ARCHIVES OF TRANSPORT
Volume 46, Issue 2, 2018

ISSN (print): *0866-9546*
e-ISSN (online): *2300-8830*
DOI: *10.5604/01.3001.0012.2109*

MULTI-OBJECTIVE OPTIMIZATION OF TRAFFIC SIGNAL TIMING USING NON-DOMINATED SORTING ARTIFICIAL BEE COLONY ALGORITHM FOR UNSATURATED INTERSECTIONS

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Abstract:

Vehicle delay and stops at intersections are considered targets for optimizing signal timing for an isolated intersection to overcome the limitations of the linear combination and single objective optimization method. A multi-objective optimization model of a fixed-time signal control parameter of unsaturated intersections is proposed under the constraint of the saturation level of approach and signal time range. The signal cycle and green time length of each phase were considered decision variables, and a non-dominated sorting artificial bee colony (ABC) algorithm was used to solve the multi-objective optimization model. A typical intersection in Lanzhou City was used for the case study. Experimental results showed that a single-objective optimization method degrades other objectives when the optimized objective reaches an optimal value. Moreover, a reasonable balance of vehicle delay and stops must be achieved to flexibly adjust the signal cycle in a reasonable range. The convergence is better in the non-dominated sorting ABC algorithm than in non-dominated sorting genetic algorithm II, Webster timing, and weighted combination methods. The proposed algorithm can solve the Pareto front of a multi-objective problem, thereby improving the vehicle delay and stops simultaneously.

Key words:

unsaturated intersection, multi-objective optimization, signal timing, artificial bee colony algorithm, vehicle delay, vehicle stops

To cite this article:

ZHAO, H., HE, R., SU, J., 2018. Multi-objective optimization of traffic signal timing using non-dominated sorting artificial bee colony algorithm for unsaturated intersections. Archives of Transport, 46(2), 85-96. DOI: https://doi.org/10.5604/01.3001.0012.2109

1. Introduction

Urban traffic problems have increasingly worsened given the increase in urban vehicle numbers and negative effects of vehicle energy consumption and exhaust emissions on the environment. Signalized intersections are an unfavorable critical node of a road network. Signal timing scheme, as the basic unit of urban traffic control, is reasonable or not, thus significantly influencing the safety and efficiency of a traffic flow (Biswas, S. et al., 2017; Kadziolka, T., and Kowalski, S., 2014). The implementation of a scientific and reasonable signal timing control at intersections is an effective method for relieving numerous traffic problems (Yu, C. et al., 2017). Therefore, researching a signal timing optimization method improves traffic efficiency, and environmental pollution is practically significant. Many methods, such as transport and road research, highway capacity manual, Sydney coordinated adaptive traffic system, and split cycle offset optimization technique methods, have been applied to improve the comprehensive efficiency of traffic control.

Webster, F. V. et al. (1958) established a steady-state stochastic delay model that is extensively used in unsaturated traffic flow. Scholars (e.g., Fawaz, W. et al., 2016) have selected the average vehicle delay as an optimization target for researching signal timing method. Cheng, C. et al. (2016) proposed a method for the bias of theoretical delay estimation. Numerous scholars have also become aware of the importance of vehicle queue length, vehicle stops, traffic capacity, energy consumption, and exhaust emissions for signal control at intersections. Lu, B. and Niu, H. M. (2010) analyzed the stochastic characteristics of traffic flow at isolated intersections, studied the deviation of the queue length of phase vehicles that correlate to the expected queue length, and suggested an optimization model for signal timing. Rakha, H. et al. (2001) reviewed state-of-the-practice models for estimating the number of vehicle stops at signalized intersections and then introduced two approaches for calculating the number of vehicle stops at unsaturated and oversaturated signalized intersections. A microscopic model was used in the former approach to compute the instantaneous partial and full stops under unsaturated and oversaturated conditions by using second-by-second speed measurements. The latter model is an analytical formulation that is derived from the proposed microscopic model that computes the number of vehicle stops for oversaturated approaches over a given analysis period. Wu, N. and Giuliani, S. (2016) proposed a model for estimating the performance of an existing signalized intersection under unsaturated flow condition based on cycle overflow probability and flow volume; the cycle overflow probability and cycle overflow can be directly measured by loop detectors at stop lines; thus, the capacity can be estimated on the basis of queuing theory. The results indicated that the model is theoretically reasonable and easy to use. Liao, T. Y. et al. (1998) developed an aggregate model for estimating intersection fuel consumption and investigated the influences of signal timing on fuel consumption. Liao, T. Y. (2013) proposed a fuel-based signal optimization model and verified through numerical experiments that the performance of the fuel-based signal optimization model is improved in terms of fuel consumption and CO_2 emissions. Lv, J. P. et al. (2013) focused on a trade-off between delay and emissions based signal optimization; in their study, a methodology was first developed for drive vehicle profiles, and a motor vehicle emission simulation was applied to estimate emissions given a macroscopic input; in addition, these authors developed and solved an optimization methodology for signal timing through a genetic algorithm; the air quality benefit by reducing vehicle emissions using an intersection signal control was demonstrated through a case study, and the quality benefit from the intersection signal control was discussed under various scenarios of cycle lengths, percentages of turning vehicles, and traffic demands on major/minor roads.

