

(2) If $\exists\, \mathrm{st}_j[k] \neq 0,\ j \in \mathrm{Road}_i$, the departing number of the flow which is different from the one that causes blockage is

$$\mathrm{obs}_i[k] = \mathrm{out}_i[k] = \min\left\{\mathrm{out}_i^{\mathrm{pot}}[k], \sum_{i \in \overline{\mathrm{Road}_m}} \mathrm{sp}_i\right\},$$

where $\overline{\mathrm{Road}_i}$ is the grids set from stop-line to the blocking point a $(a \in \mathrm{Road}_i)$. The departing number of the same flow is

$$\mathrm{obs}_i[k] = \mathrm{out}_i[k] = \min\left\{\mathrm{out}_i^{\mathrm{pot}}[k], \sum_{i \in \overline{\mathrm{Road}_m}} \mathrm{sp}_i + (1 - \mathrm{st}_a[k]) \cdot \mathrm{sp}_a\right\}.$$

In this situation, $\mathrm{ent}_{il}[k] = 0$.

Then the total number of vehicles that enter link j from link i is

$$\mathrm{in}_{ij}[k] = \sum_{m \in S_i^M} \mathrm{ent}_m^{ij}[k].$$

2.6 Flow Conservation

The lane group based queues are advanced as

$$q_m^i[k+1] = q_m^i[k] + x_m^i[k] - o_m^i[k].$$

Queues outside the approach lanes due to overflows or blockages are updated as

$$\tilde{x}_m^i[k+1] = \tilde{x}_m^i[k] - x_m^i[k] + \sum_{j \in \mathrm{downstream}(i)} f_i^{\mathrm{arr}}[k] \cdot \gamma_{ij}[k] \cdot \delta_m^{ij}.$$

The total number of vehicles queued at link i is

$$q_i[k+1] = \sum_{m \in S_i^M} \left(q_m^i[k+1] + \tilde{x}_m^i[k+1]\right).$$

The evolution of total number of vehicles present at link i is updated as

$$n_i[k+1] = n_i[k] + \sum_{j \in \mathrm{upstream}(i)} o_{ji}[k] - \sum_{j \in \mathrm{downstream}(i)} o_{ij}[k].$$

The available space of link i is stated as

$$r_i[k+1] = n_i - n_i[k+1].$$

The occupancy rate of grids of the intersection is updated on the basis of the number of vehicles that spillback.

(1) No block flow. Overflow number $\mathrm{obs}_i[k+1]$ is updated as

$$\mathrm{obs}_i[k+1] = \max\left\{\mathrm{out}_i[k] - r_l[k], 0\right\}.$$

$[\mathrm{obs}_i[k+1]/l_{\mathrm{veh}}]+1$ presents the number of grids occupied by overflow, in which former $[\mathrm{obs}_i[k+1]/l_{\mathrm{veh}}]$ grids are completely occupied, and the last is partly occupied, and its rate is

$$\mathrm{obs}_i[k+1]/l_{\mathrm{veh}} - [\mathrm{obs}_i[k+1]/l_{\mathrm{veh}}].$$

(2) Existing block flow. The overflow number $\mathrm{obs}_i[k+1]$ is updated as

$$\mathrm{obs}_i[k+1] = \mathrm{out}_i[k].$$

To other flow the number of occupied grids is $\mathrm{obs}_i[k+1]/l_{\mathrm{veh}}$; and to the same flow, this number is $\mathrm{out}_i[k] + \mathrm{obs}_i[k]$.

3 Control Model

As the phases' duration time change, the queue length at intersections and total delay also change, then the offsets need to be reset; and the changes of offsets will also make effect to the saturation degree of intersections and will cause phases duration to coordinate with them. Thus the phases duration time and offsets are unfavorable to optimization at the same time. In this paper, a bi-level programming model is constructed for this problem. Upper programming deals with phases duration time optimization and the lower optimizes offsets. In addition, the cycle is independently optimized traverse in $[C_{\min}, C_{\max}]$.

3.1 Upper Model

Its objectives are fewest total delay and maximum traffic throughput at the same time. Phase durations are the decision variables in the upper model.

$$\min \sum_{k=1}^{T} \left[\sum_{i \in S^U} h_i[k] + \sum_{s \in \text{source}} w_s[k] \right] \cdot \Delta t; \quad \max \sum_{k=1}^{T} \sum_{i \in S^{\text{out}}} \text{in}_i[k].$$

3.2 Lower Model

Optimal offsets can reduce the total delay and improve the utilization ratio of green time to a great extent. But it is difficult to deal with traffic coordination on both sides. Considering actual offsets deviating from the optimal will cause delays increase or throughput capacity reducing, we account the difference between the actual and the optimal, and take a weighted value as the objective of lower programming model.

