Multi-objective optimization of urban road intersection signal timing based on particle swarm optimization algorithm

Jia, Hongfei; Lin, Yu; Luo, Qingyu; Li, Yongxing; Miao, Hongzhi

2019

Jia, H., Lin, Y., Luo, Q., Li, Y., & Miao, H. (2019). Multi-objective optimization of urban road intersection signal timing based on particle swarm optimization algorithm. Advances in Mechanical Engineering, 11(4), 1-9. doi:10.1177/1687814019842498

https://hdl.handle.net/10356/105979

https://doi.org/10.1177/1687814019842498

Vulnerable Road User Safety and Intelligent Transportation Systems - Research Article

Advances in Mechanical Engineering

Advances in Mechanical Engineering
2019, Vol. 11(4) 1–9
© The Author(s) 2019
DOI: 10.1177/1687814019842498
journals.sagepub.com/home/ade
SAGE

Multi-objective optimization of urban road intersection signal timing based on particle swarm optimization algorithm

Hongfei Jia[1], Yu Lin[1], Qingyu Luo[1], Yongxing Li[2] and Hongzhi Miao[1]

Abstract

Currently, signal control mode is the main control method of urban road intersections. Given that the traffic efficiency of road intersections is mainly affected by signal timing schemes, it is important to optimize signal timing at road intersections. Therefore, signal timing optimization methods of urban road intersections are explored in this work. When optimizing the timing of the signal at the intersections, the selection of optimization targets play an important role. At present, there are multiple objectives considered while designing signal timing scheme, including capacity, delays, and automobile exhaust. However, from the perspective of the traveler, they are more concerned about their own delay while passing intersections. In this work, we propose a novel multi-objective signal timing optimization model with goals of per capita delay, vehicle emissions, and intersection capacity. Considering the problem characteristics of the target problem, a meta-heuristic algorithm combining difference operator, which is based on Particle Swarm Optimization Algorithm, is developed. To test the validity of proposed approach, we applied it to real-world intersection signal timing problems in China. The results show that the optimized signal timing scheme obtained by the proposed algorithm is better than the realistic one. Also, the effectiveness of the developed algorithm is demonstrated by comparing it with other efficient algorithms.

Keywords

Signal timing, per capita delay, multi-objective optimization, PSO

Date received: 25 December 2018; accepted: 14 March 2019

Handling Editor: Yanyong Guo

Introduction

Intersections are the key nodes in urban road network. There are many control forms for different types of road intersections.[1] The traffic efficiency of intersections may be affected by the control types.[2] At present, adaptive control, inductive control, and signal control are three main control methods, and signal control is still the main control mode of intersections; thus, designing a reasonable signal timing scheme is crucial to intersections.[3,4] Signal timing is used to determine the best phase time for intersections. Many signal timing methods have been widely used, for example, Webster model, ARRB model, and HCM2000.[5,6] Usually, the signal timing design is based on the minimum total delay of the vehicle passing through the intersection. In practice, intersection traffic efficiency is

[1]School of transportation, Jilin University, Changchun, China
[2]School of Civil and Environmental Engineering, Nanyang Technological University, Nanyang Avenue, Singapore

Corresponding author:
Qingyu Luo, School of transportation, Jilin University, No. 5988, Renmin Road, Changchun 130022, China.
Email: luoqy@jlu.edu.cn

influenced by many factors, for example, pedestrians and non-motor vehicle, among others.[7,8] To address this issue, researchers have proposed many signal timing approaches with multi-objective.[9]

For isolate intersection under oversaturated conditions, Li et al.[10] formulated an optimization model, in which maximum capacity and minimum queue length were taken as the optimization objectives. Jiao et al.[11] established a mathematical model to find the optimal signal timing schemes of intersection, and the model can apply to real-time traffic signal control system. Based on fuzzy logic, Schmöcker et al.[12] provided an approach to solve signal control, and the effectiveness of the approach was certified by a case application. Considering three factors, that is, mobility, safety, and environment, a methodology of signal timing was developed by Stevanovic et al.[13] Chen et al.[14] proposed a mathematical model, in which traveler delay, stops times, and capacity were taken into account, and an algorithm was designed for solving the proposed model. Lertworawanich et al.[15] presented a new methodology for oversaturated networks to optimize the signal timing controls. Overflow, delays, and maximum capacity of intersections were selected as the optimization objectives. In previous works, many scholars have studied the intersection signal optimization problem and proposed many optimization models. However, researchers rarely consider the travel own delays while building a model. No researcher has built a model with three goals that simultaneously include per capita delay, vehicle emissions, and intersection capacity. In this study, a multi-objective optimization model with the goals of per capita delay, vehicle emission, and capacity was established.