The aforementioned studies have shown that intersection signal timing can simultaneously affect different control targets. The purpose of intersection controls has gradually developed from a single objective to traffic efficiency, security, and environmental protection given the development of urban traffic control. Yang, J. et al. (2000) considered a two-phase signalized intersection as the study target and used a gray correlation analysis based on gray control theory to study the gray correlation between signal cycle time and vehicle delay, stops, and queue length. The results indicated that vehicle delay, stops, and queue length at intersections exhibit a significant gray correlation with signal cycle time; thus, a new theoretical approach to developing a class of dual-objection programming timing model, which aims to minimize vehicle delay and stops simultaneously, was proposed. Li, Y. et al. (2013) suggested a multi-objective optimization algorithm for traffic signal control. Throughput maximum and average queue ratio minimum were selected as the optimization objectives of the traffic signal control under an oversaturated condition. The simulation results showed that the signal timing plan generated by using the proposed algorithm is more efficient in managing traffic flow at an oversaturated intersection than using the commonly utilized signal timing optimization software Synchro; the proposed algorithm can search the Pareto front of a multi-objective problem domain under normal and oversaturated conditions. Yu, D. et al. (2016) considered the entire operation efficiency of the intersection comprehensive traffic capacity, vehicle cycle delay, cycle stops, and exhaust emission and selected these factors as optimization goals to establish a multi-objective function; a fuzzy compromise programming approach was used to provide different weight coefficients to various optimization objectives that convert the multi-objective function to a single-objective function; the genetic algorithm was used to obtain the optimized signal cycle and effective green time. The simulation results indicated that the proposed method can reduce vehicle delays, stops, and traffic capacity effectively. Gao, Y. F. et al. (2011) proposed a multi-objective optimization model called non-dominated sorting genetic algorithm II (NSGA II) for unsaturated intersections and solved the multi-objective optimization problems. These authors analyzed the validity of common objectives, such as average vehicle delay, stops, and queue length to signal control parameters. The results showed that the multi-objective optimization method can obtain improved comprehensive traffic benefits.

In summary, the research on multi-objective optimization of signalized intersections has become adequate recently. However, most of the optimization algorithms are based on NSGA II, and the use of other algorithms are rare. Therefore, a multi-objective optimization model, which focuses on vehicle delay and stops, is proposed in the present study under several constraints. The method presented uses the vehicle delay and stops as optimization targets, and the model is solved by non-dominated sorting artificial bee colony (ABC) algorithm. First, the present study determines the calculation method of vehicle delay and stops through a steady-state uniform-arrival analysis method of vehicle flow established by Webster because the research object in the present study is an isolated unsaturated intersection (Webster, F. V. and Cobbe, B. M. 1966; Cronje, W. B., 1983). Second, the non-dominated sorting ABC (NSABC) algorithm is used to solve the model because this algorithm has better convergence than the genetic algorithm (Szczepański, E. et al., 2014; Zou, W. P. et al., 2011; Taraska, M., and Iwańkowicz, R., 2017). Finally, a typical intersection in Lanzhou City is selected as a case study. The results demonstrate that the signal timing that was optimized in this study can effectively reduce vehicle delays and stops.

The remainder of this paper is organized as follows. The multi-objective optimization model at a signalized intersection is introduced in Section 2. An NSABC algorithm is discussed in Section 3. In Section 4, the proposed method is analyzed and compared by selecting a typical signalized intersection in Lanzhou, China. The conclusions drawn from this study are presented and summarized in Section 5.

2. Multi-objective optimization model

2.1. Optimization objective selection

Many scholars believe that the main goal of urban traffic control is to organize all kinds of traffic flow orderly and efficiently. However, urban traffic problems have developed from traffic jams and accidents to environmental pollution and energy consumption. Yang, J. et al. (2010) conducted a systematic study on the target of a traffic signal control system; the research showed that the targets of the traffic signal control should consider different benefit indexes, such as vehicle delay, vehicle queue length, traffic capacity, vehicle stops, pedestrian delays, fuel consumption, pollutant emissions, and noise pollution, and the different targets should be weighted differently in accordance with the various traffic conditions.

Wu, L. N. et al. (2015) analyzed the changing regulation of vehicle energy consumption at signalized intersections; the results showed that vehicle delay and stops clearly influence the energy consumption of a vehicle. Therefore, their study considered the influence of signal timing on vehicle delay and stops but ignored pedestrian delays. Therefore, the minimum vehicle delay and stops are selected as optimization objectives.

