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Robust Optimization of Signal Control Parameters for Unsaturated Intersection Based on Tabu Search-Artificial Bee Colony Algorithm

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ABSTRACT In order to overcome the drawback of the conventional signal timing optimization, a robust optimization algorithm for signal control parameters based on Tabu search-artificial bee colony algorithm is proposed under unsaturated flow condition. Based on the analysis of the characteristics of traffic signal control, a robust optimization model of signal control parameters is constructed by considering the minimum the average delay and the mean square error of average delay. As a consequence, the formation process of the initial solution to the bee colony is improved and the robust optimization model is solved by using the Tabu search-artificial bee colony algorithm. The proposed robust optimization model is validated by using an intersection in Zhangye City of China. The simulation results have shown that the robust optimization model and the algorithm are feasible and practicable. This robust model and algorithm can effectively deal with the volatility of traffic flow and reduce traffic delays.

INDEX TERMS Intelligent transportation systems, traffic control, artificial bee colony algorithm, robust optimal solution.

I. INTRODUCTION

With the rapid development of urbanization, the number of motor vehicles is constantly increasing, and the problem of traffic jams becomes more and more heavy. Hence, it is crucial to increase the operational efficiency for the entire transport system in order to relieve the urban traffic pressure as well as increase transport facilities. One of the effective ways to relieve the current urban traffic pressure is to adopt state-of-the-art and reasonable traffic signal control technology.

Signalized intersections are important constitutions of the urban road network. In order to improve the traffic capacity and control efficiency at intersections, many works have been done by developing real-time adaptive signal control systems [1]–[3] nowadays. However, it is still very difficult to apply it in the real world [4] due to the higher cost of implementation and maintenance.

The traditional isolated intersection control strategy including actuated control and pre-time control. Sensitive controls do not work well for oversaturated intersections and the pre-time control system implements signal control according to the preset timing scheme. Although the pre-time control has many shortcomings, it is still widely used in the current isolated intersection control system. Therefore, improving the performance of pre-time control system is the essential part to improve the traffic mobility at intersections.

Yin (2008) [5] proposed a scenario-based optimization approach to optimize average delay and delay variance. This method also considered the robustness of traffic timing and validated the rationality of the model and algorithm. Ukkusuri *et al.* (2010) [6] proposed the optimal signal control model to study the robust systems, the author conducted a numerical analysis on the roadway testing traffic network to illustrate the advantages of considering uncertainties and robustness. Li (2011) [7] proposed a discrete modeling method to describe the robust signal timing problem with the binary integer programming and developed two Dynamic programming algorithms. Wei *et al.* (2011) [8] proposed a robust optimization model for signalized control at intersections. The analysis results show that the model can effectively deal with the random error caused by the uncertainty of traffic flow. Han *et al.* (2012) [9] proposed a new hybrid integer linear programming method to solve the problem caused by dynamic traffic signal control with consideration of pollutant emissions. This approach avoids traffic congestion with minimizing vehicle delays and addressing issues related to vehicles emissions. Sacco (2014) [10] considered the traffic flow's characteristic for volatility at intersections. In addition, Sacco reconstructed three kinds of intersection capacity optimization models in stochastic programming and discussed the application of signal timing in the area of Genoa. Liu *et al.* (2015) [11] raised a two-phase online signal control strategy for dynamic networks using linear decision rules (LDR) and distributed robust optimization (DRO) techniques. Axer and Friedrich (2016) [12] described an example of signal timing estimation based on simulation datasets, and the author analyzed the signal estimation quality of different saturation samples. Wang *et al.* (2017) [13] developed a continuous vehicle delay model to derive the best conditions for intersection control. Vilarinho *et al.* (2017) [14] proposed a human-based single-intersection traffic signal control strategy to prioritize vehicles with larger passenger numbers to minimize passenger delays. The analysis results show that the proposed signal control system will effectively reduce the total delay at the intersection. Chandan *et al.* (2017) [15] proposed a single-intersection signal control strategy based on a vehicle network and compared it with an adaptive signal control solution. Yu *et al.* (2017) [16] designed a unified signal timing optimization framework and this model considered both pedestrians and vehicles at the intersection.