For the multi-objective optimization problem of signal timing, some heuristic or metaheuristic methods were adopted to deal with it, for example, simulated annealing (SA) algorithm, genetic algorithm (GA), and differential evolution (DE) algorithm. Mihăiţă et al.[16] and Yu et al.[17] proposed a nonlinear programming model to solve the signal timing problem, and presented a heuristic GA to solve the proposed model. In order to solve pedestrian phase patterns, a GA was proposed to obtain solutions for signal settings by Ma et al.[18] Sabar et al.[19] developed a memetic algorithm to optimize signal timings and solve traffic signal optimization problems. The algorithm adopted a local search algorithm to improve the exploitation power of GA. To collaborate intersection signal control and traffic flow, Sun et al.[20] established a tri-level programming model, and non-dominated sorting genetic algorithm II (NSGA II) was applied to solve phase. In this article, a metaheuristic approach combining difference operator, based on Particle Swarm Optimization (PSO) Algorithm, is developed.[21] In terms of solution algorithms, researchers have mainly focused on improving the algorithm performance, and few people make works optimized the screening of Pareto solutions. In this work, we make three contributions: (1) propose a signal timing optimization model with the goals of per capita delay, vehicle emission, and capacity; (2) in order to solve a multi-objective signal timing optimization problem, an improved Particle Swarm Optimization Algorithm (IPSO), which combines DE algorithm and PSO algorithm, is proposed; and (3) a dynamic relaxation strategy, which improves convergence and ensures the uniformity of solution set distribution, is proposed. The algorithm is compared with the currently used traffic signal control strategies, and the results show that the algorithm has better control effect. The comparisons and discussions show the competitiveness of the proposed model and meta-heuristic.

The remainder of this article is organized as follows: "Problem statement" section draws a signal timing optimization problem of intersections and develops its mathematical model. "The proposed algorithm" section proposes an efficient meta-heuristic based on PSO algorithm. "Results and discussion" section is devoted to a computational study of the proposed approach by using a case. Finally, "Conclusion" section summarizes our findings and gives some research suggestions for future study.

Problem statement

Intersection signal timing involves determining a series of ordered phases and signal time lengths. Generally, some objectives are used to measure the traffic effectiveness of intersections, such as capacity, vehicle delay, the number of parking, parking rate, queue length, and travel time. With the aggravation of automobile exhaust pollution, environmental factors, such as vehicle emissions and vehicle energy consumption, are introduced by some people when designing a signal timing for intersections.[22] Different objectives reflect different goal of intersection signal control.[23] At present, the signal timing methods considering only the total vehicle delay have gradually lost recognition.[24] Many researchers constructed multi-objective mathematical models to obtain the better signal schemes. However, to the best of our knowledge, there are few papers reported to consider per capita delay and vehicle emission simultaneously. In addition, multi-objective optimization problem for intersection signal timing can regard as NP-complete.[25] This makes it a complex combinatorial optimization problem. Thus, multi-objective optimization problem for intersection signal timing is more challenging. At present, the signal timing methods only considering the total vehicle delay have gradually lost recognition.[26] Thus, we considered the per capita delay as one of the optimization objectives as well as presented a new per capita delay model that can better describe per capita delay. Different objectives reflect different goals of intersection signal control. The main purpose of signal optimization is to improve the capacity of intersections, which means the intersection capacity must be maintained to traffic requirement. The increase in vehicle exhaust pollution has made us realize that we must balance environmental pollution when ensuring the capacity of intersections. Since the vehicle emission objective is considered, for the first time, we proposed a novel multi-objective signal timing optimization model that contains the above three targets and embodies the most urgent problem to solve while optimizing intersection signal timing.

Constraints of the model

Cycle time constraint. The sum of the green time and the loss time of each phase should be equal to the cycle time. The formula is expressed as:

$$\sum_{i}^{n} (g_i + L_i) = C \tag{1}$$

Minimum green time constraint. In general, the minimum green time is the shortest passing time of pedestrians at the intersection, and the minimum green time depends on the intersection design and pedestrian walking speed. The minimal value is given here, which can be expressed as:

$$g_i > g_{i-min} \tag{2}$$

Cycle length constraint. If cycle time is too short, it will affect vehicles passing the intersections, and it will increase the delay of vehicles if it is too long. Considering the rationality of signal timing, the cycle time is restricted to a range. The constraint can be written as:

$$C_{min} \leqslant C \leqslant C_{max} \tag{3}$$

The mathematical model

The notations used in our model are shown as follows:

i, j	phase/line index at intersections, $i, j = 1,2,\ldots, N$;
V_i	the number of vehicles of ith phase;
D	the total vehicle delay in a signal cycle;
D^e	the per capita delay in a signal cycle;
B_i	the number of the bus at ith phase;
P_i	the number of small cars at ith phase;
Φ_B	the average passenger rate of buses;
Φ_P	the average passenger rate of cars;
g_i	the effective green time of ith phase;
λ_i	the green ratio of the ith phase, $\lambda_i = g_i/C$;
q_{ij}	the traffic volume of jth approach line at ith phase;
C_{ij}	the capacity of jth approach line at ith phase;
x_{ij}	the traffic saturation of jth approach line at ith phase, $x_{ij} = q_{ij}/C_{ij}$;
S_{ij}	the lane saturation flow of jth approach line at ith phase;
y_{ij}	the saturation flow rate $y_{ij} = q_{ij}/S_{ij}$;
N_{ij}	the number of average excess retention vehicle in unit time of jth approach line at ith phase;
L_0	the approach length of the intersection (km), $L_0 = 75$m;
L_i	the loss time for the corresponding phase;
g_{i-min}	the minimum green time, $g_{i-min} = 10$s;
C	the signal cycle;
C_{max}	the maximum cycle length, $C_{max} = 200$ s;
C_{min}	the minimum cycle length for the intersection, $C_{min} = 15n$, n is the number of the intersection phase;
q_i	the arrival traffic of ith phase;
D_i	the average delay of vehicles of ith phase;
Q_i	the capacity of the approach line at ith phase;
$E(C, g)$	the vehicle emission model;
$D^e(C, g)$	the per capita delay model;
$Q(C, g)$	the intersection capacity model;
EF^{PCU}	Standard car unit emission factor, $EF^{PCU} = 5\text{g}/(\text{pcu} \cdot \text{Km})$;
EFI^{PCU}	Standard car unit idle emission factor, $EFI^{PCU} = 45\text{g}/(\text{pcu} \cdot \text{h})$.

(continued)

Delay model. In this work, the per capita delay is adopted as the optimization objective of intersection delay, which can be written as:

$$D = \sum_{i}^{n} V_i D_i \tag{4}$$

$$D^e = \sum_{i}^{n} \frac{D}{B_i \cdot \phi_B + P_i \cdot \phi_P} \tag{5}$$

where D_i is the average delay of each vehicle at ith phase. The ARRB model is used to obtain D_i,[27] which can be written as:

$$D_i = \sum_{j} \frac{c(1-\lambda_i)^2}{2(1-y_{ij})} + \sum_{j} \frac{N_{ij} x_{ij}}{q_{ij}} \tag{6}$$

$$N_{ij} = \begin{cases} \frac{C_{ij}}{4}\left[(x_{ij}-1) + \sqrt{(x_{ij}-1)^2 + \frac{12(x_{ij}-x_{ij0})}{C_{ij}}}\right], x_{ij} > x_{ij0} \\ 0, x_{ij} < x_{ij0} \end{cases} \tag{7}$$

$$\text{where}\, x_{ijo} = 0.67 + \frac{s_{ij} g_i}{600} \tag{8}$$

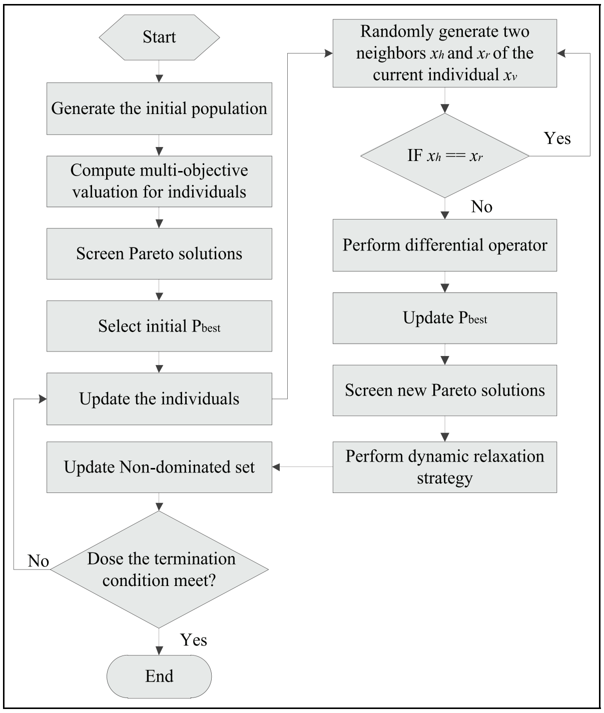

Figure 1. Flowchart of IPSO.

Traffic capacity. The capacity of intersection equals to the sum of each phase capacity, which can be written as:

$$Q_i = \sum_j s_{ij}\left(\frac{g_i}{C}\right) \tag{9}$$

$$Q = \sum_i^n Q_i \tag{10}$$

where Q represents the capacity of the intersection.