2.2. Objective function

The vehicle delay and stops at the intersection are selected as the control targets by using the unsaturated intersection as the research object. The purpose of optimization is to minimize the control targets in a signal cycle.

Webster, F. V. et al. (1958) established a steady-state stochastic delay model that is still widely used for unsaturated traffic flow. The vehicle arrival rate at the analysis interval is assumed to remain stable and typically follow a Poisson distribution. In addition, Webster developed the analysis of vehicle delay by using a steady-state stochastic delay model. The Webster delay model considers the steady-state uniform arrival and random delays of the vehicle flow in the unsaturated state, and the vehicle delay can be calculated as follows:

$$d = \frac{c(1-g/c)^2}{2(1-(g/c)x)} + \frac{x^2}{2q(1-x)} - 0.65\left(\frac{c}{q^2}\right)^{1/3} x^{2+5(g/c)}, \tag{1}$$

where d denotes the average delay for all vehicles at the intersection approach, c is the cycle time of the signalized intersection, g is the effective green time, q is the vehicle arrival rate of the intersection approach, and x is the saturation level of the intersection approach. x can be obtained as follows (Webster, F. V. et al., 1958):

$$x = \frac{c \times q}{g \times s}, \tag{2}$$

where s denotes the saturation flow of the intersection approach. The average delay of all controlled vehicles at the intersection can be easily obtained and calculated as follows:

$$Z_1 = \frac{\sum_{i=1}^{n} q_i \times d_i}{\sum_{i=1}^{n} q_i}, \tag{3}$$

where Z_1 denotes the average delay for all vehicles at the intersection, n is the number of intersection approaches, q_i is the vehicle arrival rate of the i th approach, and d_i is the average delay of the i th approach.

Owing to the control of the intersection signal, several of the vehicles that traverse the intersection decelerate and stop to wait and then accelerate again to leave the intersection. Thus, another objective function of the optimization model in the present study is the vehicle stops at the intersection. The vehicle stops at the intersection approach in a cycle can be modeled in accordance with Webster's calculation method without considering the incomplete stop (Quan, Y. S., 1989). We can obtain the vehicle stops at the intersection approach as follows:

$$R = \frac{1-g/c}{1-q/s}, \tag{4}$$

where R denotes the vehicle stops at the intersection approach, and the other variables are the same as above.

Thus, the average stops for all controlled vehicles at the intersection can be obtained as follows:

$$Z_2 = \frac{\sum_{i=1}^{n} q_i \times R_i}{\sum_{i=1}^{n} q_i}, \tag{5}$$

where Z_2 denotes the vehicle stops at the intersection, R_i is the vehicle stops of the i th approach, and the other variables are the same as above.

2.3. Constraint condition

2.3.1. Constraint of the saturation level

The present study considers the unsaturated intersection as the research object, and Webster's steady-state stochastic delay model is used to analyze the vehicle delay and stops at the intersection. Thus, considering the saturation level of the intersection at the time of signal timing is necessary to ensure the validity of the model analysis. This study shows that Webster's model has a favorable applicability when the saturation level of the approach is satisfied

$x_i < 0.9$ (He, J. J., and Hou, Z., 2012). Therefore, the model of the present study requires the saturation level to also satisfy the abovementioned condition.

2.3.2.Constraint of pedestrian crossing

We should fully consider the shortest time of the pedestrian pass through at the intersection with signal timing. Otherwise, a phase of pedestrians cannot pass through the intersection during the green time, thereby affecting traffic safety and efficiency (Ma, W. J., et al., 2015). Therefore, the green time of each phase is satisfied $g_j > t$, where t denotes the shortest time of the pedestrian, pass through the intersection to avoid the fact that pedestrians cannot safely cross the road.

2.3.3.Constraint of signal cycle

In the traffic control, the signal cycle should be flexibly controlled in accordance with traffic flow. In general, the signal cycle setting is relatively brief to reduce the vehicle delay when the traffic flow is low. However, a signal cycle that is excessively brief will result in vehicles and pedestrians being unable to safely pass through the intersection. Signal cycle settings are extended to improve the traffic capacity of the intersection when the traffic flow is heavy. However, drivers and pedestrians cannot stand and will violate the signal rules when the signal cycle is excessively extended. Thus, to implement traffic control scientifically, studies have shown that the signal cycle should satisfy $15m < C < 200$, where m denotes the number of signal phase.

2.4. Multi-objective optimization model

Owing to the above analysis, the signal cycle C and green time g_j of each phase are used as decision variables, and the multi-objective optimization model for signalized intersection is as follows:

$$\min \quad Z = (Z_1, Z_2), \tag{6}$$

$$s.t. \quad x_i < 0.9, \tag{7}$$

$$g_j > t, \tag{8}$$

$$15m < C < 200, \tag{9}$$

$$l + \sum_{j=1}^{m} g_j = C, \tag{10}$$

where i denotes the intersection approach, j is the signal phase, and l is the loss time per cycle. Eq. (6) minimizes the average delay and stops at the intersection simultaneously. Eq. (7) is the constraint of saturation level per intersection approach. Eq. (8) is the constraint of the pedestrian that passes through the intersection. Eq. (9) is the constraint of the signal cycle. Eq. (10) constrains the sum of the signal loss time, and the green time of each phase is equal to the signal cycle.

