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Research Article

Real-Time Arterial Coordination Control Based on Dynamic Intersection Turning Fractions Estimation Using Genetic Algorithm

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Real-time arterial coordination control is crucial for urban transportation systems and is partially dependent on dynamic turning flows at intersections. Few existing researches employ such information due to the restrictions of traffic surveillance systems. This paper presents a model framework for real-time arterial coordination control based on dynamic intersection turning fraction estimation, including three submodels: (1) a parameter optimization model to estimate dynamic intersection turning fractions using detected link counts at entering and exiting approaches; (2) a nonlinear model using minimum delay as an objective to optimize the time-varying public cycle for the arterial road based on the estimated turning flows; and (3) a revised optimization model to achieve real-time offset and split for the arterial road using the novel uninterrupted ratio as objective function. Two revised genetic algorithms are developed to solve the first and third submodels, respectively, and an ordinary optimization algorithm is designed for the second submodel. Time-varying public cycle, offset, and split constitute the real-time arterial coordination control scheme together. The general model framework removes most of the assumptions of conventional arterial control models and provides a time-varying timing plan. Simulation experiments using actual data indicate that the proposed model yields much better results than the existing methods.

1. Introduction

Real-time traffic signal control, especially arterial coordination control, is important for intelligent transportation systems (ITS), and the dynamic turning movement flows, that is, the dynamic origin-destination (O-D) flows at intersections, are valuable input data for signal control. However, under current traffic surveillance systems, the dynamic turning movement flows are impossible to be collected directly. Therefore, the dynamic turning fraction estimation from detected real-time link counts has been studied extensively during the past two decades.

Most researches about dynamic fractions estimation have constructed time-varying interrelations between intersection turning flows to be estimated and detected link counts at entering and exiting approaches and have proposed a series of optimization models, for example, Nihan and Davis (1987) [1], Nihan and Davis (1989) [2], Bell (1991) [3], and Jiao et al. (2005) [4]. All these models were presented as parameter optimization formulations and were solved using traditional optimization or heuristic approaches.

To improve the estimation efficiency for on-line applications, some other works about dynamic O-D flows estimation have fallen within the scope of state-space methods and have formulated several efficient estimation models using Kalman filtering, for example, Ashok and Ben-Akiva (2002) [5], Bierlaire and Crittin (2004) [6], Lin and Chang (2007) [7] and Lou and Yin (2010) [8]. All these models focused on dynamic O-D flows estimation for freeway corridors or general road networks with rather high efficiency. Of course, they can also be transformed to estimate dynamic turning fractions at intersections; for example, Jiao et al. (2014) [9] proposed a Bayesian combined model to estimate intersection fractions, integrating Kalman filtering and back propagation neural model running simultaneously.

With respect to the arterial coordination traffic signal control, mainly two groups of models have been developed, including maximum green wave band (MGWB, or

MAXBAND) method [10, 11] and minimum delay method [12]. Most existing arterial coordination control models have been further developed based on the above two methods, including some real-world traffic signal control systems, such as Sydney Coordinated Adaptive Traffic System (SCATS) [13] and Split, Cycle and Offset Optimization Technique (SCOOT) [14]. All these models and systems have contributed a great deal to urban traffic management systems. However, very few of them employed the valuable information of dynamic O-D flows or dynamic intersection turning fractions due to the restrictions of current traffic surveillance systems. Moreover, existing arterial control models have some limitations as follows: the distance between two adjacent intersections should be approximately equal, and not longer than 800 meters; arriving vehicles must follow some given distribution; the timing plan remains unchanged during some intervals; and so forth. Therefore, the revised model which can eliminate these limitations is quite necessary.

This paper will develop a real-time arterial coordination control model with the estimated dynamic turning fractions as input data, and both the arterial control model and the turning fraction estimation model lend themselves to formulations as rather complex optimization models. Existing researches have proved that heuristic approaches or swarm intelligence algorithms are rather suitable for complicated optimization models, for example, genetic algorithm (GA) [15–17] and ant colony optimization algorithm (ACO) [18–20]. This paper will also design two revised genetic algorithms to solve the dynamic turning fraction estimation model and real-time arterial control model, respectively.

The rest of this paper is organized in the following sections. Section 2 describes the basic problem, as well as the general model architecture. Section 3 presents the model framework for real-time arterial coordination control, including dynamic intersection turning fraction estimation model, real-time public signal cycle optimization model, and real-time offset and split optimization model. Section 4 designs three algorithms to solve the above three models, respectively, including two revised genetic algorithms and a classical optimization algorithm. Section 5 illustrates the results of a case study through simulation experiments using practical data. Section 6 concludes this paper and suggests some future research directions.