Vehicle emission model. The main pollutants of motor vehicle exhaust emission include carbon monoxide, hydrocarbons, and nitrogen oxides, in which the proportion of carbon monoxide, nitrogen oxides, and hydrocarbons is 70%, 15%, and 15%, respectively.[28,29] Thus, the vehicle emission is represented by carbon monoxide (CO).[30] The CO calculation is formulated as:

$$E_{CO} = \sum_i^n \left(EF_{co}^{PCU} \times q_i \times L_0 + \frac{1}{3600}\left(EF_{co}^{PCU} \times q_i \times D_i\right)\right) \tag{11}$$

Multi-objective optimization model. By considering the optimal Pareto solutions under multiple constraints, we formulate a mathematical programming model which can be written as:

$$\min F(C,\ g) = \min[E(C,\ g),\ D^e(C,\ g),\ -Q(C,\ g)] \tag{12}$$

$$\text{s.t}\begin{cases} \sum_i^n (g_i + L_i) = C \\ g_i > g_{i-min} \\ C_{min} \leqslant C \leqslant C_{max} \end{cases} \tag{13}$$

where negative expression symbol before $Q(C,\ g)$ not meaning the value of $Q(C,\ g)$ is negative, which expresses Pareto relationship between $Q(C,\ g)$ and the other two goals.

The proposed algorithm

PSO is a population-based stochastic optimization technique proposed by Kennedy and Eberhart.[31] PSO is inspired by mimics of the swarm behavior of insects, beasts, birds, and fish. These swarms search for food in a cooperative way, in which each member of the swarm changes its search pattern by learning from its own and other members' experience. At present, PSO algorithm has been widely used in optimization problems in various fields due to its good optimization ability. DE algorithm is an efficient global optimization algorithm, which is a group-based heuristic search algorithm.[32] Each individual in the group corresponds to a solution vector. The basic idea of the algorithm is to generate a new individual by summing the vector difference between any two individuals in the population and the third individual, and then compare the new individual with the corresponding individual in the contemporary population to choose the better one. In order to utilize the advantages of the two algorithms, an IPSO is proposed to handle the signal timing problem in this section. The improved PSO is combined with DE operator for population update, and a dynamic relaxation strategy is introduced for ensuring the uniformity of solution set distribution.[33,34] Figure 1 describes the main process of the proposed algorithm. More detailed descriptions are given as follows.

Solution encoding and initialization

Designing an effective encoding method plays an important role in metaheuristic algorithm, which decides how to perform solutions and provides more information. Moreover, a good solution performance can simplify decoding process and decrease algorithm running time. In our algorithm, an integer encoding was adopted for individual coding, where an individual expressed by coding is $X = (C, g_1, g_2, g_3, \ldots, g_n)$. X represents the signal timing scheme, in which each element corresponds to signal cycle or green time, that is, $C; g$ represents the signal cycle, green time, respectively.

Thus, we can obtain the initial population, where initial population is expressed as:

$$\text{Indi} = \begin{bmatrix} X_1 \\ X_2 \\ \cdots \\ X_{mn} \end{bmatrix} = \begin{bmatrix} C_{11} & g_{12} & \cdots & g_{1n} \\ C_{21} & g_{22} & \cdots & g_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ C_{m1} & g_{m2} & \cdots & g_{mn} \end{bmatrix} \tag{14}$$

Population update

The basic PSO algorithm produces new particles by using speed and position update of each particle. In the proposed algorithm, the hybrid difference operator is used to update individuals, which combines differential operator and inertia weight. The hybrid difference operator is formulated as:

$$X_v(t) = \lceil X_v(t) + w \times \text{rand} \times [(P_{best} - X_v(t)) + (X_h(t) - X_r(t))] \rceil \tag{15}$$

where w represents the inertia weight; $X_m(t)$, $X_h(t)$, and $X_r(t)$ represent different individuals of tth generation, and $v, h, r = 1, 2, \ldots, Popsize, v \neq h \neq r$; P_{best} represents the best individual; rand represents the random number function; and $\lceil\rceil$ represents integer function. The inertia weight is formulated as:

$$w = w_{max} - (w_{max} - w_{min}) \times \frac{iter}{MaxIt} \tag{16}$$

where w_{max} and w_{min} represent the maximum inertia factor and minimum inertia factor, respectively. The value of w_{max} and w_{min} is defined as 1.2 and 0.1. *MaxIt* and *iter* are the maximum evolution times and current evolution times.

