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Intersection Traffic Control Based on Multi-Objective Optimization

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ABSTRACT Currently, most traffic control methods at intersections rely on the control of signal lights. However, most signal lights operate in the traditional fixed timing mode, which cannot adjust the timing based on the time-varying traffic flow. To solve the problem, this paper constructs a signal timing control model to optimize road capacity, delay time and the number of stops at the intersections, under the following constraints: cycle time, effective green light time and the maximum number of vehicles in each direction of intersection. To solve the model, the standard dragonfly algorithm (DA) was improved by a hybrid mutation operator, which ensures the diversity of solution set. The proposed model and algorithm were compared with the Webster model through simulations in an actual scene and on a virtual platform. The comparison fully proves the advantages of our model and algorithm.

INDEX TERMS Traffic control, multi-objective optimization, dragonfly algorithm (DA), signal timing, intersection.

I. INTRODUCTION

In recent years, traffic overload has become a thorny problem in urban road system. The problem can be partly attributed to the increase of motor vehicles and the lag of infrastructure. However, the fundamental reason lies in the lack of scientific control of traffic, especially that at intersections.

In the urban road network, there are two kinds of intersections: those with signal lights and those without. For an intersection with signal lights, the key of traffic control is the dynamic signal timing based on accurate prediction of traffic flow; for an intersection without signal lights, the traffic control mainly aims to effectively prevent collisions based on precise positions of vehicles [1]–[2].

Currently, the traffic control at intersections heavily relies on the control of signal lights. Most signal lights operate in the traditional fixed timing mode. The most prominent defect with this mode is the inability to adjust the timing based on the time-varying traffic flow, which results in the waste of road resources. To overcome the defect, this paper constructs a multi-objective timing optimization model, and introduces an intelligent algorithm to quickly find a high-quality solution to the model.

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Most of the efficient signal control models are improved versions of classical methods, such as Transport Road Research Laboratory (TRRL) method, the Highway Capacity Manual (HCM) method and the Australian Road Research Board (ARRB) method [3]–[5]. These methods provide a good theoretical basis for analyzing the relationship between signal timing and the indices of intersection performance. But they also face several limitations in practical application. The TRRL and HCM only apply to simple traffic scenarios, for they merely consider vehicle delay and calculate the best cycle through multiple approximations. The ARRB introduces the number of stops to illustrate the vehicle delay, but does not quantify the stop compensation coefficient. Compared with the existing research, this paper proposed a multi-objective programming dynamic timing model based on accurate traffic flow prediction, and intelligent algorithm was used to solve it. It is conducive to the intelligent traffic lights to sense the traffic flow at the intersection in time. The proposed algorithm in this paper can well realize the collision avoidance between vehicles at signal less intersections.

II. LITERATURE REVIEW

The signal timing at intersection can be realized through single-point control and collaborative control. Henry *et al.* [6] created an optimization model to minimize the vehicle delay at two-phase controlled intersections, which is the first optimization model for signal timing at intersections. Jiang *et al.* applied fuzzy control to the signal timing at intersections, and designed a fuzzy signal controller, which mainly selects the fuzzy control rules from numerous rules [7]–[9]. Tan *et al.* [10] proposed a timing rolling optimization algorithm to minimize the vehicle delay, paving the way to long-term global optimization of signal control parameters at intersections.

Lin *et al.* [11] constructed a signal priority procedure model to minimize the vehicle delay and the weighted average number of vehicles stops. Sun *et al.* [12] studied the oversaturation state of intersections, and constructed an optimization model that minimizes the waiting time of the first vehicle in the waiting queue. Liu and Xu [13] set up a simple calculation model of the main line phase difference of intersections, which requires the following inputs: the green signal ratio, the driving time per vehicle, the distance between intersections, and the length of the public cycle.