2. General Model Architecture

The general model architecture of the arterial coordination control is shown in Figure 1.

Figure 1 illustrates a typical arterial corridor, the layout scheme of detectors, and the flow of the arterial coordination control. Detectors are placed at both entering and exiting approaches of each isolated intersection to collect the entrance and exit link counts, which are fundamental input data for the whole model framework. The general model consists of the following three submodels:

(1) dynamic turning fraction estimation model: to estimate dynamic turning fractions or turning flows based on detected link counts;

(2) nonlinear signal control model for intersection: to achieve the optimized cycle length of each intersection based on the estimated intersection turning flows, with the maximum one as the public cycle length of the arterial road;

(3) arterial coordination control model: to optimize the offset and split of the arterial road based on the achieved public cycle length.

All three models will be illustrated in detail in the following sections.

3. Real-Time Arterial Coordination Control Model

3.1. Dynamic Intersection Turning Fraction Estimation. For each isolated intersection, the time-varying link counts at entering approach $\Omega_i(k)$ and exiting approach $\Theta_j(k)$ are detected instantaneously, where i and j denote the index of entering and exiting legs, $i = 1, \ldots, r$, $j = 1, \ldots, s$; k indicates the time interval. The dynamic turning flows $\eta_{ij}(k)$ shows the number of vehicles entering the intersection from leg i during interval k and leaving the intersection from leg j. Further, we define $\xi_{ij}(k)$ as the dynamic intersection turning fractions; therefore,

$$\xi_{ij}(k) = \frac{\eta_{ij}(k)}{\Omega_i(k)}. \tag{1}$$

Without considering travel time to cross the intersection, similar estimation problems have been studied in several papers. As described in our previous work [4], to accommodate the possible outliers in the detected input data, a least absolute deviation (LAD) formulation is much more robust than traditional least square (LSQ) form [3] in the objective function. Therefore, the LAD model to estimate dynamic turning fractions at intersection level is formulated as follows:

$$\begin{aligned} \min \quad & Z = \sum_k \sum_j \left| \Theta_j(k) - \sum_i \Omega_i(k)\, \xi_{ij}(k) \right| \\ \text{s.t.} \quad & \begin{cases} 0 \le \xi_{ij}(k) \le 1 \\ \sum_j \xi_{ij}(k) = 1 \\ \xi_{ij}(l) = \xi_{ij}(k), \quad l = k+1, \ldots, k+K. \end{cases} \end{aligned} \tag{2}$$

In (2), the turning fractions are assumed to be constant within continuous K intervals for each step to make the model overdetermined, along with a dynamic updating mechanism to incorporate the time-varying turning fractions.

3.2. Optimization of Real-Time Public Cycle. Estimated turning movement flows provide abundant input data for the traffic signal control at single intersections. To minimize