In the previous studies, all the models were based on an optimization goal to enter the average traffic flow during a time period or enter the maximum traffic flow to get the research results. However, the traffic system is a complex system with randomness, nonlinearity and discreteness. The actual traffic flow has fluctuating characteristics and there are many uncertainties. The uncertainties exist in difference moment of a day, and even exist in different days at the same time. Using the averaged streams is not a smart choice, especially when there is a large variation of traffic flow in different time periods. If the maximum traffic volume is taken as the input, it will lead to a conservative optimizations result. The further study might focus on the question regarding "How to further improve system performance based on the existing basis".

In this paper, our research team members determine the mathematical model of the signal timing at the intersection, and then build a robust optimization model for the traffic flow fluctuation characteristics. Afterwards the improved artificial bee colony algorithm is used to find the global solution. Finally, the model and algorithm are verified by using a real existing problem. The rest of the paper is structured as follows: Section II describes the existing problem and the establishment of the proposed mathematical model. Section III establishes a robust optimization model for the signal control parameters at the intersection. Section IV is the design and improvement of the artificial bee colony algorithm. Section 5 is the case study and Section 6 is the conclusion.

II. PROBLEM DESCRIPTIONS AND ESTABLISHMENT OF MATHEMATICAL MODEL

Figure 1 shows a typical intersection with traffic flow distribution. There are three types of traffic diversions for each entry road using four-phase signal. The first phase is used to release the straight traffic and the right turn traffic flow from the east and west approaches; the second phase is used to release the left turn traffic flow from the east and west approaches; the third signal phase is used to release the straight traffic and the right turn traffic from the south and north approaches; The fourth signal phase is used to release the left turn traffic flow from the south and north approaches. Intersection traffic flow distribution map is shown in Fig. 1 and Intersection phase plan is shown in Figure 2. This study aims to provide the optimal phase timing and thereby minimize the traffic delay at intersections.

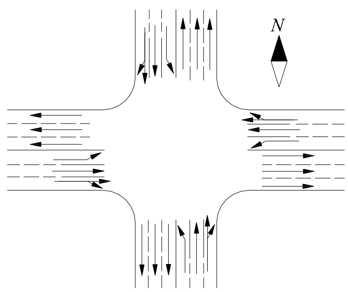

FIGURE 1. Intersection traffic flow distribution map.

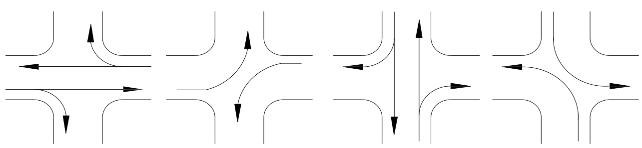

FIGURE 2. Four-phase program.

The first phase The second phase The third phase The fourth phase

For under-saturated condition, we use the Webster delay formula to calculate the delay; each vehicle delay at the intersection is calculated from equation (1).

$$d = \frac{C(1-\lambda)^2}{2(1-\lambda x)} + \frac{x^2}{2q(1-x)} + 0.65\left(\frac{C}{q^2}\right)^{\frac{1}{3}} x^{(2+5\lambda)} \quad (1)$$

where d is the average delay per vehicle, and its unit is s/pcu; C is the period duration, and its unit is s; q is the traffic flow actually reached by the inlet road, and its unit is pch/h; λ is green split; x is the degree of saturation. The first term in formula (1) is the delay happens when the arrival vehicles is uniformly distributed in the lane, which is called uniform delay. The second term is the delay caused by the randomness of the arrival of the vehicle, which is called the random delay. The third value is smaller. In the actual calculations, we can ignore it. Equation (1) can be transformed into the following equation:

$$d = \frac{C(1-\lambda)^2}{2(1-\lambda x)} + \frac{x^2}{2q(1-x)} \tag{2}$$

Taking the typical four-phase intersection as an example, the total delay formula of the intersection will be achieved as shown in equation (3):

$$\bar{d} = \sum_{i=1}^{4}\sum_{j=1}^{2}\left\{q_{ij}\left[\frac{C(1-\lambda_i)^2}{2(1-\lambda_i x_{ij})} + \frac{x_{ij}^2}{2q_{ij}(1-x_{ij})}\right]\right\} \tag{3}$$

where q_{ij} is the traffic volume at the j^{th} entry of phase i, and its unit is pch/h; x_{ij} is the traffic saturation on the j^{th} entry of phase i; λ_i is green split of phase i.

The optimization process is to provide the effective green time for all 4 phases. The following equation is the constraint to be satisfied:

$$t_1 + t_2 + t_3 + t_3 = C - L \tag{4}$$

where L is the total loss time, and its unit is s.

Taking into account the safety needs of pedestrians crossing the street, the minimum green time per phase is more than a certain value e (the minimum green time here is 10s), then the timing of each phase must meet the conditions:

$$e \le t_i \le C - L - 3e \tag{5}$$

Considering the constraint of maximum saturation, a reasonable signal timing design should ensure that the saturation of each phase intersection is too small. Therefore, this timing scheme avoids the phenomenon of traffic jams at the intersection. The minimum green time requirement for each phase should satisfy the following formula:

$$t_i = g_{e_i} \ge \frac{Cy_{i,\max}}{0.85} \tag{6}$$

Vehicle average delay $D$is expressed as follows:

$$D = \bar{d}/Q \tag{7}$$

where D *is*average vehicle delay, $\bar{d}$ is the total delay at the intersection, Q is the total amount of traffic volume at the intersection.

III. INTERSECTION SIGNAL CONTROL PARAMETERS ROBUST OPTIMIZATION MODEL

A. OBJECTIVE FUNCTIONS AND CONSTRAINTS OF ROBUST OPTIMIZATION

Due to the fluctuating characteristics of traffic flow and considering the influence of uncertainties on traffic signal control optimization strategy, the robust optimization method proposed in the literature [17] is adopted to establish robust optimization model of signal control parameters at intersections. Our research team introduces a set of scenarios $\Omega = \{1, 2, \cdots, S\}$ to describe the traffic flow and assume that for the S^{th} scenario, the probability of occurrence is P_s, $\sum_{s=1}^{S} P_s = 1$. The author defines the objective function value for each scenario as D_s, $D_s = \bar{d}_s/Q_s$. Therefore, the objective function of robust optimization model of intersection signal control parameters can be expressed as (8).

$$\text{Min } J = \sum_{s=\Omega} P_s D_s + \omega\sqrt{\sum_{s=\Omega} P_s (D_s - \sum_{s=\Omega} P_s D_s)^2} \tag{8}$$

where $J$is the overall performance indicator; ω is weight coefficient; D_s is the s^{th} scene of the average vehicle delay. We can see from formula (8), the first term measures optimality robustness, whereas the second term is a measure of model robustness. The authors pursue the minimum value of J so that the average delay and the mean square error of average delay of the intersections under various conditions become minimum. It ensures the timing of the intersection of the program is robust and constraints are (4), (5), (6) and (7).

B. SET THE SCENE COLLECTION

The fluctuation of traffic flow exists in a certain period of time. The traffic flow changes for each phase are calculated respectively at the same period of different working days (for example, the morning rush hour). Sampling period is 15min, the total duration is 5 days. In order to reduce the amount of computation, this paper adopts the classic K-means clustering method to select more than 10 clusters as the final optimized scenario set which obtained from the field.

IV. IMPROVED ARTIFICIAL BEE COLONY ALGORITHMS

The robust optimization model for the signal control parameters at the intersection described above is a typical non-linear optimization problem. The traditional calculation method is difficult to solve. Through the local optimization behavior of each individual worker bee, the global optimal value finally emerges in the group with a faster convergence rate. This paper attempts to use artificial bee colony algorithm to solve the optimization model.