Chen *et al.* [14] proposed a planning model to optimize green light time, vehicle speed, intersection distance and cycle, and used the model to maximize the signal timing parameters. Talab *et al.* [15] integrated the fuzzy processing ability of fuzzy control and the self-learning ability of neural network, and built a signal timing model of main intersections, which effectively improves the real-time performance and accuracy of the control system. Kou *et al.* [16] applied the multi-agent technology to the signal timing model of the main intersections, creating a multi-agent timing model.

Song *et al.* [17] investigated the internal mechanism of the vehicle delay at intersections, and modelled the relationship between vehicle delay and adjacent phase difference. Hao *et al.* [18] proposed a departure-arrival model of intersections with cooperative control, solved it with genetic algorithm (GA), and thus realized the cooperative control of phase difference on urban trunk roads. With the aid of the GA, Nguyen *et al.* optimized the rules of the fuzzy controller of traffic signals at intersections, and achieved the optimal signal timing [19], [20].

Considering the normal distribution of traffic speed in road sections, Zhou and Wang [21] designed a parameter setting strategy for phase difference based on the theory of probability, with the aim to minimize the number of stops and the delay time. Under the constraints of phase saturation, effective green light time and total signal cycle time, Lin *et al.* [22] proposed a nonlinear function model of signal timing for a single intersection in urban area, in an attempt to minimize the mean delay time and the number of stops; the proposed model was separately solved by the traditional GA and GA-based simulated annealing (SA) algorithm; the results show that the two algorithms can effectively shorten the vehicle delay.

III. MULTI-OBJECTIVE OPTIMIZATION MODEL OF TRAFFIC LIGHTS AT INTERSECTIONS

A. MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM

In an ideal situation, we want to control the signal of the intersection so that all indicators can reach the optimal value, but in reality, it is often impossible, because there may be some conflict between different indicators, so we must make a choice.

Multi-objective evolutionary algorithm is a stochastic search algorithm mimicking the natural selection and evolution of living beings [23]. The algorithm can strike a perfect balance between all optimization objectives.

In multi-objective optimization, there is no single optimal solution to maximize all objective functions under given constraints, but a set of Pareto optimal solutions. For practical problems, some of the Pareto optimal solutions must be selected according to the understanding of the problem and the preference of decision makers.

The following concepts should be defined first before solving multi-objective optimization problems:

(1) Pareto dominance
Solution x^0 Pareto dominates $x^1 (x^0 > x^1)$ if and only if:

$$\begin{cases} f_i\left(x^0\right) \geq f_i\left(x^1\right) i = 1, 2, \ldots, M \\ f_i\left(x^0\right) > f_i\left(x^1\right) \exists i \in \{1, 2, \ldots, M\} \end{cases}$$

(2) Pareto optimal solution
Solution x^0 is a Pareto optimal solution, if and only if $\neg\exists x^1 \colon x^1 > x^0$.

(3) Pareto optimal solution set
Pareto optimal solution set is the set of all Pareto optimal solutions $P_s = \left\{x^0 \mid \neg\exists x^1 > x^0\right\}$.

(4) $\varepsilon-$dominance
For $x^1, x^2 \in D, x^1$ has $\varepsilon-$dominance over x^2 $(x^1 > \varepsilon^{x^2})$, if and only if $f\left(x^1\right) - \varepsilon_i \leq f(x^2)$, $\forall i \in$ $1, 2, \ldots, M$ and $\exists i, f\left(x^1\right) - \varepsilon_i < f(x^2)$.

(5) $\varepsilon-$similar Pareto set
Set F_s is an $\varepsilon-$similar Pareto set of F, if and only if there exists $\exists x' \in F_s$ for $\forall x \in F$.

(6) $\varepsilon-$Pareto solutions set
Set F^{ε} is the $\varepsilon-$Pareto solutions set of set F, if and only if $F^{\varepsilon} \subseteq P_s$.

In an ideal situation, the intersection signals should be controlled to optimize the values of all indices. However, this is often impossible in reality, for some indices are conflicting with each other.

In general, the evaluation indices of intersection performance fall into three categories: road utilization rate, travel time efficiency and environmental benefit. The signal timing scheme is greatly affected by the actual capacity of the intersection and the actual obstruction degree.