Relaxation domination strategy

The method can provide sufficient signal timing schemes for the intersection. However, how to gain Pareto frontier fast plays a key role in evolutionary multi-objective optimization. Based on the Pareto dominance relation, we can compare the two solutions by using the dominant information.[35,36] In this study, many similar signal timing schemes are obtained through the basic domination relations. In order to improve convergence and ensure the uniformity of solution set distribution, a dynamic relaxation strategy is proposed, in which dynamic relaxation factor is used to relax the basic domination relation. Dynamic relaxation factor is formulated as:

$$A_o = \begin{cases} A_o + \dfrac{\text{Max}(PD_o) - \text{Min}(PD_o)}{Num - 1}, & \text{if } Num > Narc \\ e^{-7}, & \text{if } Num < Narc \end{cases} \tag{17}$$

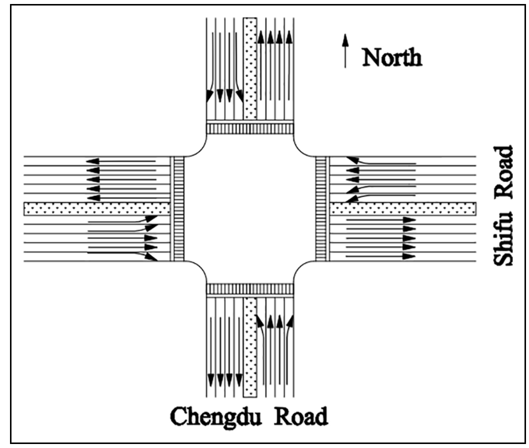

Figure 2. Intersection geometry.

$$PD_o = |Val_{m,l} - Val_{m,l+1}| \tag{18}$$

where $m = 1,2,\ldots, M$; $l = 1,2,\ldots, Num$; A_o is dynamic relaxation factor of object o; PD_o is the distance set between neighbor solution of non-inferior solution for object o; $Val_{m,l}$ is the value of mth non-inferior solution for object o; Max is the maximum value function; Min is the minimum value function; M is the number of object; *Num* is the number of non-inferior solution; and *Narc* is the set scale of dominating solution.

Results and discussion

Case design

To check the efficiency of the proposed algorithm, the algorithm is applied to a simple four-way intersection in Jinzhou, China. The layout of intersection is shown in Figure 2.

The intersection has four phases; phase diagram is shown in Table 1. After investigation, the traffic volume of intersection is shown in Table 2, and figures in brackets denote the number of lanes. The single lane saturation flow rate of vehicle is 1200 veh/h in this study.

Analysis of calculating results

The proposed algorithm is implemented in MATLAB R2012a and runs on an AMD E2-3000M APU (1.80 GHz/4.00G RAM) PC with a Windows 7 operating system. In the proposed algorithm, the size of archive set is set to 10, that is, the number of Pareto frontier which can be got in each run is 10. The Pareto solutions are shown in Table 3 in the four runs. The first column denotes the runs, and the second column shows the Pareto optimal solutions corresponding to each run. The third one is the signal timing plans. The next three columns show f_1 (per capita delay), f_2 (capacity), and f_3 (vehicle CO emission) values of the Pareto solutions, respectively. The seventh column provides the computational time for getting the solutions.

Table 1. Intersection signal phase diagram.

Signal phase				
Phase sequence	First phase	Second phase	Third phase	Last phase

Table 2. Traffic volumes of the intersection.

Entrances	Lanes	Motor vehicle flow (veh/h)	
North entrance	Straight (2) Right Left	552 348 252	1152
South entrance	Straight (2) Right Left	516 132 108	756
East entrance	Straight (2) Right Left (2)	564 252 216	1032
West entrance	Straight (2) Right Left (2)	672 180 444	1296

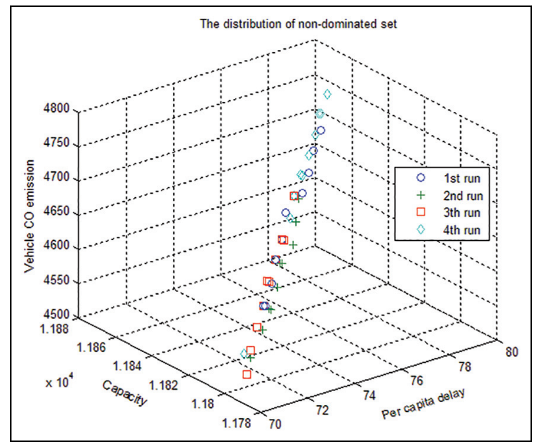

Figure 3. Space distribution of Pareto solutions.

Figure 3 shows space distribution of Pareto solutions in the four runs. From Figure 3, we can know Pareto solutions is highly similar in four runs, which denotes that the presented algorithm performance is stable. Table 4 shows the comparison results with the realistic signal timing schemes. The proposed algorithm scheme is selected from Table 3 to make an intuitive contrast, and it just is a representative of the Pareto solution. From Table 3, we can know that the range of values worth of f_1, f_2, and f_3 are stable in an interval, that is, $f_1 \in [70–80]$, $f_2 \in [4550–4750]$, and $f_3 \in [11{,}800–11{,}899]$. From Table 3 and Table 4, it can be seen that the vehicle emission and the per capita delay are decreased to a certain extent compared with the existing timing scheme in a signal cycle. In addition, the total capacity decreases slightly due to the decrease of the signal cycle.

