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LONG SHORT-TERM MEMORY NEURAL NETWORK-BASED INTERSECTION SIGNAL TIMING OPTIMIZATION METHOD

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ABSTRACT
Traffic congestion at road intersections constrains the sustainable development of cities. Signal control is an effective way to relieve intersection congestion. The traditional timed signal timing method cannot fit the real situation of traffic operation and therefore cannot achieve the best fit between signal timing and traffic operation. Therefore, based on Long Short-Term Memory (LSTM) neural network model, a novel signal control method was proposed in the research. Through the predicted flow, the signal control parameters were estimated. The simulation was conducted based on the data collected from Zibo Public Security Bureau and showed that the approach proposed in this research operates better than the conventional control method. In detail, average vehicle delay, queue length, and queuing frequency were reduced by 14.56%, 12.46% and 11.54%, respectively. The method proposed in this study can provide traffic managers with better signal control patterns to alleviate traffic congestion.

KEYWORDS: Traffic control; Signal optimization; LSTM; Simulation

1. INTRODUCTION
Traffic congestion at urban road intersections is widespread and traffic efficiency is poor [1]. It is well known that traffic congestion has led to huge economic losses [2]. In Beijing and Shanghai, for example, the daily cost due to traffic congestion is about 1 billion RMB. In addition, the average speed of motor vehicles is generally below 30km/h in congested environments, which obviously increases greenhouse gas emissions. Therefore, the impact of traffic congestion on social sustainable development cannot be ignored.

One of the effective methods for relieving traffic congestion is to set up reasonable signal control for intersections [3]. Since signal control can orderly characterize the operation of motor vehicles [4-5] and ensure traffic safety [6-8]. Specifically, by assigning superior signal timing parameters, the intersection capacity and green light utilization can be satisfactorily improved and motor vehicle delays can be reduced [9].

To establish a better signal timing method, transportation professionals at home and abroad are competing to conduct research. For example, Noaeen et al [10] and Essa et al [11] proposed a network-wide traffic information control model to efficiently determine and optimal linear quadratic control was introduced, pointing out that the real-time traffic information control model is important for the development and improvement of intelligent transportation systems. Zheng et al [12] proposed a linear traffic information control method with polyhedral uncertainty to alleviate traffic congestion in urban road networks.

Meanwhile, turnover changes in traffic conditions are considered and therefore predictive control methods are embedded in the model theory. Thus, improving the robustness and fitting performance of the confidence control model in a non-stationary environment. To efficiently determine the green light duration, radio frequency identification sensors were employed to determine the congestion at intersections; then, traffic signals were adjusted across traffic density indicators to minimize traffic congestion [13]. In addition, artificial intelligence and machine learning methods were also embedded in signal control approaches, which has been widely noticed and applied. Advanced control technologies have provided traffic control authorities with new control ideas [14] as well as reduce the probability of road traffic crashes [15]. These studies are valuable and meaningful since they can continuously alleviate traffic congestion at urban intersections.

In total, signal control at intersections has a substantial impact on both the operation of traffic flow and road traffic safety. However, most advanced research results were proposed based on the traffic of developed countries. It is well known that the operational characteristics of urban intersections are substantially different between China and developed countries, and the research results may not be directly transferable for application. Therefore, this study was conducted to investigate the signal control strategies of urban intersections in China. The purpose is to provide better signal timing strategies for signal control engineers in China.

2. DATA COLLECTION

To conduct this study, traffic flow data at city intersections were retrieved from the license plate recognition system maintained by the Zibo Public Security Bureau. The system accurately records information about vehicles in the intersection, such as license plate, traffic flow, lane occupancy and vehicle arrival time. The specific data collection site is intersection of Lu-tai road and Shi-ji road in Zibo City. The lane diagram of this intersection is shown in Figure 1.

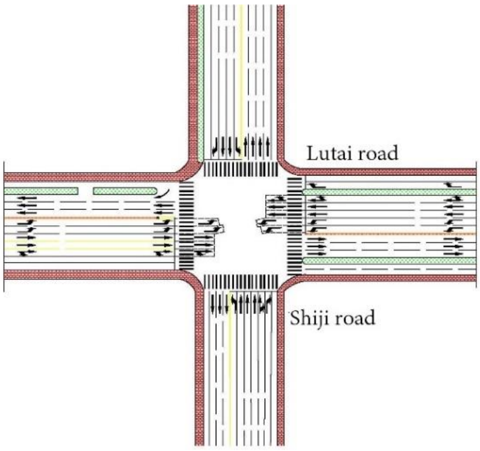

Figure 1. Current status of the intersection of Lu-tai road and Shi-ji road

The signal timing for the intersection of Lu-tai road and Shi-ji road is shown in Table 1.