3. Algorithm selection and design

3.1. Selection of the algorithm

The average delay and stops of a vehicle provide different mapping relationships with signal timing parameters. Thus, the proposed model is a typical multi-objective optimization problem. The ABC algorithm is a new group of intelligent algorithms that are developed by Karaboga on the basis of simulating the foraging behavior of a honey bee swarm. The ABC algorithm has been attracting considerable attention because it has fewer control parameters and has better search performance than other intelligence algorithms. Zou, W. P. (2011) demonstrated that the multi-objective ABC algorithm has higher search performance than other multi-objective algorithms, such as multi-objective genetic and multi-objective particle swarm algorithms. Therefore, we select the multi-objective ABC algorithm to solve the model.

3.2. Related concepts

The following definitions are presented in accordance with the previous study (Zou, W. P. et al., 2011):

Definition 1. X_1 dominates X_2 is expressed as $X_1 \succ X_2$. For the minimum optimization problem, if and only if $f_j(X_1) \le f_j(X_2)$, $j = 1, 2, \cdots, M$, and $f_j(X_1) < f_j(X_2)$, then $\exists j \in \{1, 2, \cdots, M\}$.

Definition 2. If the individual X_i is a non-dominated individual in the population W, if and only if $\neg\exists X_j \in W$, then $X_j \succ X_i$.

Definition 3. Let $P = \{X_i \mid \neg\exists X_j \succ X_i; X_i, X_j \in W\}$, then P is called Pareto optimal. Pareto optimal solutions are also called efficient, non-dominated, and non-inferior solutions.

Definition 4. For the individual X_i, which belongs to population W, NP_i denotes the number of individuals, which dominate X_i. Then, the individuals with the same NP values have the same Pareto levels.

Definition 5. Individuals of the same Pareto rank are sorted by the value of each objective function. For each individual X_i, the distance between X_{i+1} and X_{i-1} is calculated in accordance with each objective function, and the crowded distance of the individual X_i is obtained by summarizing the calculated results.

Definition 6. Excellent individuals have a low Pareto rank, whereas improved individuals have a remarkable crowded distance when the Pareto rank is equal.

3.3. Original ABC algorithm

The ABC contains three groups, namely, employed, onlooker, and scout bees. The numbers of employed and onlooker bees are equal. Each food source represents a potential solution to the optimization problem. Each employed bee can only be attached to a food source, and each food source can only be attached to an employed bee. The employed bees exploit the food source, carry the information about the food source back to the hive, and share this information with the onlooker bees. The onlooker bees select an excellent food source for exploitation. If a food source is adequate, then it can attract additional onlooker bees. Similarly, a food source may not be exploited by any onlooker bee. The scout bee randomly finds a new source in the global search space when a food source is exhausted. The ABC algorithm will achieve the optimal food source in the global search space through the collaboration of the three bee groups. If a bee group is searching in a D-dimensional space, then all food sources can be expressed as the set $X = \{x_i = (x_{i1}, x_{i2}, \cdots, x_{iD}) \mid i = 1, 2, \cdots, SN\}$,

where SN denotes the number of food sources, which are equal to the number of employed and onlooker bees. The onlooker bees select a food source in accordance with the probability that is proportional to the quality of such food source when all food sources have been exploited by the employed bees. Thus, favorable food sources attract more onlooker bees than unfavorable food sources. The scout bee will discard the food source and randomly find a new source in the global search space when a food source is not renewed in continuous $\lim it$ times by the employed and onlooker bees; thus, the algorithm can be prevented from falling into the local optima. A detailed description of the standard ABC algorithm is as follows:

The ABC algorithm is the first to initialize food sources and the value of a $\lim it$. The search space of the algorithm is determined in accordance with the actual optimization problem, and Eq. (11) is used as the initialized food sources.

$$x_{ij} = \min_j + rand(0,1)(\max_j - \min_j), \tag{11}$$

where $i = 1, 2, \cdots SN$, $j = 1, 2, \cdots D$, D is the dimensional of the search space, $\max_j$ and $\min_j$ correspond to the maximum and minimum of the j th dimensional, and $rand(0,1)$ is a random number between the uniformly distributed (0,1). Simultaneously, the maximum stagnation times of the food sources are determined. A large value will affect the breadth search capabilities of the algorithm, and a small value will affect the depth search capabilities of the algorithm.