Seeley (1995) [18] firstly proposed a self-organizing model of bee colony algorithm in his book called *The Wisedom of the Hive*in 1995; Yang (2005) [19] proposed a virtual simple bee colony algorithm considering two parameters and applies it to solve the numerical optimization problem. There are some other researchers proposed a new model of bee colony algorithm and analyzed its performance [20, 21]. Yannis *et al.* (2009) [22] utilized a hybrid algorithm based on artificial bee colony algorithm and greedy random adaptive search process. Mohammad (2013) [23] proposed a dynamic subgroup-based artificial bee colony algorithm considering the advantages of fast convergence and good robustness in finding the global optimum.

A. TRADITIONAL ARTIFICIAL BEE COLONY ALGORITHM

In the natural world, honeybees are a group of insects, which population intelligence is achieved through the exchange of individuals among groups. This group includes queen bees, worker bees and drones. The worker bees go out to find a honey source and return to the hive through 'the pendulum Tail Dance' exchanges information with other worker bees (such as honey direction, distance, richness, etc.), and then finds the best honey source. Artificial bee colony algorithm selection worker bees as the research object, the worker bees are divided into nectar gatherer, observation bee, reconnaissance bee, including nectar gatherer and observation bee each accounted for half of the population. There is a one-to-one correspondence between mining bee and honey source, that is, the number of honey sources near the honeycomb is equal to the number of mining bees. The honey source represents a feasible solution and the quality of the honey source is represented by the degree of fitness. In addition, the optimal honey source is the optimal solution, and the information exchange and feedback between the worker bees is the process of finding the optimal solution. In the artificial bee colony algorithm, the corresponding relationship between bee honey collection behavior and function optimization problems is shown in Table 1.

TABLE 1. The corresponding relationship between bee honey collection behavior and function optimization problems.

Honey behavior	Optimization problem
The location of honey	A feasible solution to the optimization problem
The amount of nectar from honey	The quality of the feasible solution (fitness function value)
Finding nectar speed	Feasible solution optimization speed
Maximum nectar	The optimal solution of optimization problem

Note: This section is added in the section of traditional artificial bee colony algorithm and explains ABC in more detail.

Artificial bee colony algorithm generates SN initial population, each solution is a nectar source, each nectar source is a D-dimensional vector $x_{ij}(i = 1, 2, \cdots, SN; j = 1, 2, \cdots, D)$, D is the number of optimization parameters, SN is the number of solutions (the number of nectar sources); the total number of artificial bee colony algorithm cycle is MCN. According to equation (9), SN initial solutions are generated randomly.

$$x_{ij} = x_{ij} + rand(0, 1)\left[(x_{ij})_{\max} - (x_{ij})_{\min}\right] \tag{9}$$

where x_{ij} is the solution generated during the initialization phase; $(x_{ij})_{\max}$ and $(x_{ij})_{\min}$ is the upper and lower bound; $rand(0, 1)$ is a random number between 0 and 1.

In the initialization phase, the location of nectar source is randomly generated by formula (9). Mining bees picked honey back to the honeycomb and then share the information about the nectar source. In the second phase, after the bee shares the information, a new nectar source is selected in the vicinity of the previous nectar source according to the previously recorded information of the nectar source. In the third stage, each observation bee selects nectar according to the nectar information shared by the mining bees. The more nectar at a nectar source, the greater the probability that the nectar source is chosen. When a nectar source is abandoned, a new nectar source is randomly selected by the reconnaissance bee and replaces the previous nectar source. In the artificial bee colony algorithm, the position of nectar source represents a feasible solution. The nectar number of nectar source represents the quality of feasible solution. The number of mining bees and observing bees is equal to the number of solutions. Mining bees and reconnaissance bees generate a new candidate position near the original nectar source position and calculate the fitness of the new solution. The artificial bee colony algorithm uses formula (10) to generate a new candidate position. The formula is as follows:

$$V_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}) \tag{10}$$

where V_{ij} is the location of the newly generated nectar source; $i, k \in \{1, 2, \cdots, SN\}$ and $j \in \{1, 2, \cdots, D\}$ are randomly selected from the set, but k cannot be equal to j; φ_{ij} is random number between -1 and 1, which controls the production of nectar around nectar source x_{ij}.