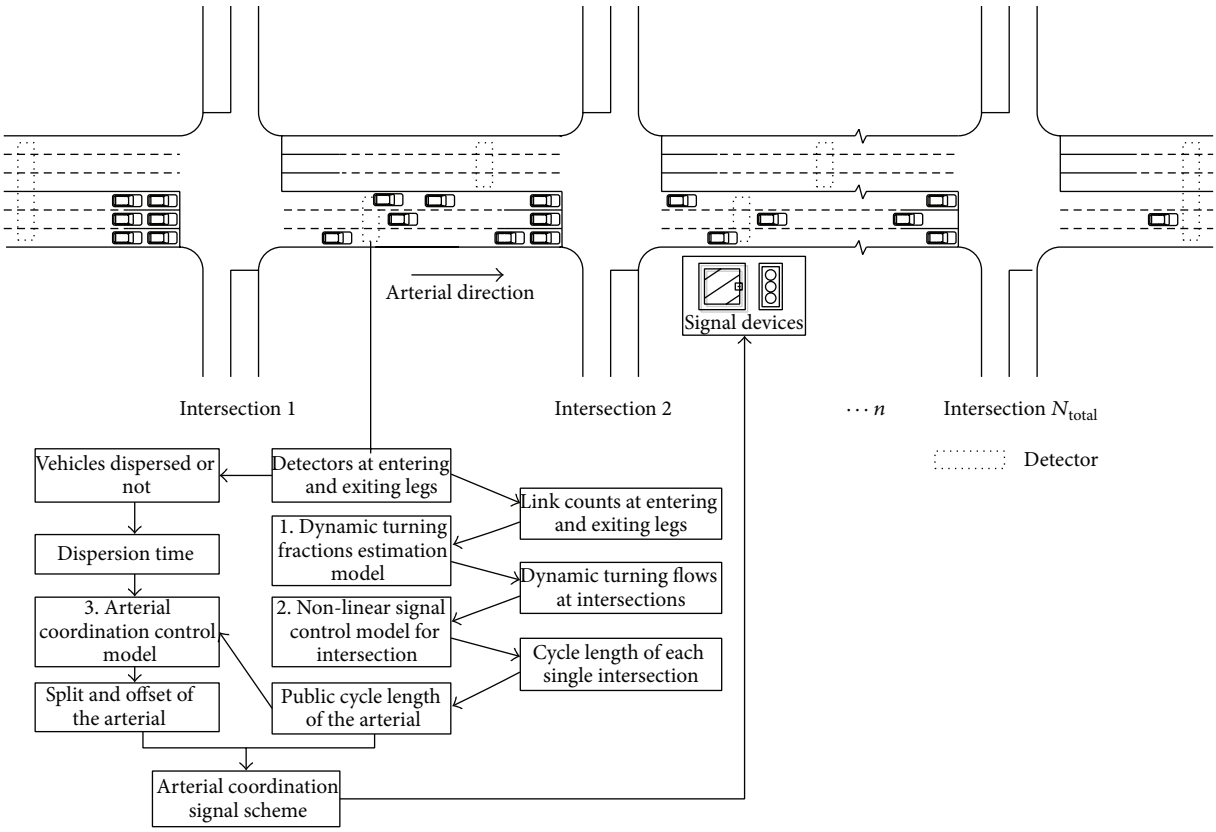


Figure 1: Architecture of the arterial coordination control.

the delay at intersections, a nonlinear optimization model is formulated to optimize the signal cycle length:

$$\begin{aligned} \min \quad D &= \sum_{x=1}^{m} d_x \\ &= \sum_{x=1}^{m} \left[\frac{T\left(1 - G_x^e/T\right)^2}{2\left(1 - \mathrm{VOC}_x\right)} + \frac{\left(1 - \left(\sum_{x=1}^{n} l_x\right)/T\right)^2}{2\left(\sum_{x=1}^{m} l_x\right)/T} \right] \\ \text{s.t.} \quad & \begin{cases} \sum_{x=1}^{m} \left(G_x^e + Y_x + R_x\right) = T \\ \mathrm{green}_{x,\min} \le G_x^e \le \mathrm{green}_{x,\max} \\ \sum_{x=1}^{m} \left(G_x^e + l_x\right) \le T_{\max} \\ G_x^e \ge 0, \qquad 1 \le x \le m. \end{cases} \end{aligned} \tag{3}$$

Symbols in (3) are illustrated as follows:

D: objective function, equaling the total delay time during all phases;

d_x: average delay time during phase x;

T: cycle length;

m: number of phases during one cycle;

G_x^e: effective green time during phase x;

VOC_x: volume-to-saturation flow ratio during phase x, that is, the volume over capacity (VOC);

l_x: start-up lost time of phase x (3 seconds in this paper);

Y_x: yellow change interval of phase x (3 seconds in this paper);

R_x: red clearance interval of phase x (3 seconds in this paper);

$\mathrm{green}_{x,\min}$: minimum green time during phase x;

$\mathrm{green}_{x,\max}$: maximum green time during phase x;

$T_{\max}$: maximum cycle length (180 seconds in this paper).

Based on the estimated dynamic turning flows in Section 3.2, VOC_x can be achieved easily. Together with other detected parameters, (3) can be solved, and the optimized cycle length of each single intersection can be determined. Furthermore, since the turning flows keep changing in each interval, the optimized cycle length updates momentarily; that is, the optimized cycle length for each single intersection is real-time in nature.

The maximum cycle length is employed as the public cycle length of the arterial road for further researches.

3.3. Optimization of Real-Time Offset and Split for Arterial Coordination Control. Based on the public cycle length, we further formulate an optimization model for arterial coordination control to optimize the real-time split and offset.

In drivers' common sense, if they do not or seldom need to stop at intersections, they will feel rather comfortable, even if the speed is not very high and there exist some delays. Therefore, different from existing models, this paper defines a new index, uninterrupted ratio, to describe the effects of the model. It is equal to the percentage of vehicles which cross the intersection without interruptions. Consider

$$M_n = \frac{\mathrm{Num}'_n}{\mathrm{Num}_n}, \tag{4}$$

where Num'_n is the number of vehicles crossing the intersection n without interruption, Num_n is the total number of vehicles crossing the intersection n, and M_n is the uninterrupted ratio at intersection n.