Therefore, this paper attempts to optimize the signal timing scheme of unsaturated traffic flow at intersections by multi-objective evolutionary algorithm, under the constraints of cycle time, effective green light time and the maximum number of vehicles in each direction of intersection. The optimization objectives include road capacity, delay time and the number of stops.

B. MULTI-OBJECTIVE OPTIMIZATION MODEL

Before setting up the multi-objective optimization model, it is necessary to define the vehicle delay. Common vehicle delay models include Webster model, Akcelik model and HCM model [24]–[26].

Assuming that the traffic flow obeys the Poisson distribution, the vehicle delay in different phases of intersections can be obtained by the simulation technology in Webster model. Akcelik model is extended from the HCM model to calculate vehicle delay under oversaturation. Hence, this paper adopts the Akcelik model is used to simulate the vehicle delay.

The mean delay of all vehicles can be defined as:

$$\bar{d} = \sum_{i=1}^{n} d_{ij}^{r} p_{ij}^{r} \Big/ \sum_{i=1}^{n} p_{ij}^{r}$$

where, p_{ij}^{r} is the traffic flow from phase i to phase j; d_{ij}^{r} is the average delay of each vehicle from phase i to phase j in the r-th cycle.

The traffic capacity of an intersection can be defined as:

$$r = A_{ij} \times \beta_k = \sum_{j=1}^{n-1} \sum_{i=1}^{n} r_{ij}$$

where, A_{ij} is the saturation flow rate from phase i to phase j; β_k is the green signal ratio of the k-th phase; r_{ij} is road capacity.

The number of stops refers to the number of stops per vehicle entering the intersection. The Webster model mainly considers the complete stopping scenario, while the Akcelik takes account of both complete stopping and incomplete stopping. The number of stops can be defined as:

$$s_{ij}^{r} = \alpha\left(\frac{1-\beta_k}{1-l_{ij}^{r}} + \frac{N_{ij}^{r}}{Cp_{ij}^{r}}\right)$$

where, l_{ij}^{r} is the flow ratio; N_{ij} is the number of stranded vehicles; C is the cycle count of signal light; α is the correction factor of the number of stops.

The mean number of stops per cycle can be defined as:

$$\bar{s} = \sum_{i=1}^{n} h_{ij}^{r} p_{ij}^{r} \Big/ \sum_{i=1}^{n} p_{ij}^{r}$$

where, h_{ij}^{r} is the number of stops per vehicle from i to phase j in cycle r.

Next, the following constraints were added to the multi-objective optimization model:

The total duration can be defined as:

$$C = \sum_{k=1}^{n} (g_k + w_k)$$

where, g_k is the effective green light time of phase k; w_k is the loss time of phase k, n is the number of phase.

The effective green time can be defined as:

$$g_k > g_{kmin}$$

where, g_{kmin} is the minimum green light time of phase k.

The cycle can be defined as:

$$C_{min} \le C \le C_{max}$$

where, C_{min} is the minimum signal cycle (the cycle length is just enough to release the vehicles arriving at the intersection); C_{max} is the maximum signal cycle, which varies with road capacity and vehicle delay.

The queue length can be defined as:

$$N_{ij}^{r} < N_{ijmax}^{r}$$

where, N_{ijmax}^{r} is the maximum number of stranded vehicles in the road:

$$N_{ijmax}^{r} = \frac{I_{ij}}{\bar{V} \cdot C}$$

where, I_{ij} is the distance between adjacent intersections; $\bar{V}$ is the mean length of vehicles.