Assume $t_{ij}^{\text{arr}}[k]$ is the straight flow travel time from departing intersection i to joining to the end of queue of downstream intersection j at k-th cycle, and $t_{ji}^{\text{wv}}[k]$ is the time that starting wave propagates from the stop-line to the end of queue at downstream link j. Obviously, the optimal offset between intersection i and j satisfies following rule (downstream direction):

$$\varphi_{ij}^{\text{opt}}[k] = (t_{ij}^{\text{arr}}[k] \bmod C) - t_{ji}^{\text{wv}}[k].$$

$\Delta t_{ij}[k]$ is the absolute difference between actual offset and the optimal:

$$\Delta t_{ij}[k] = \left| \varphi_{ij}^{\text{opt}}[k] - \varphi_{ij} \right|.$$

Considering traffic flow on both sides, we take the weighted value as the objective of the lower model:

$$\min \sum_{i,j \in I} \Delta t_{ij}[k] \cdot \text{ent}_{ij}[k],$$

where $\mathrm{ent}_{ij}[k]$ is the volumes of traffic that travel from intersection i to j at k-th cycle.

3.3 Constraints

(1) Cycle and phase duration

$$C \in [C_{\min}, C_{\max}]; \quad g_{np} \in [g_{\min}, g_{\max}]; \quad \sum_{p \in P_n} g_{np} = C, \quad n \in S_N,$$

where g_{np} is p-th phase duration of intersection n.

(2) Offsets normalization

$$\varphi_{n,n+1} \in [0, C], \quad n \in S_N$$

(3) Offsets of adjacent intersections

$$g_{n+1} + \varphi_{n,n+1} + t_{n+1} \geq g_n, \quad n \in S_N,$$

where t_{n+1} is the time that stops wave propagating to upstream intersection n,

$$t_{n+1,n} = L_i / \lambda_i,$$

λ_i is the speed of stop wave.

(4) Signal on lane groups

$$g_n^p[k] = \begin{cases} 1 & \text{if } \sum_{j=1}^{p-1} g_{nj} < \mathrm{mod}(k - \varphi_n, C) \leq \sum_{j=1}^{p-1} g_{nj} + g_{np}, \\ 0 & \text{otherwise}, \end{cases}$$

$p \in P_n$, $n \in S_N$. When $g_n^p[k]$ is equal to 1, it means that the p-th phase of intersection n is green, and 0 corresponds to red.

4 Heuristic Ant Algorithm

The ant colony algorithm [6, 8, 11] initially was used to solve optimization problems, and now is extensively used in multi-objective optimization, data classification, data clustering, pattern recognition, signal processing and robot control, etc. It has many advantages: (1) no centralized control constraint to ensure that the algorithm has strong robustness; (2) parallel distributed algorithm model to make full use of multi processors; (3) no special requirements at the continuity of the question; (4) easy to realize. Therefore, we choose the ant algorithm to solve the control model.

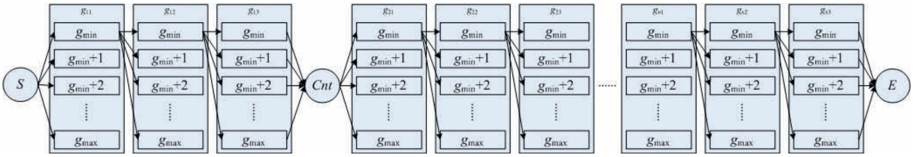

Figure 3. Solution space of the upper model.

4.1 Solution Space

Take a road network with n intersections and each intersection has m phases as an example. In the upper model, the number of independent decision variables of each intersection is $m - 1$, and the total number is $n(m - 1)$, under a confirmed cycle. Discretizing each phase space and connecting them will form the optimization space of the upper model, as shown in Figure 3. Ants begin moving from S node, and choose their next node forward one by one, according to the pheromone between nodes, till E node. Then a complete path from S to E is generated, and it can be translated to the control scheme of the road network.

The solution space of the lower model is similar to the upper model. Its optimization is sequent and after the upper model, but an independent process.