According to Figure 1, to formulate the arterial coordination control model, we must know the vehicle dispersion time first. Taking n as the key intersection, there are two situations when vehicles arrive at it along the arterial direction.

Situation 1. Travel time from intersection $n-1$ to n is shorter than dispersion time of vehicles accumulated at intersection n during last cycle, and vehicles from intersection $n-1$ have to wait for some time to cross the intersection n. Consider

$$t'_n \le \frac{\int_{t_n+\lambda_n C+(N-1)C}^{t_n+NC} k_n q_n(\tau)\, d\tau}{S_n}, \tag{5}$$

where t'_n is the travel time for vehicles to travel from intersection $n-1$ to n; t_n is the offset between intersection $n-1$ and n; C is the public cycle length obtained from Section 3.2; λ_n is the split of intersection n along the arterial direction; N is an integer number; k_n is the volume adjustment coefficient; $q_n(\tau)$ is the arrival flow rate function at intersection n, which can be assumed to follow any random distribution, and the Poisson distribution is used in this paper; S_n is the capacity of intersection n along the arterial direction.

Then, the dispersion time of vehicles at intersection n is formulated as follows:

$$T_n = \frac{\int_{t'_n}^{t_n+C} k_n q_n(\tau)\, d\tau + \int_{t_n+\lambda_n C+(N-1)C}^{t_n+NC} k_n q_n(\tau)\, d\tau}{S_n}. \tag{6}$$

In the numerator of (6), there are a total of two items. The first item is the undispersed queue vehicles during last cycle, and the second item is the vehicles arriving at intersection n from the upstream intersection $n-1$.

Situation 2. Travel time from intersection $n-1$ to n is longer than dispersion time of vehicles accumulated during last cycle, and vehicles from intersection $n-1$ can cross intersection n directly without waiting. Consider

$$t'_n > \frac{\int_{t_n+\lambda_n C+(N-1)C}^{t_n+NC} k_n q_n(\tau)\, d\tau}{S_n}. \tag{7}$$

In this situation,

$$T_n = 0. \tag{8}$$

According to the definition of the uninterrupted ratio, we can formulate

$$M_n = \frac{\mathrm{Num}'_n}{\mathrm{Num}_n} = \frac{\int_{t_n+T_n}^{t_n+\lambda_n C} q_n(\tau)\, d\tau}{\mathrm{Num}_n}. \tag{9}$$

Furthermore, to maximize the sum of uninterrupted ratio at all intersections, the real-time arterial coordination control model is formulated as

$$\begin{aligned} \max \quad & f(t_n, \lambda_n) = \sum_n \frac{\int_{t_n+T_n}^{t_n+\lambda_n C} q_n(\tau)\, d\tau}{\mathrm{Num}_n} \\ \text{s.t.} \quad & \begin{cases} t_n \ge 0 \\ 0 \le \lambda_n \le \lambda_{n,\max}, \end{cases} \end{aligned} \tag{10}$$

where $\lambda_{n,\max}$ denotes the maximum split along the arterial direction (0.8 in this paper) of intersection n.

Based on the public cycle length C and the vehicle dispersion time T_n, we can obtain the real-time offset t_n and the split λ_n of each intersection along the arterial by solving the nonlinear optimization problem in (10).

From the model formulation, we can find out that there is no limitation about geographic scheme of the arterial road or vehicle arrival distribution, and the optimized offset and split remain updated along with the time interval.

4. Solution of the Model

4.1. Genetic Algorithm for Dynamic Turning Fraction Estimation at Intersections. Since the objective function of (2) is a LAD formulation and there are equality constraints in the model, it is very difficult to be solved using traditional optimization method. Therefore, we develop a revised genetic algorithm (GA) for solution. The turning fractions $\xi_{ii}(k)$ are assumed to be 0; that is, the U-turn phenomena are neglected here.

We borrow the GA from our previous work [4] directly, and two important issues are described as following:

4.1.1. Encoding and Decoding. We use the binary encoding method in this paper. According to the equality constraint in (2), as well as the assumption that there is no U-turn at intersections, there are $s-2$ independent turning fractions for each entering approach. Totally, there are $r(s-2)$ independent turning fractions for an intersection during one time interval. These turning fractions to be estimated can be written as a matrix with r rows and $s-2$ columns.