At the employed bee stage, each food source will be exploited by all the employed bees, and the ABC algorithm is expressed as follows:

$$\begin{aligned} V_i = \{&x_{i1}, x_{i2}, \cdots, x_{ipara} + rand(\text{-}1,1) \\ &(x_{ipara} - x_{kpara}), \cdots, x_{iD}\} \end{aligned}, \tag{12}$$

where V_i is a new food source obtained from the old one X_i, $para$ is a random number in the range (1,D), $rand(\text{-}1,1)$ is a random number in the range (-1,1), X_k is the randomly selected food source, and x_{ipara} and x_{kpara} correspond to the attribute values of the $para$ th dimensional of X_i and X_k. Furthermore, determining whether to retain V_i in accordance with the greedy rules is necessary. If V_i is better than X_i, then X_i is discarded, and the stagnation number of V_i is reset to 0. However, if V_i is not better than X_i, then V_i is discarded, and the stagnation number of X_i should be added by 1.

At the onlooker bee stage, an onlooker bee selects a food source depending on the probability value p_i that is associated with such food source; p_i is calculated by using the following equation:

$$p_i = \frac{fit_i}{\sum_{j=1}^{SN} fit_j}, \quad (13)$$

where fit_i is the fitness of food source i. If the fitness of the food source is high, then the probability of being selected is high. In the minimum optimization problem, the target function value of the food source must be converted into the fitness value. The onlooker bee searches for the new food source from the selected food sources in accordance with Eq. (12). Greedy rules are also used to decide whether to retain new food sources or not. If the new food source is better than the old food source, then the old one will be replaced by the new food source. Otherwise, the new food source should be discarded.

At the scout bee stage, if the maximum number of stagnation times for all food sources is greater than the $\lim it$, then the food source is discarded. New food sources are randomly generated in the global search space. The scout bee in each iteration can only evolve the food source with the maximum number of stagnation times because the number of scout bees is 1. The flow of the ABC algorithm is illustrated in Figure 1.

3.4. Multi-objective ABC algorithm

In accordance with the non-dominated sort definition and ABC algorithm, the NSABC algorithm is applied as follows:

Step 1. Randomly produce SN food sources, and constitute a candidate solution set W.

Step 2. The employed bees evolve each candidate solution of the candidate set W in accordance with Eq. (12), and the generated new candidate V_i is recorded in the set T, $T = T \cup V_i$.

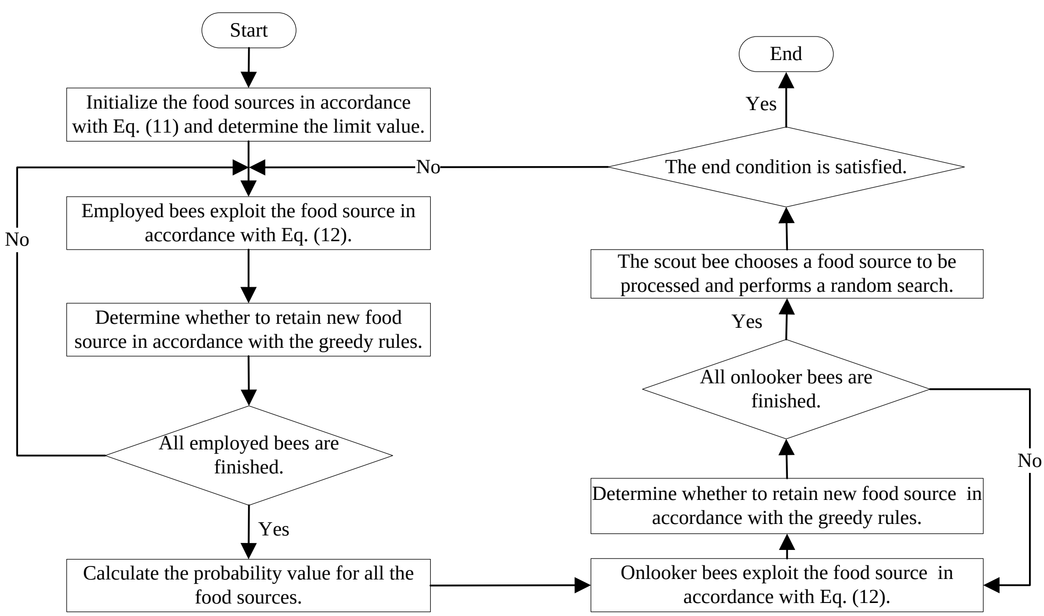


Fig. 1. Flowchart of the ABC algorithm

Step 3. Let $T = T \cup W$, and sort individuals of the set T. All candidate solutions in W are replaced by the first SN candidate solutions in T. Then, the set T is emptied.

Step 4. Calculate the probability value p_i of all candidate solutions in W in accordance with Eq. (14). All onlooker bees use the roulette method to select the candidate solutions, which have a high p_i to evolve in accordance with Eq. (12), and the generated new candidate V_i is recorded in the set T, $T = T \cup V_i$.

$$P_i = \frac{D_i - \min(D_i)}{\max(D_i) - -\min(D_i)}, \quad (14)$$

where D_i denotes the number of solutions to be dominated by the candidate solutions x_i.