After determining a new generated nectar source, the authors compare the amount of nectar with that of the original nectar source x_{ij}. If the new nectar is in a better position than the old one (or the same as the old one), then replace the old one with the new one; otherwise, leave the old nectar source in the same position. Therefore, greedy mechanism is used in the selection of old and new sources of honey. The greedy guidelines ensure that the population can retain elite individuals so that the evolutionary direction does not recede. If nectar x_{ij} is searched after three cycles without any improving, the nectar will be given up. At this point, mining bees transformed into reconnaissance bees, and according to equation (9), bees randomly search for a nectar source to replace the original nectar source. When the mining bees complete the search, then mining bees share information in the dance area, the investigation bees is about to choose nectar source according to equation (11). The formula is as follows:

$$p_i = \frac{fit_i}{\sum\limits_{n=1}^{SN} fit_n} \tag{11}$$

where p_i is the probability value associated with nectar source; fit_i represents the fitness value of nectar x_{ij}.

B. IMPROVED ARTIFICIAL BEE COLONY ALGORITHM

Because the basic bee colony algorithm has a weak local searching ability, and the searching process is blind and random, the accuracy of the algorithm is not high enough to fall into the local optimal solution. In order to solve this problem, the process of initial and replacement of bee colony is improved and the initial value of the solution is uniformly distributed globally to increase the possibility of searching convergent to the global optimal solution. Also, let β be the maximum fitness value for each iteration. Reconnaissance bees in the process of generating a new solution, if the resulting value of the new solution fitness is less than β, the fitness value is eliminated directly. If the new fitness value is higher than the parameter, the previous β value is replaced directly. For each iteration, β is always greater than or equal to the maximum fitness value, and the value of β is matched with the parameter Limit to avoid falling into the local optimal solution.

1) THE INITIAL SOLUTION GENERATION PROCESS

To overcome the randomness of the initial solution produced by Eq. (9), add the parameters l in Eq. (9). The formula is as follows:

$$x_{ij} = (x_{ij})_{\min} + rand\left(\frac{l-1}{SN}, \frac{l}{SN}\right)\left[(x_{ij})_{\max} - (x_{ij})_{\min}\right]$$
$$l = 1, 2, \cdots, SN. \tag{12}$$

By this strategy, we can change the selection range of random numbers from the original (0, 1) to the inter-cell corresponding to each solution and make sure that no two initial solutions are in the same cell. In this way, the initial solution can be evenly distributed in the entire solution interval.

2) IMPROVE SEARCH STRATEGY

Drawing on the concept of Tabu list in the Tabu search algorithm, we set up β ($\beta \geq fit_{i\max}$, $fit_{i\max}$ is the maximum fitness value in each iteration), which is compared with the new solution obtained by each reconnaissance bee. If the new solution has a fitness value greater than β, then, replace the value of β with that value. If the fitness value is less than or equal to the β value, we reserve the β value until the fitness value of the new solution is greater than the β value, replace it, and the nectar source above β will continue to attract the following bee. The nectar source below β will be discarded and the value will be tabulated into Tabu list.

3) TABOO SEARCH - ARTIFICIAL BEE COLONY(TS-ABC) ALGORITHM STEPS AND ALGORITHM FLOW CHART

Let *MCN* be the maximum number of iterations; *Cycle* is the number of iterations;*SN* is the number of nectar source in the bee colony; *Limit* is the maximum number of access to nectar source, if the value exceeds*Limit*, we will abandon the nectar source; *VN* is the number of visits; *bf* is the best honey source.