Under the above optimization indices and constraints, the following optimization model can be established to optimize the road capacity, vehicle delay and number of stops:

$$\min f_o = \bar{d} \cdot \bar{s} / C$$

s.t.

$$\begin{cases} C == \sum_{k=1}^{n} (g_k + w_k) \\ g_k > g_{kmin} \\ C_{min} \le C \le C_{max} \\ N_{ij}^{r} < N_{ijmax}^{r} \end{cases}$$

IV. IMPROVED DA FOR MODEL SOLUTION

A. STANDARD DA

The DA, a swarm intelligence algorithm, is inspired by the static and dynamic swarming behaviors of dragonflies [27]. These behaviors can be mathematically described as follows:

(1) Separation
Separation is the static collision avoidance from others in the neighborhood:

$$Q_i = -\sum_{j=1}^{N} Y - Y_j$$

where, Y and Y_j are the locations of the current individual and the j-th neighbor, respectively; N is the number of neighboring individuals.

(2) Alignment
Alignment indicates speed matching to the other individuals in neighborhood:

$$B_i = \frac{\sum_{j=1}^{N} S_j}{N}$$

where, S_j is the speed of the j-th neighbor.

(3) Cohesion
Cohesion refers to the tendency of individuals towards the center of the mass of the neighborhood:

$$C_i = \frac{\sum_{j=1}^{N} Y_j}{N} - Y$$

(4) Attraction to a food source
Once a food source is detected, the individuals will be attracted towards it:

$$A_i = Y^+ - Y$$

where, Y^+ is the location of food source.

(5) Deflection from enemies
The dragonflies seek to stay away from enemies:

$$O_i = Y^- + Y$$

where, Y^- represents the location of enemies.

The swarming behaviors of dragonflies are the combination of the above five behaviors. Next, it is necessary to calculate the step vector (ΔY) and location vector (Y). The step vector can be defined as:

$$\Delta Y_{t+1} = \alpha Q_i + \beta B_i + \gamma C_i + \delta A_i + \varepsilon O_i + \mu \Delta Y_t$$

where, α, β, γ, δ and ε are weights of the five behaviors, respectively; μ is inertia weight; t is the number of current iterations.

If there are neighbors, the location vector of an individual can be defined as:

$$Y_{t+1} = Y_t + \Delta Y_{t+1}$$

If there is no neighbor, the individual will take a random walk. In this case, the location vector can be defined as:

$$Y_{t+1} = Y_t + RW(d) \times Y_t$$

where, d is the dimension of location vector; $RW()$ is the walk behavior function.

B. IMPROVED DA

Despite its good performance, the DA faces premature convergence and relatively low accuracy in practical application. The two defects are resulted from the lack of communication between dragonflies. When all dragonflies fly towards the same direction (the current optimal solution), the diversity of the swarm will decline, adding to the risk of falling to the local optimum trap. Hence, the global search ability will deteriorate rapidly, and the local search ability will also be affected in the later period.

To solve the defects, this paper combines Gaussian mutation and Cauchy mutation into a hybrid mutation factor to enhance swarm diversity [28]. The hybrid mutation factor inherits the merits of Gaussian mutation and Cauchy mutation, thereby improving the convergence speed and quality.

The step of Gaussian mutation depends on mean μ and variance σ. The calculation process of Gaussian mutation can be defined as:

$$Y_t' = Y_t + g_s G_d(0, 1)$$

where, $G_d(0, 1)$ is random Gaussian number obeying normal distribution; d is the dimension of the optimization problem; g_s is the step of Gaussian mutation:

$$g_s = random(+, -)\sqrt{2\ln(2\pi\varphi_s)}$$

where, φ_s is a random number between 0 and $f_{Gaussian}()$:

$$f_{Gaussian}(x) = \frac{1}{\sigma\sqrt{2\pi}} exp^{\frac{(x-\mu)^2}{2\sigma^2}}$$

Cauchy mutation comes from Cauchy density function, which is similar to Gaussian density function in shape. The difference between the two functions is that the Cauchy density function is slow in reaching the x-axis. The calculation process of Cauchy mutation can be defined as:

$$Y_t' = Y_t + g_c \rho_d$$

where, ρ_d is a random value; g_c is the step of Cauchy mutation:

$$g_c = random(+, -)\sqrt{\frac{1}{\pi\tau_c} - 1}$$

where, τ_c is a random number between 0 and $f_{Cauchy}()$:

$$f_{Cauchy}(x) = \frac{1}{\pi} \times \frac{1}{1 + x^2}$$

The specific steps of the improved DA are as follows:

Step 1: Initialize the dragonfly swarm, maximum number of iterations, dimension of the problem, inertia weight, domain radius and other parameters.
Step 2: Generate the initial location and step size vectors of dragonflies randomly, and set $t = 1$.
Step 3: Calculate the objective function value of each dragonfly.
Step 4: Construct a non-dominated solution set and store it in an external file.
Step 5: Compare the external file capacity with the preset upper limit. If the former is greater, remove the solution set by the dynamic maintenance strategy until the capacity requirements are met.
Step 6: Update the weights and inertia weights of the five behaviors, and the inertia weights decrease linearly with t in the interval [0.6, 0.9].
Step 7: Update step vector ΔY_{t+1}.
Step 8: Update the domain radius. If a dragonfly has at least one neighbor, update the step vector and location vector; Otherwise, update the location vector only.
Step 9: Update global location through hybrid mutation.
Step 10: Check if the dragonfly location falls within the boundary of the problem domain. If not, correct the location.
Step 11: Update $t = t + 1$. If t is below the maximum number of iterations, go to Step 3; otherwise, terminate the algorithm.

V. SIMULATION AND RESULTS ANALYSIS

A. SIMULATION SCENE

To verify their effectiveness, the proposed model and algorithm were simulated with an actual intersection. As shown in Figure 1, the intersection consists of east-west and north-south urban trunk roads. Each of the four entrances has a right turn lane, and a straight/left turn lane. This arrangement can

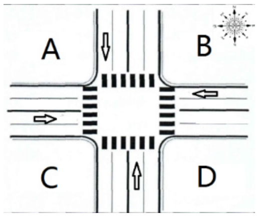

FIGURE 1. The actual intersection.

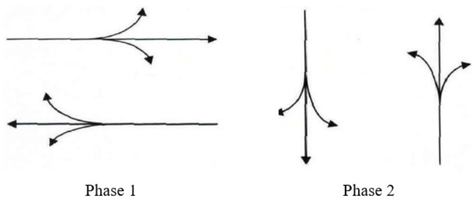

FIGURE 2. Phase setting of the intersection.

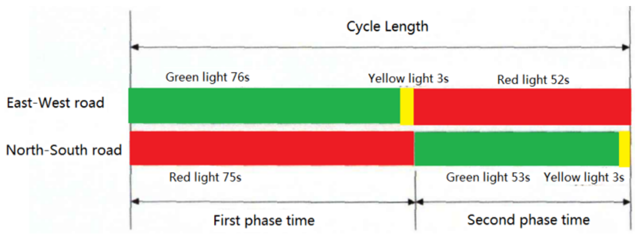

FIGURE 3. Phase timing of the intersection.

TABLE 1. Traffic attributes of intersection.

Entrance	Traffic flow direction	Corrected saturated flow	Peak hour traffic flow	Flow ratio
East entrance	Straight/left turn	1,608	409	0.2544
	Right turn	956	146	0.1527
West entrance	Straight/left turn	1,608	669	0.4160
	Right turn	956	203	0.2123
South entrance	Straight/left turn	1,438	228	0.1586
	Right turn	866	309	0.3568
North entrance	Straight/left turn	1,438	196	0.1363
	Right turn	866	141	0.1628

easily cause congestion both in peak hours and in off-peak hours. In reality, there are many vehicles passing and stopping at the intersection, resulting in a high occurrence of collisions and a low traffic efficiency.

For the straight going motor vehicles, the change of the signal light is consistent with that of non-motor vehicles and pedestrians, and falls into two phases. The phase setting and phase timing of intersection are shown in Figures 2 and 3, respectively. The traffic flow direction, corrected saturated flow, peak hour traffic flow and flow ratio are listed in Table 1.