Step 5. Execute the same operation as Step 3.

Step 6. The scout bee processes the individual in the candidate set T.

Step 7. If the algorithm satisfies the end condition, then select all non-dominated solutions in the candidate set W as Pareto solutions. Otherwise, return to Step 2.

4. Case study

A typical intersection in Lanzhou City is selected to verify the effect of the proposed method. The intersection has four approaches, and the geometrical characteristic is depicted in Figure 2. This intersection has three phases. The first phase is used to release the straight, right, and left traffic flows in the eastern and western approaches. The second phase is used to release the straight traffic flow in the southern and northern approaches. The third phase is used to release the left traffic flow in the southern and northern approaches. The straight traffic flow in the southern and northern approaches is not subject to signal control. For 10 consecutive days, the traffic flow between 10 and 11 AM was investigated. The average traffic flow of each approach is displayed in Table 1.

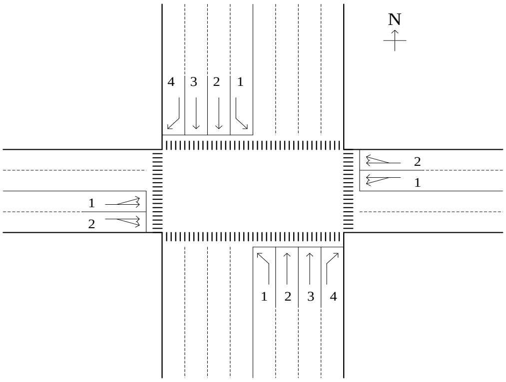


Fig. 2. Geometric configuration of an intersection

On the basis of an actual survey, Shao, C. Q. et al. (2011) analyzed the factors that influence the saturation flow of the intersection. The saturation flow of each lane is set at the intersection as presented in Table 2. Similarly, the parameters t, v_r, a_1, a_2, f_1, f_2, f_3, f_4 are set as 20 *s*, 48 *km/h*, -1.56 *m/s²*, 1.14 *m/s²*, 0.31 *ml/s*, 1.34 *ml/s*, 0.28 *ml/s*, and 0.64 *ml/s*, respectively. The optimization model can be solved by investigating traffic data and setting parameters. However, the NSABC algorithm is selected to solve the model using VC ++6.0 to obtain the Pareto solution set of this model because the proposed model is a typical multi-objective optimization problem.

Table 1. Traffic flow of the lanes (*pcu/h*)

Approach	Eastern		Western		Southern				Northern			
Lane	1	2	1	2	1	2	3	4	1	2	3	4
Traffic volume	295	432	468	324	180	266	274	173	205	263	241	324

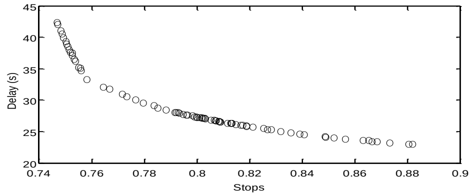
Table 2. Saturation flow of the lanes (*pcu/h*)

Approach	Eastern		Western		Southern				Northern			
Lane	1	2	1	2	1	2	3	4	1	2	3	4
Saturation flow	1368	1402	1488	1539	1454	1656	1656	1506	1505	1620	1620	1420

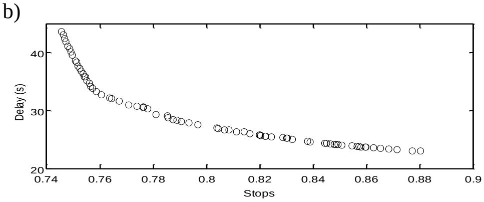
4.1. Analysis of the convergence process

The population size SN = 100 and iteration G = 400 in the ABC algorithm are set. The convergence results are demonstrated in Figure 3(a) after completing the experiment. From the convergence results, the number of non-dominated solutions in the candidate solution is 82, and the dispersion of the solution is uniform. The figure exhibits that the ABC algorithm can solve the model. The results of convergence comparison through various algorithms with different iteration G and iterations are illustrated in Figure 3 to verify the improved convergence efficiency of the ABC algorithm.