The decoding process is further represented as

$$\begin{aligned}
\xi_{i1} &= \frac{\mathrm{ch}_{i1}}{\left(2^{L_{\mathrm{GA}}}-1\right)} \\
&\vdots \\
\xi_{i(i-1)} &= \left(1-\sum_{j=1}^{i-2}\xi_{ij}\right)\times\frac{\mathrm{ch}_{i(i-1)}}{\left(2^{L_{\mathrm{GA}}}-1\right)} \\
\xi_{ii} &= 0 \\
\xi_{i(i+1)} &= \left(1-\sum_{j=1}^{i}\xi_{ij}\right)\times\frac{\mathrm{ch}_{ii}}{\left(2^{L_{\mathrm{GA}}}-1\right)} \\
&\vdots \\
\xi_{i(s-1)} &= \left(1-\sum_{j=1}^{s-2}\xi_{ij}\right)\times\frac{\mathrm{ch}_{i(s-2)}}{\left(2^{L_{\mathrm{GA}}}-1\right)} \\
\xi_{is} &= 1-\sum_{j=1}^{s-1}\xi_{ij},
\end{aligned} \tag{11}$$

where ch_{ij} is a decimal real number transformed from the binary code of ξ_{ij} and L_{GA} is the length of each chromosome. As stated before, there is one turning fraction which is dependent on other $s-1$ results, and we assume it to be as the one corresponding to the exiting approach with the index s.

Through the decoding method in (11), the estimated turning fractions will satisfy both equality and inequality constraints in (2); therefore, we do not need to perform the truncation and normalization processes [1], which are usually employed in turning proportions estimation.

4.1.2. Fitness Function. Since GA always tries to search for the maximum fitness of chromosome in the evolution process, we introduce a positive number to transform the objective function to the following fitness function:

$$\mathrm{Fit} = \frac{U}{Z}, \tag{12}$$

where U is a positive constant and Fit is the fitness function.

The overall steps and other issues are similar to our previous work and some other existing GAs. We code this GA using M language of MATLAB software and then obtain the estimated dynamic turning fractions for each single intersection.

4.2. Solution of Real-Time Public Cycle Length Optimization at Intersections. Since (3) is an ordinary nonlinear optimization problem, it can be solved directly using existing mathematical methods. We code this model using Lingo software, and then obtain the optimized cycle length of each single intersection. The maximum one is taken as the public cycle length for the arterial road.

4.3. Genetic Algorithm for Real-Time Offset and Split Optimization at Arterial Corridors. Due to the integral formulation in the objective function of (10), its solution is very difficult. Here, we also design a GA for solving [15–17]. The overall steps are described as follows.

Step 1 (encoding). A real-coded scheme is adopted here to represent the feasible solutions during the GA evolution process.

Step 2 (fitness function). Since the objective function of (10) is a maximum formulation, we take it as the fitness function directly, as shown in the following equation:

$$\mathrm{Fit} = f\left(t_n, \lambda_n\right) = \sum_n \frac{\int_{t_n+T_n}^{t_n+\lambda_n C} q_n(\tau)\, d\tau}{\mathrm{Num}_n}. \tag{13}$$

Step 3 (selection). The classical Roulette wheel selection approach is employed for the selection operation in this paper.

Step 4 (crossover). Crossover operation is employed to pass the excellent genes of parent chromosomes to children chromosomes and to generate new chromosomes. In this paper, we use the following method to implement the crossover operation:

$$\begin{aligned}
\mathrm{chr}_{yj}^{\delta+1} &= \mathrm{chr}_{yj}^{\delta}\left(1-\mu\right) + \mathrm{chr}_{zj}^{\delta}\mu, \\
\mathrm{chr}_{zj}^{\delta+1} &= \mathrm{chr}_{zj}^{\delta}\left(1-\mu\right) + \mathrm{chr}_{yj}^{\delta}\mu,
\end{aligned} \tag{14}$$

where μ is a random number between $[0, 1]$, $\mathrm{chr}_{yj}^{\delta+1}$ and $\mathrm{chr}_{zj}^{\delta+1}$ are genes from children chromosomes, $\mathrm{chr}_{yj}^{\delta}$ and $\mathrm{chr}_{zj}^{\delta}$ are genes from parent chromosomes, δ is the index of current generation, and j is the index of gene in the chromosome.