To further illustrate the effectiveness of the algorithm, we executed NSGA-II and genetic algorithm direct search toolbox (GADST) for the case.[37] The GADST is the GA toolbox which included a gamultiobj function for solving the multi-objective optimization. The compared results between three algorithms of different *Popsize* (population size) and g_{max} (the maximum iteration count) are given in Table 5. It is noted that the size of Pareto frontier is 10 in three different algorithms. The last column lists the evaluation index of Pareto frontier spatial distribution which is designed to show the diversity of Pareto solution set.[38] Evaluation index is formulated as

$$S = \sqrt{\frac{1}{|PF|}\sum_{m=1}^{|PF|}\left(d_{ed} - d_{avg}\right)^2} \quad (19)$$

where S represents evaluation index of Pareto frontier spatial distribution; PF is the Pareto optimal solution vector; d_{ed} is the Euclidean distance between neighbor solutions; and d_{avg} is the average value of d_{ed}.

From Table 5, the following conclusions can be obtained that refer to running time and S values in the algorithms.

1. The diversity and uniformity solutions of the Pareto solution obtained from the proposed algorithm is better than NSGA-II and GADST;
2. The computational time of our algorithm is superior to GADST and NSGA-II under the same hardware environment.

Based the above case analysis, the proposed algorithm is workable and efficient to deal with a signal timing optimization problem for urban road intersections.

Table 3. Produced Pareto solutions of the proposed algorithm.

Runs	No.	The signal timing plans	f_1	f_2	f_3	Used time (s)
1	1	{25,20,23,14,102}	78.80	4706	11861.68	1.36
	2	{24,19,22,14,99}	76.92	4655	11847.22	
	3	{24,19,23,14,100}	77.54	4672	11851.62	
	4	{25,20,22,14,101}	78.18	4689	11857.32	
	5	{23,19,20,13,95}	74.17	4615	11826.11	
	6	{23,20,21,13,97}	75.43	4656	11837.10	
	7	{22,18,20,13,93}	72.90	4576	11816.0	
	8	{23,18,20,13,94}	73.52	4596	11819.47	
	9	{23,19,21,13,96}	74.79	4633	11830.44	
	10	{23,18,19,13,93}	72.91	4576	11815.18	
2	1	{24,18,20,13,95}	74.15	4615	11823.0	1.29
	2	{25,19,21,13,98}	76.03	4669	11837.45	
	3	{25,18,21,13,97}	75.39	4652	11830.87	
	4	{23,17,20,13,93}	72.88	4576	11812.87	
	5	{24,17,20,13,94}	73.51	4596	11816.42	
	6	{25,18,19,13,95}	74.17	4615	11822.34	
	7	{23,17,19,13,92}	72.28	4557	11808.56	
	8	{25,17,21,13,96}	74.76	4633	11824.32	
	9	{24,17,19,13,93}	72.90	4576	11812.14	
	10	{23,17,18,12,90}	70.76	4551	11795.35	
3	1	{24,19,20,13,96}	74.79	4633	11829.61	1.28
	2	{23,19,21,13,96}	74.79	4633	11830.44	
	3	{23,19,20,13,95}	74.17	4615	11826.11	
	4	{22,19,20,13,94}	73.55	4596	11822.66	
	5	{24,20,21,13,98}	76.05	4669	11840.56	
	6	{22,18,20,13,93}	72.90	4576	11816.0	
	7	{23,19,19,13,94}	73.56	4596	11821.83	
	8	{22,18,18,13,91}	71.68	4536	11807.41	
	9	{22,18,19,13,92}	72.29	4557	11811.68	
	10	{22,17,18,13,90}	71.03	4516	11800.77	
4	1	{24,20,21,13, 98}	76.05	4669	11840.56	1.31
	2	{26,21,23,13,103}	79.18	4753	11862.89	
	3	{25,20,21,13,99}	76.68	4687	11844.07	
	4	{26,21,22,13,102}	76.67	4687	11844.90	
	5	{24,20,22,13,99}	78.56	4737	11858.56	
	6	{25,20,22,13,100}	77.29	4704	11848.39	
	7	{25,20,23,13,101}	77.91	4721	11852.76	
	8	{25,21,23,13,102}	78.56	4737	11859.39	
	9	{24,19, 21,13,97}	75.41	4652	11833.92	
	10	{21,18,19,12,90}	70.78	4551	11799.26	

Table 4. Comparison results between proposed method and current signal scheme.