(1) The initial solution is generated by equation (12).

(2) Reconnaissance bees compare the fitness of *SN* initial feedback information. The probability of observing bees is chosen according to equation (11), and the number of visits *VN* is added up to equal the current maximum fitness value.

(3) In the cycle stage: ň mining bees guide the observation honey bee to visit. At the same time, accumulate the number of visits *VN*. in the meantime, the mining bees search for the current nectar source and provide feedback information when the bee changes information next time. If the fitness value is higher than the β value, the mining bee continues to be the mining bee; if the fitness value is lower than the β value, then we continue to search according to the formula (10) and count the values below the β value into Tabu list. The β value is updated to the maximum fitness value of the current iteration.

(4) If *VN*> *Limit*, then repeat step (1); otherwise, the current nectar source is discarded, and the number of iteration cycles is accumulated.

(5) The calculated result reaches the optimal solution or reaches the maximum number of iterations, and then outputs the result.

Algorithm flow is showed in Figure3.

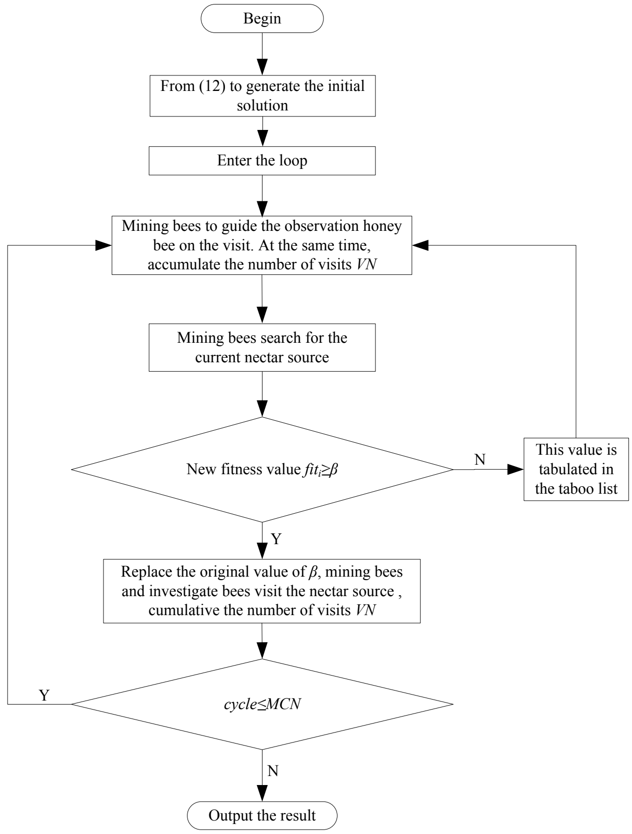

FIGURE 3. The flow chart of the improved artificial bee colony algorithm.

V. CASE STUDIES

This paper chooses the intersection at Qingnian West Street and Laodong Street in Zhangye, China as an example. The intersection's traffic flow diagram is shown in Figure4. According to the method stated in the literature [24,25],

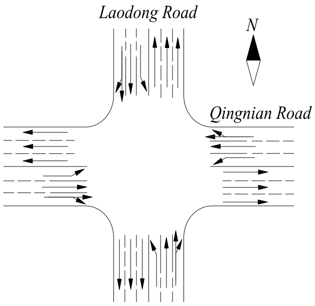

FIGURE 4. Canalization diagram of the intersection.

TABLE 2. Traffic control period.

Name	period	symbol
Early off-peak	0:00-6:30	q1
Early peak	6:30-9:00	q2
Morning off-peak	9:00-11:00	q3
Noon peak	11:00-13:00	q4
Noon off-peak	13:00-17:00	q5
Evening peak	17:00-19:30	q6
Evening off-peak	17:00-24:00	q7

TABLE 3. Average hourly traffic flow and lane saturation flow during each traffic control period (unit:pcu/h).