Step 5 (mutation). Mutation operation is implemented to ensure the local random search ability of GA, as well as to produce new children chromosomes. The following method is designed for the mutation operation:

$$\begin{aligned}
\psi &= \rho\left(1-\frac{\delta}{\Delta_{\max}}\right)^2, \\
\mathrm{chr}_{yj}^{\delta+1} &= \begin{cases} \mathrm{chr}_{yj}^{\delta} + \psi\left(\mathrm{chr}_{yj}^{\delta} - \mathrm{chr}_{yj,\min}^{\delta+1}\right), & \omega \geq 0.5 \\ \mathrm{chr}_{yj}^{\delta} + \psi\left(\mathrm{chr}_{yj,\max}^{\delta+1} - \mathrm{chr}_{yj}^{\delta}\right), & \omega < 0.5, \end{cases}
\end{aligned} \tag{15}$$

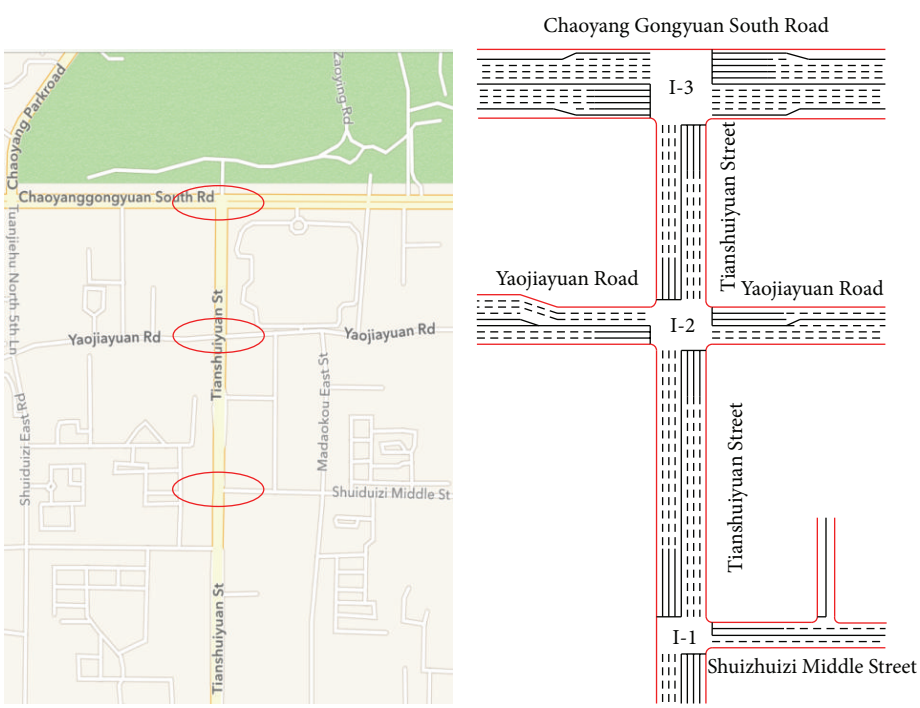
where ρ and ω are random numbers between $[0, 1]$, $\mathrm{chr}_{yj,\min}$ is the lower bound of chr_{yj}, $\mathrm{chr}_{yj,\max}$ is the upper bound of chr_{yj}, and $\Delta_{\max}$ is the maximum generations.

Some important controlling parameters of the GA are set as follows: the population size is 60, the maximum number of generations is 120, the crossover rate is 0.7, and the mutation rate is 0.01.

We also code this GA using M language of MATLAB software and then obtain the optimized offset and split for the arterial road.

Table 1: Signal timings.

Scheme	Intersection	Cycle length (s)	Arterial split	Offset (s)
Current	I-1	85	0.52	
	I-2	90	0.53	—
	I-3	118	0.26	
MAXBAND	I-1	95	0.72	—
	I-2		0.60	22
	I-3		0.30	19
Proposed model-Cycle 1	I-1	101	0.70	—
	I-2		0.64	25
	I-3		0.30	22
Proposed model-Cycle 2	I-1	98	0.75	—
	I-2		0.62	26
	I-3		0.30	23
Proposed model-Cycle 3	I-1	92	0.76	—
	I-2		0.66	25
	I-3		0.30	22
Proposed model-Cycle 4	I-1	95	0.72	—
	I-2		0.64	26
	I-3		0.30	23
Proposed model-Cycle 5	I-1	100	0.75	—
	I-2		0.62	25
	I-3		0.30	22



(a) (b)

Figure 2: Graphical illustration of the case study arterial road.

5. Case Study

To investigate the performance of the proposed model framework, this paper implements a case study using practical data and the effects of the arterial control are evaluated through traffic simulation.

An arterial corridor around Tianshuiyuan block in Chaoyang district, in Beijing city, is taken as the case study area. Figure 2 presents a graphical illustration of the area.

Tianshuiyuan Street is the arterial road to be studied, and there are three intersections along it. Intersection (I-2) is employed as the key intersection, which is a crossroad with four approaches. The arterial direction is from south to north, that is, from I-1 to I-3.