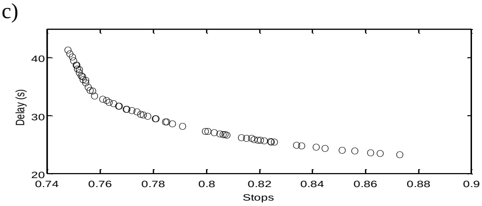
a)



b)



c)



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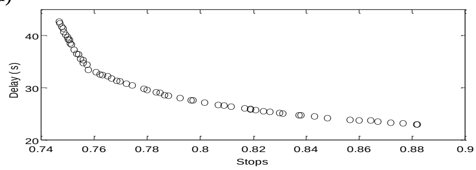

Fig. 3. Convergence results under various SN and G values:
(a) $SN = 100$ and $G = 400$;
(b) $SN = 100$ and $G = 300$;
(c) $SN = 100$ and $G = 200$;
(d) $SN = 100$ and $G = 100$

Figure 3 displays that the ABC algorithm can obtain the optimal solution quickly. In the case of different iterations, the algorithm results and the Pareto frontier are relatively close. The number of non-dominated solutions obtained by the four algorithms is 82, 79, 65, and 61. The number of iterations of the algorithm clearly influences the number of non-dominated solutions, and the effect on the Pareto frontier is unclear. The results demonstrate that the ABC algorithm can effectively solve the model.

4.2. Analysis of the influence of signal cycle on control targets

The control parameters mainly include signal cycle and green signal ratio for the signal control of the isolated intersection. The influence of signal cycle on traffic benefit is more apparent than the green signal ratio. Therefore, this study focuses on analyzing the influence of the signal cycle on each control target. We select the convergence results with SN = 100 and G = 400 for analysis. The correlation between vehicle delay and signal cycle is depicted in Figure 4, and the correlation between vehicle stops and signal cycle is demonstrated in Figure 5.

In Figures 4 and 5, the signal cycle range of the Pareto is set to 70–200 *s*. In this range, the average delay of all vehicles at the intersection increases with the signal cycle given the extended waiting time of vehicles at signalized intersections, and the vehicle stops decrease nearly linearly with the increase in the signal cycle. From the Pareto solution set, the range of vehicle delay is 22–43 *s*, and the vehicle stop range is 0.74–0.88.

Vehicle delay and stops are conflicting control targets, and the effective optimization of timing parameters can achieve a reasonable balance of control targets. The experimental results show that the vehicle delay is brief, but the vehicle stop is lengthy when the signal cycle is short. The vehicle stops decrease continuously, but the vehicle delay increases with the signal cycle. Figures 4 and 5 exhibit that one control target is excellent, but the other target is unfavorable when the signal cycles are 70–90 and 160–200 *s*. A target is slightly improved without regard for a substantial increase in the other target. A change in the signal cycle can lead to improvements in a target when the signal cycle is 90–160 *s*. However, the negative benefits of the other target are acceptable. We can achieve a reasonable balance of vehicle delay and stops through the flexible adjustment of the signal cycle in this range.