Traffic control period	The first phase		The second phase		The third phase		The fourth phase	
	EAS	WAS	EATL	WATL	SAS	NAS	SATL	NATL
q_1	135	144	25	30	121	98	35	18
q_2	610	480	126	73	576	436	80	45
q_3	351	310	75	45	321	210	45	32
q_4	475	398	98	60	450	324	65	38
q_5	298	325	65	27	387	245	39	47
q_6	598	450	116	86	610	425	68	51
q_7	289	284	55	28	216	169	45	32
Saturated flow	2000	2000	960	960	1800	1800	960	960

Note: EAS represents east approach straight, WAS represents west approach straight, EATL represents east approach turn left, WATL represents west approach turn left, SAS represents south approach straight, NAS represents north approach straight, SATL represents south approach turn left, NATL represents north approach turn left.

the traffic control period of this intersection during the working day is divided into seven traffic periods as shown in Table 2. The average traffic flow at the intersections in the seven periods is shown in Table 3.

The traffic flow during each time interval at the intersection exists fluctuates. We use the statistical method to calculate the traffic flow scenario sets for each 15-minute traffic flow at different weekdays during the same time period with the total duration of 5 days. For example, the scene of the morning peak is shown in Table 4.

In this paper, Tabu search-artificial bee colony algorithm (TS-ABC) and genetic algorithm (GA) are respectively

TABLE 4. Morning peak scene set (unit: pcu/15min).

Scene set	The first phase		The second phase		The third phase		The fourth phase	
	EAS	WAS	EATL	WATL	SAS	NAS	SATL	NATL
1	148	119	31	19	143	110	22	13
2	155	123	30	20	145	108	19	9
3	158	118	34	17	147	112	21	10
4	148	121	28	18	141	107	17	11
5	150	120	33	17	145	115	23	13
6	153	125	31	15	147	109	18	8
7	149	119	32	17	138	110	25	9
8	157	117	34	20	149	112	23	10
9	159	116	35	18	139	111	16	13
10	155	122	30	20	141	104	18	15

TABLE 5. Signal timing parameters.

Traffic control period	Phase time / (s)				
	The first phase	The second phase	The third phase	The fourth phase	Signal cycle
q_1	18	12	19	11	60
q_2	31	21	29	19	100
q_3	25	18	24	18	85
q_4	28	21	25	19	93
q_5	30	16	26	15	89
q_6	30	20	25	21	96
q_7	25	17	23	15	80

used to calculate the seven traffic control periods on the MATLAB platform. The parameter settings are listed as follows: The maximum number of iterations MCN=200, The number of nectar sources SN=20, The maximum number of access limit=20,ω =1. Based on the TS-ABC algorithm, seven traffic control signal timing parameters are shown in Table 5. A comparison of the control performances between robust models and deterministic models is shown in Figure 5. It demonstrates that the proposed robust model has outperformed the deterministic model in all traffic periods. Taking the early peak as an example, the optimized convergence curve of TS-ABC algorithm and genetic algorithm is demonstrated in Fig6. TS-ABC converges more quickly as compared to GA, reaching to a good convergence rate after 20 iterations whereas it took 40 iterations for GA. The average vehicle delay of the intersection calculated by TS-ABC algorithm and GA algorithm is shown in Fig.7.

As can be seen from Figure 5, for signalized intersections, the average delay calculated by the proposed robust optimization model is less than the traditional parameter-based optimization model. Especially for a large time span from the morning off-peak to the evening off-peak hours and the

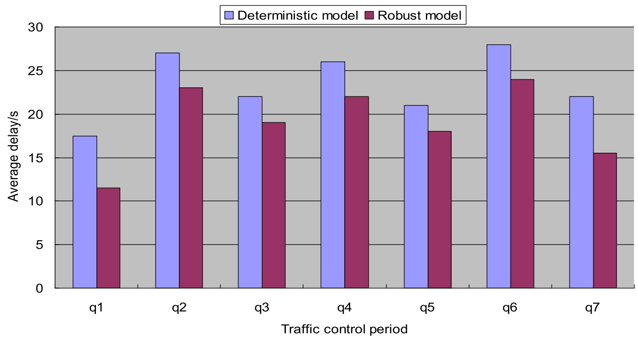

FIGURE 5. Control performance comparison.