4.2 Heuristic Rules

As we see, the solution space of the traffic optimal control is so huge that the probability of finding the global optimal solution is very small if we only choose random search strategy to guide the algorithm. If a more efficient algorithm is wanted, reliable heuristic rules are important, which can help to efficiently reduce invalid search, guide ants to search for better solutions, and enhance the efficiency of the algorithm. In traffic optimal control problems, a proper split ratio to each phase can ensure that each phase acquires sufficient green time, and well balance delay. Keep this in mind; the heuristic rules of the ant algorithm are designed based on split ratio, and help to find better split ratio.

Assume the i-th ant found solution $\mathrm{sln}_i^{\mathrm{gen}}$ at gen. Take $\mathrm{sln}_i^{\mathrm{gen}}$ as the control scheme into the road network for simulation, and acquire its heuristic knowledge $\mathrm{kn}_i[\mathrm{gen}]$ at gen.

(1) If $\mathrm{sln}_i^{\mathrm{gen}}$ is appropriate (means no links are overflowed), firstly, sort the arterial delay of each intersection, and we can lock on the intersection called $\mathrm{DI}^{\mathrm{gen}}$, which has the maximal arterial delay. $\mathrm{kn}_i[\mathrm{gen}]$ of ant i is primary to increase the ratio that the arterial green time of $\mathrm{DI}^{\mathrm{gen}}$ to corresponding time of its upstream and downstream intersections at $(\mathrm{gen}+1)$. Secondly, sort each intersection's phases

by their delay separately, and $\mathrm{kn}_i[\mathrm{gen}]$ is secondary to increase the green ratio of the phase that has the maximal delay.

(2) If $\mathrm{sln}_i^{\mathrm{gen}}$ is not appropriate (means some links are overflowed), we can lock on the corresponding intersection called $\mathrm{DI}^{\mathrm{gen}}$, which has no sufficient throughput for overflow traffic. $\mathrm{kn}_i[\mathrm{gen}]$ is to decrease corresponding phases' green time of the intersection that is upstream of $\mathrm{DI}^{\mathrm{gen}}$, and increase corresponding phases' green time of the intersection, which is downstream of $\mathrm{DI}^{\mathrm{gen}}$.

$\mathrm{kn}_i[\mathrm{gen}]$ is separately between each ant. With the iteration process, the knowledge set kn_i $(i = 1, 2, \ldots, \mathrm{ant}\,C)$ of ant i is constructed. $\mathrm{kn}_i^{\mathrm{best}}$ is the best knowledge in kn_i, which is used to conduct ant i for better solution at gen. The update rule of $\mathrm{kn}_i^{\mathrm{best}}$ is as follows:

As to ant i. Assume the current generation is gen (gen ≥ 2), $\mathrm{kn}_i^{\mathrm{best}}$ in kn_i was acquired from d ($d <$ gen), and the objective value of its corresponding solution is $\mathrm{obj}_i[d]$. The objective value of current solution (at gen) is $\mathrm{obj}_i[\mathrm{gen}]$, and the extractive knowledge is $\mathrm{kn}_i[\mathrm{gen}]$. If $\mathrm{obj}_i[\mathrm{gen}] < \mathrm{obj}_i[d]$, then update $\mathrm{kn}_i^{\mathrm{best}}$ to $\mathrm{kn}_i[\mathrm{gen}]$, or else keep the original value.

4.3 Update Pheromone

After completing search of a generation, pheromone is updated on the basis of weighted objective values:

$$\tau_{i\to i+1}[c+1] = \rho\tau_{i\to i+1}[c] + \sum_{i\in \mathrm{ants}} \Delta\tau_i; \quad \Delta\tau_i = Q/\mathrm{obj}_i[c].$$

4.4 Algorithm Steps

(1) gen = 1.

(2) Generate gen-th solution; the solution must satisfy its heuristic rules, and if not, the solution will be regenerated.

(3) Execute the macro traffic model; and acquire the weighted objective value, then update the global best objective value, and conserve the global best solution.

(4) Make a solution analysis, and acquire heuristic rules $\mathrm{kn}_i[\mathrm{gen}]$, and then update kn_i as mentioned in Section 4.2.

(5) Update pheromone as mentioned in Section 4.3.

(6) If gen = maxGen, output the global best solution; or else back to Step 2.