B. RESULTS ANALYSIS

The simulation results of our model were compared with those of the Webster model (Table 2).

As shown in Table 2, in peak hours, our model optimized the signal light and effective green light time, and reduced the mean delay and number of stops from the levels of the

TABLE 2. Comparison of simulation results.

Time	Model	Cycle	Green light time	Mean delay	Number of stops	Maximum road capacity
Peak hours	Our model	85	53	18	0.755	3,680
	Webster model	127	62	22	1.125	3,720
Off-peak hours	Our model	88	40	26	0.885	3,890
	Webster model	98	43	35	0.965	3,770

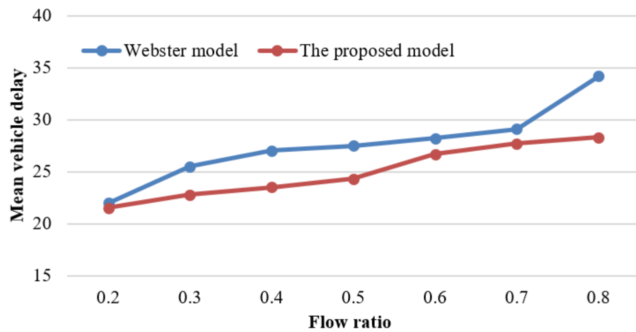

FIGURE 4. Comparison of mean vehicle delays.

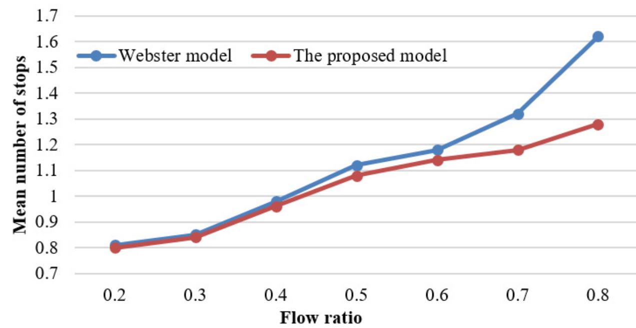

FIGURE 5. Comparison of mean number of stops.

Webster model; in off-peak hours, our model achieved the shorter mean delay and the smaller number of stops, and the greater road capacity.

To further verify its feasibility, our model was compared with the Webster model through a simulation on the virtual simulation platform. Figures 4 and 5 present the mean vehicle delays and mean number of stops of the two models, respectively.

As shown in Figure 4, when the flow ratio was low at the intersection, the Webster model achieved a similar mean vehicle delay as that of our model. When the flow ratio was medium and high, our model achieved a much shorter mean vehicle delay than the Webster model.

As shown in Figure 5, when the flow ratio was low, our model slightly outperformed the Webster model in the mean number of stops; as the flow ratio increased to a relatively high level, the advantage of our model became increasingly prominent. The poor effect in the early stage is mainly due to the comprehensive consideration of the delay time, parking times and other performance indicators in our model.

When the traffic is very smooth, part of the timing performance is sacrificed. With the increase of traffic flow, the performance of the improved algorithm is gradually reflected.

To sum up, our model has a comparable performance as the Webster model at a low flow ratio. When the flow ratio is relatively high, our model far outperforms the latter. In this case, our model can effectively reduce the mean delay of vehicles passing through the intersection, lower the number of stops, and enhance the overall performance of the intersection.

VI. CONCLUSIONS

In this paper, under the background of establishing intelligent transportation, the traffic flow control technology of intersection, which is the key object of traffic control and guidance, is studied. This paper constructs a signal timing optimization model for multiple objectives, including vehicle delay, road capacity and number of stops. Next, a hybrid mutation factor was introduced to improve the standard DA, with the aid of dynamic maintenance of external file. The improved DA was adopted to solve the proposed optimization model. The feasibility of the proposed model and algorithm were fully verified through actual scene simulation and virtual simulation. Therefore, we use bionic algorithm to solve the dynamic timing problem of intersections very well.

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