To collect the field data, we implemented a survey around the case area and collected a great deal of data, including the time-varying entering and exiting link flows at all three intersections, the geographical information of the arterial, the existing signal timing plan, and queue length, delay time, and number of stops at all three intersections. All information needed in the case study can be extracted from the above survey data.

We further implemented the proposed model, as well as the existing MAXBAND method. Table 1 reports cycle length, arterial split, and offset of each intersection from current scheme, MAXBAND model, and the proposed model.

In the current scheme, all three intersections have fixed timing plans, and the arterial road is not coordinated at all. For the proposed model, we take 5 cycles, as examples here, and the public cycle length, arterial split, and offset are all illustrated in Table 1. We can also find out that all signal timings of the proposed model are updated in each cycle; therefore, they are real-time in nature.

To further evaluate the effects of the proposed model, we select three indices as evaluation criteria, including queue length, delay time, and number of stops. All these indices of current scheme were obtained through the field survey. Since it is impossible to adjust the signal timings in real world just for this case study, we simulated both MAXBAND method and the proposed model using Vissim software [21].

Figure 3 shows the simulation environment. The road network was created based on an original AutoCAD file, and the surveyed entering link counts at three intersections were taken as the input data, together with the current turning proportions and signal timings. Using the above three indices as evaluation criteria, the simulation model was calibrated by adjusting some parameters, such as speed, acceleration, and priority rules. The timings from the proposed methodology were then input to the simulation model, and all three evaluation indices under proposed timings were extracted through some detectors laid in the road network in Vissim.

We further compared the three simulated evaluation indices with those from current traffic control scheme. Tables 2, 3, and 4 report queue length, delay time, and number of stops, respectively.

The detailed graphical comparisons of the three evaluation indices are further illustrated in Figures 4, 5, and 6.

From Tables 2, 3, and 4 and Figures 4, 5, and 6, we can reach the following results.

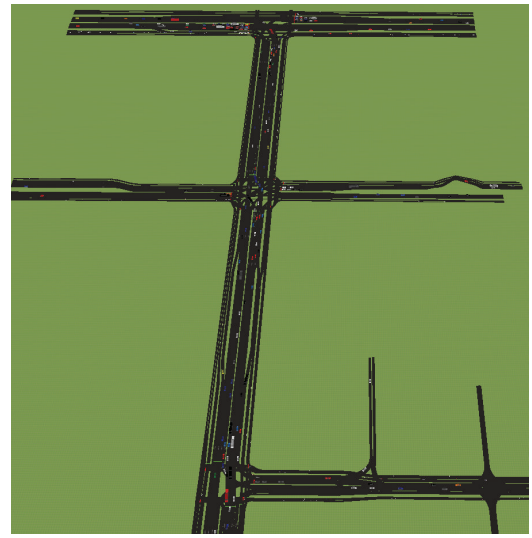


Figure 3: Graphical illustration of the simulation environment.

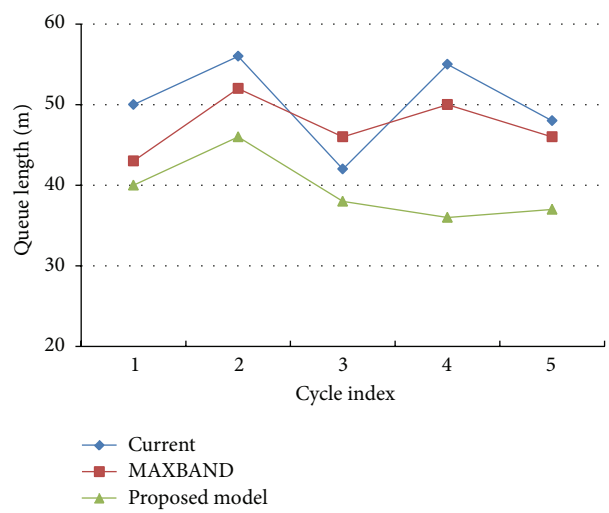


Figure 4: Graphical illustration of queue length.

(1) Generally, the proposed arterial coordination control model yields the best results during all cycles in terms of all three indices, including queue length, delay time, and number of stops.

(2) The MAXBAND method also outperforms current scheme during most cycles in all three indices, because the current timing plan is not coordinated along the arterial.

(3) For delay time, the proposed model gets a little worse result than MAXBAND in the first cycle, which is due to some unknown reasons, but it is still better than the current scheme and does not influence the general outstanding performances of the proposed model.

Table 2: Comparison of queue length.