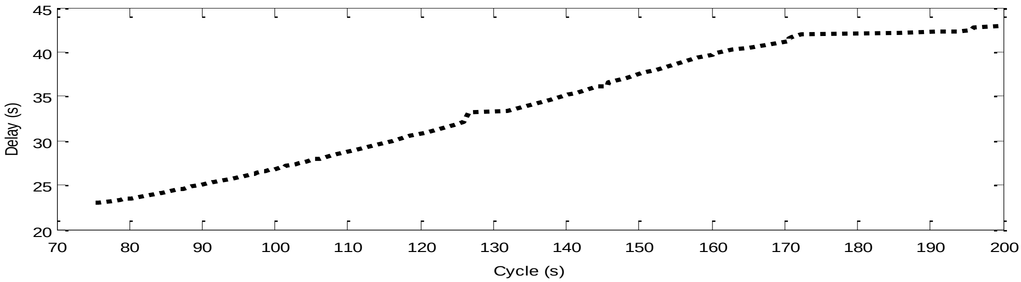

Fig. 4. Correlation between vehicle delay and signal cycle

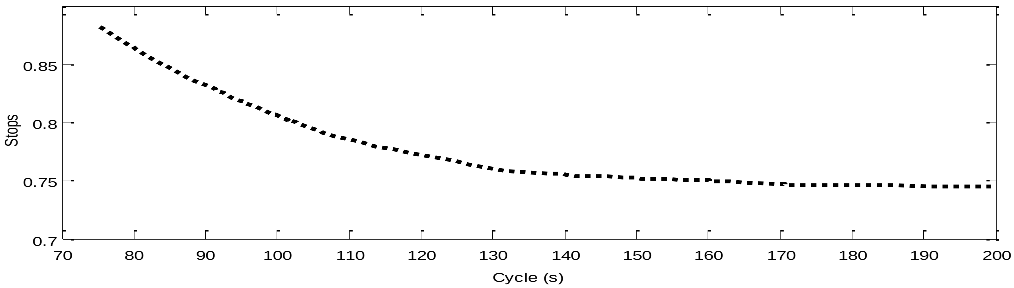

Fig. 5. Correlation between vehicle stops and signal cycle

4.3. Comparison with other algorithms

The proposed algorithm is compared with other algorithms in this section to further illustrate the advantages of the NSABC algorithm. The proposed model is a multi-objective optimization model. The non-dominated sorting genetic algorithm, which is widely used in the traffic field, is applied to solve the NSGA II model. Furthermore, a linear weighted method is used to transform the multi-objective optimization model that is proposed in this study into a single objective optimization model, which is solved by the standard ABC algorithm called ABC. Based on the vehicle delay and stop model proposed by Webster, the signal control targets of an intersection are established in this study. Thus, the Webster signal timing method is selected to compare the signal timing algorithm, which we call Webster. First, we can compare the NSABC with the NSGA II. The population size SN and iteration G in the NSABC and NSGA II are set to 100 and 400, respectively. The crossing and mutation rates of the NSGA II are set to 0.8 and 0.1, correspondingly. The convergence results of the two algorithms are relatively close but exhibit differences. In this study, the convergence of the two algorithms is more dominant than their Pareto solution set. We can conclude that the algorithm has an improved convergence performance. The domination number of the convergence result of an algorithm is determined by the convergence result of another algorithm. The convergence performances of the two algorithms are compared to solve the Pareto front. The comparison results of the two algorithms are summarized in Table 3.

Table 3 presents that the convergence of the NSABC dominates the convergence of the NSGA II, and the dominance result is 14. However, the convergence of the NSGA II dominates the convergence of the NSABC, and the result is 2. The dominance results show that the convergence performance of the NSABC is better than the NSGA II. Thus, selecting the NSABC algorithm to solve the model is reasonable.

Table 3. Comparison results of the two algorithms

Dominance relation	NSABC dominance NSGA II	NSGA II dominance NSABC
Dominance result	14	2

Furthermore, the timing results of the NSABC are compared with ABC and Webster. The population size SN and iteration G of ABC are set to 100 and 400, respectively, because ABC and Webster can only provide a timing result. However, the NSABC provides a non-inferior set. Thus, a reasonable mechanism must be adopted to select reasonable timing results from the solution set. On the basis of the previous analysis, this study selects any solution randomly from the reasonable part of the non-inferior solution set and compares this solution with ABC and Webster. The comparison results are reflected in Table 4.

Table 4. Timing results of the different algorithms (s)

Algorithm	Phase 1	Phase 2	Phase 3	Cycle	Delay	Stops
NSABC	74	24	20	127	31.56	0.76
ABC	63	32	25	114	33.08	0.79
Webster	20	11	9	49	14.53	0.86

Table 4 summarizes the timing results of the three algorithms that demonstrate obvious differences. The Webster method does not consider the constraints of the model. The analysis from the angle of vehicle delay, timing results of the Webster algorithm, NSABC algorithm, and ABC algorithm become increasingly unfavorable. The analysis from the angle of vehicle stops and timing results of the NSABC, ABC, and Webster algorithms also become increasingly unfavorable. Overall, the timing results of the NSABC are relatively reasonable, and the two control targets, namely, vehicle delay and stops, are balanced. The timing results of the Webster algorithm based on the delay minimization of vehicle stops are disregarded. The ABC method considers the two objectives. The timing results are relatively acceptable, but the results are dominated by the NSABC algorithm. Based on the above analysis, we can conclude that the comprehensive traffic benefit obtained by the NSABC algorithm is enhanced.

5. Conclusion

In this study, we considered the delay and stops of vehicles that traverse intersections and proposed a multi-objective optimization model of a fixed-time signal control parameter of the unsaturated intersection. The signal cycle and green time length of each phase were used as decision variables under the constraint of the saturation level of the approach and signal time range, and a typical intersection in Lanzhou City was selected as the case study on the basis of the NSABC algorithm for solving a multi-objective optimization model. The effectiveness of the proposed algorithm was verified from different perspectives on the basis of the actual survey data. The proposed algorithm was verified to possess favorable convergence by setting different parameters of the algorithm. The influence of the signal cycle on the control targets was analyzed on the basis of the convergence results of the algorithm. At a certain range, the vehicle delay will increase with the signal cycle, but the stops will decrease. The vehicle stops increase, whereas the delay will be reduced with the signal cycle. We analyzed the Pareto front and determined that the conflict targets can be effectively balanced only when the signal cycle changes at a reasonable range. However, a target slightly improves without regard for a substantial increase in the other target when the signal cycle is beyond the reasonable range. The proposed algorithm was compared with other algorithms, that is, the NSGA II, ABC, and Webster algorithms. The Pareto frontier obtained by the proposed method is superior to the NSGA II. Furthermore, the proposed algorithm can achieve better comprehensive traffic benefit than the other two algorithms. However, this study disregards the method for formulating the signal timing in accordance with the Pareto set, and only a reasonable range of decisions is provided. Further research will be conducted on the decision-making method in accordance with Pareto sets on the basis of the actual traffic and preference of decision makers.

Acknowledgments

This work was fully supported by the National Nature Science Foundation of China (Grant No. 61364026). Any opinions, findings, conclusions, or recommendations expressed in this paper do not reflect the views of the Government of China in terms of the Innovation and Technology Support Program of the Innovation and Technology Fund.

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