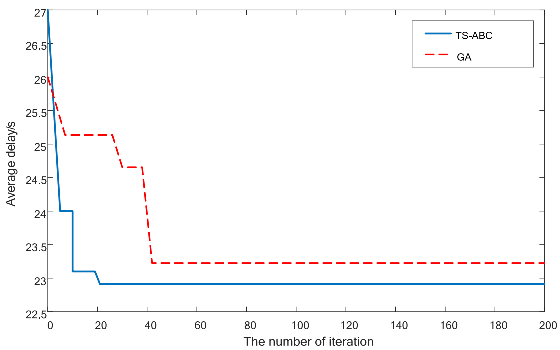

FIGURE 6. Convergence curve.

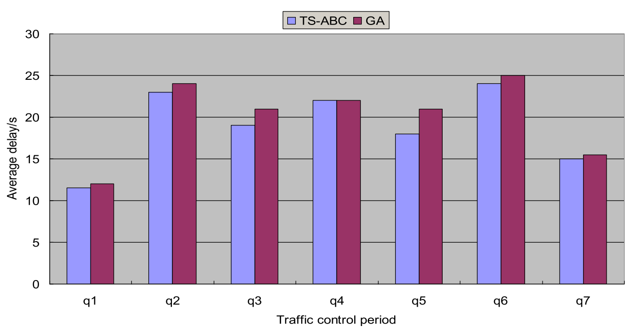

FIGURE 7. Delay comparison chart.

delay can be greatly reduced. Looking at Fig. 6 and Fig. 7, TS-ABC algorithm is superior to GA algorithm in terms of its control performance. From Fig. 6, TS-ABC algorithm is used to calculate several sets of data during the early peak period with vehicle average delay (23s) and evolutionary algebra (21s). For GA algorithm, vehicle average delay is 23.5 s and the evolution of the algebra is 41s. It can be seen that TS-ABC algorithm is better than GA algorithm in terms of average delay and convergence rate. As can be seen from Figure 7, the artificial bee colony algorithm is similar to the genetic algorithm in the low traffic volume periods (such as the early off- peak and the evening off-peak), but during the medium and high traffic periods (such as early peak, morning peak, noon peak, afternoon peak, and evening peak), TS-ABC algorithm is obviously surpassed compared with GA algorithm.

VI. CONCLUSIONS

In this paper, the optimization objective is to minimize the average vehicle delay at the signalized intersection and minimize the mean square deviation of the average delay at the intersections. Aiming at solving the randomness of traffic flow fluctuation, a robust optimization model is constructed with TS-ABC which is a powerful global optimization tool and a robust optimal solution is calculated at the end. The robust optimal solution not only considers the optimality of the solution but also considers the volatility of the traffic flow. Through the simulation testing experiment, the deterministic model is compared with the robust model in our research. The analysis results show that the average delay of the traffic signal timing scheme obtained by the robust model is smaller and the robust model can effectively deal with the random difference caused by using the uncertainty of traffic flow. It will enhance the signal control performance of the intersection with strong robustness. The comparison between TS-ABC algorithm and GA algorithm shows that the average delay calculated by TS-ABC algorithm is much smaller than the GA algorithm for mid-high traffic intensity, and the analysis result is obviously better than GA algorithm. The analysis results show that the proposed robust optimization model and TS-ABC algorithm are feasible in our current research. Furthermore, the future study will focus on optimization traffic signal control parameters at the intersection when traffic flow is saturated or oversaturated.

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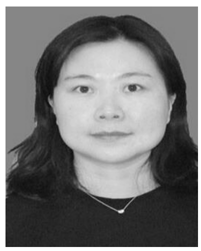

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