	The signal timing scheme					Per capita delay (s)	Capacity (pcu/h)	Vehicle emission (g/h)
	C	g_1	g_2	g_3	g_4			
Current signal scheme	161	34	30	41	36	121.93	4889	12,237.12
The proposed algorithm	100	25	20	22	13	77.29	4704	11,848.39

Conclusion

This work studies a multi-objective optimization issue of intersection signal timing schemes design and established a mathematics model for it. In the proposed model, per capita delay, traffic capacity, and vehicle emissions as optimization goals are presented. An efficient meta-heuristic based on PSO is proposed to handle the model. To cope with the diversity of algorithm

Table 5. Comparison results in different algorithms.

No.	g_{max}	*Popsize*	Method	Running time (s)	S
1	50	50	IPSO	0.38	95.34
			NSGA-II	2.86	199.48
			GADST	5.43	363.14
2	50	100	IPSO	0.71	86.56
			NSGA-II	3.68	172.99
			GADST	22.01	378.93
3	100	50	IPSO	0.77	93.02
			NSGA-II	2.62	191.05
			GADST	7.28	349.83
4	100	100	IPSO	1.29	73.80
			NSGA-II	6.72	176.07
			GADST	25.72	391.30

IPSO: improved Particle Swarm Optimization; NSGA-II: non-dominated sorting genetic algorithm II.

and the uniformity of archive set, a difference operator and a dynamic relaxation strategy are developed. The algorithm is tested by using an actual case, and the results show that the presented algorithm can obtain signal timing schemes. The performance is superior to the current signal scheme obviously. In addition, the effectiveness of the proposed algorithm was verified by comparing it with GADST and NSGA-II, and the optimal/near optimal Pareto solution can be obtained in reasonable time. In this work, the traffic situation of urban road intersections will have a significant improvement by applying this method. In this approach, traffic emission issues and traffic control strategies are combined, which can provide technical support for improving the service level of the entire road transportation system and promote the sustainable development of urban transportation.

Despite the good performance of the developed approach been certified, some limitations are existing. This article only studies the regular traffic flow, and mixed traffic flow may need to be taken into consideration. Besides, the algorithm needs to be further applied for a vehicle road collaborative environment. All of them are future efforts for us.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by the Science Technology Development Project of Jilin Province (Grant No. 20190303124SF) and Graduate Innovation Fund of Jilin University (Grant No. 101832018C004).

ORCID iD

Yu Lin https://orcid.org/0000-0002-4866-6325

References

1. Araghi S, Khosravi A and Creighton D. A review on computational intelligence methods for controlling traffic signal timing. *Expert Syst Appl* 2015; 42: 1538–1550.
2. Khamis MA and Gomaa W. Adaptive multi-objective reinforcement learning with hybrid exploration for traffic signal control based on cooperative multi-agent framework. *Eng Appl Artif Intel* 2014; 29: 134–151.
3. Alhajyaseen WKM, Ratrout NT, Assi KJ, et al. The integration of dynamic lane grouping technique and signal timing optimization for improving the mobility of isolated intersections. *Arab J Sci Eng* 2016; 42: 1–12.
4. Li X. The symmetric intersection design and traffic control optimization. *Transport Res C: Emer* 2018; 92: 176–190.
5. Han K, Liu H, Gayah VV, et al. A robust optimization approach for dynamic traffic signal control with emission considerations. *Transport Res C: Emer* 2016; 70: 3–26.
6. Roshandeh AM, Levinson HS, Li Z, et al. New methodology for intersection signal timing optimization to simultaneously minimize vehicle and pedestrian delays. *J Transp Eng* 2014; 140: 04014009.
7. Zhou X, Feng M, Li H, et al. Optimization of signal timing at critical intersections for evacuation. *Procedia Engineer* 2016; 137: 334–342.
8. Ghanbarikarekani M, Sohrabi S and Vefghi A. Optimization of signal timing of intersections by internal metering of queue time ratio of vehicles in network scale. *Promet* 2016; 28: 205–214.
9. Yu D, Tian X, Xing X, et al. Signal timing optimization based on fuzzy compromise programming for isolated signalized intersection. *Math Probl Eng* 2016; 2016: 1682394.
10. Li Y, Yu L, Tao S, et al. Multi-objective optimization of traffic signal timing for oversaturated intersection. *Math Probl Eng* 2013; 2013: 182643.
11. Jiao P, Li R and Li Z. Pareto front-based multi-objective real-time traffic signal control model for intersections using particle swarm optimization algorithm. *Adv Mech Eng* 2016; 8: 1–15.
12. Schmöcker JD, Ahuja S and Bell MGH. Multi-objective signal control of urban junctions framework and a London case study. *Transport Res C: Emer* 2008; 16: 454–470.
13. Stevanovic A, Stevanovic J, So J, et al. Multi-criteria optimization of traffic signals: mobility, safety, and environment. *Transport Res C: Emer* 2015; 55: 46–68.
14. Chen X, Qian D and Shi D. Multi-objective optimization method of signal timing for the non-motorized transport at intersection. *J Transport Syst Eng Inform Technol* 2011; 11: 106–111.
15. Lertworawanich P, Kuwahara M and Miska M. A new multiobjective signal optimization for oversaturated networks. *IEEE T Intell Transp* 2011; 12: 967–976.
16. Mihăiţă AS, Dupont L and Camargo M. Multi-objective traffic signal optimization using 3D mesoscopic simulation and evolutionary algorithms. *Simulat Model Pract Theor* 2018; 86: 120–138.