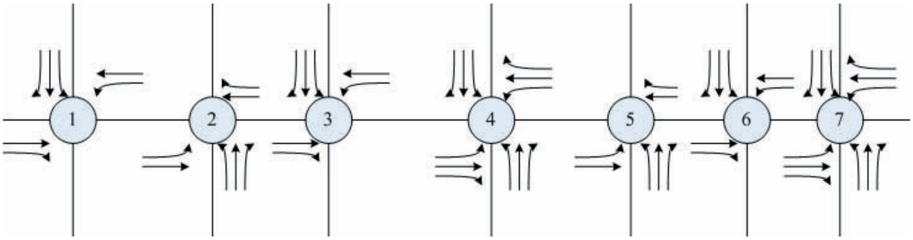

Figure 4. Road network for numerical tests.

Demand scenario	Demand entries (veh/h)										
	1:N	1:W	2:S	3:N	4:N	4:S	5:S	6:N	7:N	7:S	7:E
Low	455	472	435	357	530	584	531	508	579	509	464
Medium	665	894	723	809	745	800	600	870	835	800	772
High	1149	1326	1071	900	1019	1092	1188	1137	968	1141	1160

Table 2. Traffic demand.

5 Numerical Tests

5.1 Parameters

The network for tests is shown in Figure 4, and some model parameters are given below:

(1) The free speed is set to 36 km/h for arterial, that is a normal value in modern cities; and the minimum density is set to 12.4 veh/km·lane.

(2) Jam density is set to 130.4 veh/km·lane, equal to the maximal number of vehicles stored in a link of 1 km long; and the minimum speed is 8 km/h, the normal value in modern cities.

(3) Average length of vehicles is 7.62 m, and links length is $\{240, 160, 290, 320, 180, 220\}$.

(4) Traffic demand is shown in Table 2.

The signal timing constraints are given below.

(1) Common cycle length is between 50 s and 150 s.

(2) Minimal split duration is 8 s and the maximal is 60 s, normal values for signal set.

Scenarios		Results		
		Proposed model	TRANSYT-7F	Improvement (%)
Low	Total delay (veh-min)	2107.8	2183.6	−3.47
	Total queue time (veh-min)	1022.2	1053.7	−2.99
	Throughput (veh)	2620	2676	2.09
Medium	Total delay (veh-min)	4264.6	4310.4	−1.06
	Total queue time (veh-min)	2488.5	2510	0.86
	Throughput (veh)	4220	4172	1.15
High	Total delay (veh-min)	7513.4	8836.2	−14.97
	Total queue time (veh-min)	5118	6119.1	−16.36
	Throughput (veh)	5838	5703	2.37

Table 3. Simulation results.

The parameters of the ant colony algorithm are set as follows:

(1) The number of ants is 20.

(2) The maximum generation is set to 500.

(3) Initial pheromone is equal between every nodes, and Q is set to 1000, $\rho = 0.8$.

5.2 Results and Analysis

The proposed model is coded in C++ and tested on Pentium E5500 2.8GHz processor and 3G RAM, running Windows 7. The signal plans are designed in 0.5 hours under three traffic demand scenarios. The results are shown in Table 3, compared with Transyt-7F.

As indicated in Table 3, the proposed method in the paper has better performance in most results than Transyt-7F, especially in high demand scenario.

In the low scenarios, a shorter cycle length is obtained from the proposed method with the objective of minimizing the total time spent in the network. Therefore, the proposed method outperforms Transyt-7F in terms of total system delay and queue times, but yields less system throughput due to the relatively larger percentage of lost time in the cycle length.

In the medium scenarios, the proposed method obtained a better scheme than Transyt-7F. Its total delay time and total queue time are lower, because of the upper optimization objectives. Its throughput is also lower, which is benefit from the lower optimization objective, to obtain both sides traffic coordination, and so helps to improve the average speed on links.

In the high scenarios, severe blockages between lane groups and upstream-downstream links in the network can be observed in simulations. Even though Transyt-7F tries to select a longer cycle to maximize the phase capacity for this scenario, it may increase the chance of blockages due to higher arrival rates to downstream links. In contrast, the proposed method coordinately adjusts upstream and downstream arterial green ratio, and can efficiently avoid spillback.

6 Conclusions

This study has proposed an optimization method for road network signal timing. Firstly, analyze the movement of traffic flow at gridding intersections, and propose the macro grid model of the intersection. Then the model used in the paper for control simulation is constructed, combined the macro intersections model with the networks transmission model. Secondly, the bi-level optimization control model is constructed, using minimal delay and maximal throughput as its upper objectives, and optimal traffic coordination on both sides as its lower objective. Then we design the heuristic ant algorithm to solve the problem. The results comparison with Transyt-7F indicates that the proposed method has better performance in traffic control optimization, especially in high demand scenarios.

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