Cycle	Current (m)	MAXBAND (m)	Proposed model (m)	Improvement (%)	
				Over current	Over MAXBAND
1	50	43	40	20.0	7.0
2	56	52	46	17.9	11.5
3	42	46	38	9.5	17.4
4	55	50	36	34.6	28.0
5	48	46	37	22.9	19.6
Average	50.2	47.4	39.4	21.0	16.7

Table 3: Comparison of delay time.

Cycle	Current (s)	MAXBAND (s)	Proposed model (s)	Improvement (%)	
				Over current	Over MAXBAND
1	29	26	27	6.9	−3.9
2	35	32	30	14.39	6.3
3	28	31	26	7.1	16.1
4	32	30	28	12.5	6.7
5	30	29	27	10.0	6.9
Average	30.8	29.6	27.6	10.2	6.4

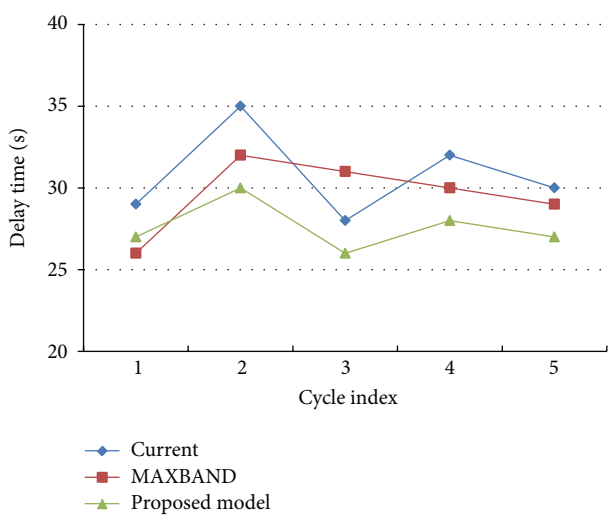


Figure 5: Graphical illustration of delay time.

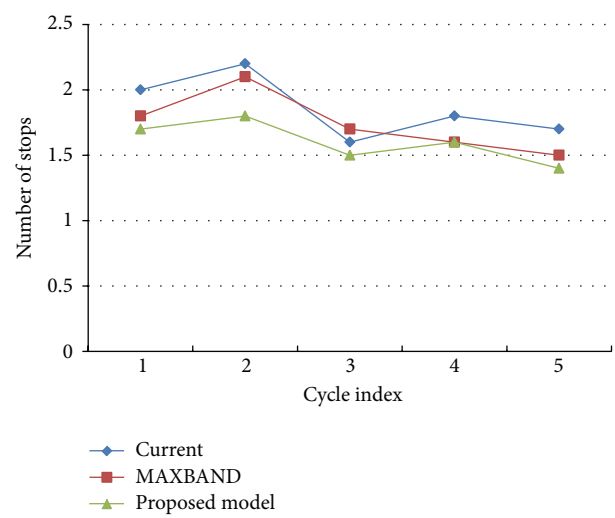


Figure 6: Graphical illustration of number of stops.

6. Conclusions

This paper presents a general model framework for real-time arterial coordination control. To provide important input data for the arterial control, this study first proposes a dynamic intersection turning fraction estimation model using the least absolute deviation formulation and designs a genetic algorithm for solution, integrating revised encoding and decoding methods. Based on the estimated time-varying turning proportions, this paper develops a nonlinear optimization model based on minimum delay to optimize the real-time cycle of each single intersection along the arterial road, and the maximum cycle is taken as the public arterial cycle. Furthermore, this paper puts forward a novel optimization model based on minimum uninterrupted ratio and develops a genetic algorithm to optimize both offset and split of the arterial road, which are also time-varying. Time-dependent public cycle, offset, and split constitute the real-time timing plan of arterial coordination control scheme together. The proposed model removes most of the restrictions of conventional arterial control models and is a real-time control method in nature. The simulation experiments based on field data have confirmed the outstanding performances of the proposed model framework compared with both current scheme and MAXBAND method.

This paper can be enhanced in following directions. The first is to further consider the opposite direction of the arterial corridor and construct a bidirectional arterial coordination

Table 4: Comparison of number of stops.

Cycle	Current	MAXBAND	Proposed model	Improvement (%)	
				Over current	Over MAXBAND
1	2	1.8	1.7	15.0	5.6
2	2.2	2.1	1.8	18.2	14.39
3	1.6	1.7	1.5	6.3	11.8
4	1.8	1.6	1.6	11.1	0.0
5	1.7	1.5	1.4	17.7	6.7
Average	1.86	1.74	1.6	13.6	7.7

control model. The second is to extend the model to a wide area and develop a regional coordination control model. And the third is to integrate all three submodels in the framework together and formulate an accurate and efficient combined model.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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