17. Yu H, Ma R and Zhang H. Optimal traffic signal control under dynamic user equilibrium and link constraints in a general network. *Transport Res B: Meth* 2018; 110: 302–325.
18. Ma W, Liao D, Liu Y, et al. Optimization of pedestrian phase patterns and signal timings for isolated intersection. *Transport Res C: Emer* 2015; 58: 502–514.
19. Sabar NR, Le MK, Chung E, et al. A memetic algorithm for real world multi-intersection traffic signal optimisation problems. *Eng Appl Artif Intel* 2017; 63: 45–53.
20. Sun Z, Lu H and Qu W. Tri-level programming model for combined urban traffic signal control and traffic flow guidance. *J Cent South Univ* 2016; 23: 2443–2452.
21. Kennedy J. Particle swarm optimization. In: Sammut C and Webb GI (eds) *Encyclopedia of machine learning*. Boston, MA: Springer, 2011, pp.1942–1948.
22. Manolis D, Diakaki C, Papamichail I, et al. Simulation investigations of the coordinated traffic-responsive signal control strategy TUC with actuation at the local junction level. *Eur Transport Res Rev* 2018; 10: 25.
23. Ma CX, Hao W, Wang AB, et al. Developing a coordinated signal control system for urban ring road under the vehicle-infrastructure connected environment. *IEEE Access* 2018; 6: 52471–52478.
24. Moghimi B, Safikhani A, Kamga C, et al. Cycle-length prediction in actuated traffic-signal control using ARIMA model. *J Comput Civil Eng* 2018; 32, https://ascelibrary.org/doi/10.1061/%28ASCE%29CP.1943-5487.0000730
25. Costa BC, Leal SS, Almeida PE, et al. Fixed-time traffic signal optimization using a multi-objective evolutionary algorithm and microsimulation of urban networks. *T I Meas Control* 2016; 40: 1092–1101.
26. Ma CX, He RC and Zhang W. Path optimization of taxi carpooling. *PLoS ONE* 2018; 13: 0203221.
27. Akçelik R and Rouphail NM. Estimation of delays at traffic signals for variable demand conditions. *Transport Res B: Meth* 1993; 27: 109–131.
28. Webster FV. Traffic signals. *Road Res Tech Paper* 1966; 56: 206–207.
29. Ma CX, Hao W, Xiang W, et al. The impact of aggressive driving behavior on driver injury severity at highway-rail grade crossings accidents. *J Adv Transport* 2018; 2018: 9841498.
30. Li X, Li G, Pang SS, et al. Signal timing of intersections using integrated optimization of traffic quality, emissions and fuel consumption: a note. *Transport Res D: Tr E* 2004; 9: 401–407.
31. Kennedy J and Eberhart R. Particle swarm optimization. In: *Proceedings of the 1995 IEEE international conference on neural networks*, Perth, WA, Australia, 27 November–1 December 1995, pp.1942–1948. New York: IEEE.
32. Price K and Price K. Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces. *J Global Optim* 1997; 11: 341–359.
33. Zhang X, Gao L, Wen L, et al. A hybrid algorithm based on tabu search and large neighbourhood search for car sequencing problem. *J Cent South Univ* 2018; 25: 315–330.
34. Siala M, Hebrard E and Huguet MJ. A study of constraint programming heuristics for the car-sequencing problem. *Eng Appl Artif Intel* 2015; 38: 34–44.
35. Li M, Xue H and Shi F. Optimization of traffic signal parameters based on distribution of link travel time. *J Cent South Univ* 2017; 24: 432–441.
36. Lin Y, Jia H, Yang Y, et al. An improved artificial bee colony for facility location allocation problem of end-of-life vehicles recovery network. *J Clean Prod* 2018; 205: 134–144.
37. Deb K, Pratap A, Agarwal S, et al. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE T Evolut Comput* 2002; 6: 182–197.
38. Lu YX. *Improvement and application research of NSGA-II multi-objective optimization algorithm*. Taiyuan, China: Taiyuan University of Technology, 2017.