Table 1 Current status of signal timing at the intersection of Lu-tai road and Shi-ji road

Time Period	East-west straight/s	east-west left turn/s	North-south straight/s	North-south turn left/s	Cycle time/s
7:00-8:45	65	50	40	35	190
8:45-16:30	45	30	35	30	140
16:30-18:30	70	60	40	35	205
18:30-7:00	45	35	30	30	140
7:00-8:45	30	25	30	25	110

To ensure the validity of modeling observations, pre-processing of traffic data is implemented. Specifically, duplicate and missing data were manually removed while ensuring an adequate sample size; the remaining traffic observations were used for subsequent modeling.

3. METHODOLOGY

3.1 Long-short term memory neural network

In this research, Long Short-Term Memory (LSTM) neural network was employed to predict real-time traffic flow. The LSTM was improved from Recurrent Neural Network (RNN). It solves the drawback that the RNN are too sensitive to short-term data and thus improves the prediction accuracy [16]. This approach is suitable for modeling the time-dependence of traffic flow data since it preserves useful information from the previous time. The composition of the LSTM model includes three gating structures: input gates, forgetting gates and output

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gates. The specific model structure and modeling methods were described in Moradzadeh et al [17] and Afrin et al [18].

3.2 A novel signal control method

(1) Phase design constraints

Intersection signal phase set $\varepsilon=\left[\varepsilon_1,\varepsilon_2,\cdots,\varepsilon_i,\cdots,\varepsilon_j\right]$. In this research, $\varepsilon=\left[\varepsilon_1,\varepsilon_2,\varepsilon_3,\varepsilon_4,\varepsilon_5,\varepsilon_6,\varepsilon_7,\varepsilon_8\right]$. The specific signal control phase is shown in Figure 2,

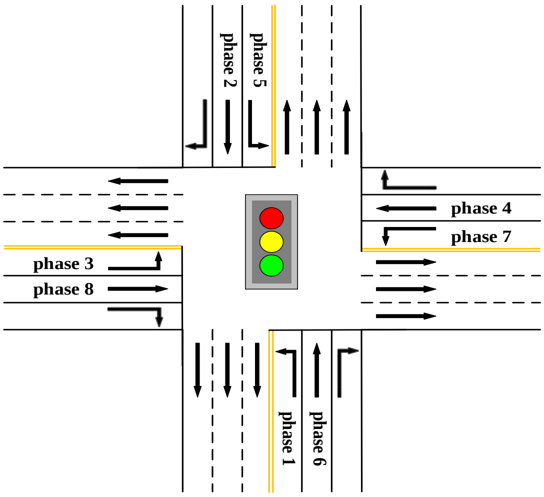

Fig. 2 Intersections signal phase marking diagram

The signal phase conflict matrix of the intersection can be expressed as:

$$W=\begin{bmatrix} w_{11} & \dots & w_{1i} & \dots & w_{1j} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ w_{i1} & \dots & w_{ii} & \dots & w_{ij} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ w_{j1} & \dots & w_{ji} & \dots & w_{jj} \end{bmatrix} \tag{1}$$

When ε_i and ε_j conflict with each other, $w_{ij}=w_{ji}=1$; otherwise, $w_{ij}=w_{ji}=0$. Further, the constraint condition of signal phase can be expressed as,

$$\begin{cases} 1\le\sum_{v} z_{j,v}\le 2 & j,v\in N^+,\ z\in[0,1] \\ z_{j,v_1}\cdot z_{j,v_2}=1 & v_1,v_2\in v,\ |v_1-v_2|<2 \\ w_{ij}\cdot w_{ji}\left(z_{j,v}+z_{i,v}\right)=1 & w_{ij}=w_{ji}=1,\ i\in N^+ \\ \left(1-w_{ij}\right)\left(1-w_{ji}\right)z_{j,v}\cdot z_{i,v}=1 & w_{ij}=w_{ji}=0 \end{cases} \tag{2}$$

When signal phase j belongs to signal phase v, $z_{j,v}=1$; otherwise, $z_{j,v}=0$. There are V signal phases in one signal cycle, and $v\in V$.

(2) Signal Timing Constraints

The signal period C_a takes on a range of values as:

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$$\begin{cases} C_\alpha = g_1 + g_2 + \cdots + g_v + l & C_{min} \le C_\alpha \le C_{max} \\ C_{min} = 0.5C_m & C_\alpha < C_{min} \\ C_{max} = 2max\left\{C_0, C_p\right\} & C_\alpha > C_{max} \end{cases} \tag{3}$$

where g_v indicates the length of the green light; l represents the sum of yellow light time and full red time. The value range of green light duration g_v is,

$$\begin{cases} g_{min} \le g_v \le g_{max} \\ g_{v,\,min} = max\left\{0.5 g_{v,\,min\,P}, g_{v,\,min\,S}\right\} \\ g_{v,\,max} = 0.7C_\alpha \end{cases} \tag{4}$$

where $g_{v,\,min\,P}$ indicates the length of pedestrian crossing; $g_{v,\,min\,S}$ indicates the time required for queuing vehicles to cross the intersection.

For a signal-controlled intersection, the higher the traffic flow, the longer the signal period required. Too long signal period will lead to vehicle delay, queue length and queue times increase. Therefore, a signal control function model is constructed based on vehicle delay, queue length and number of queues. As shown below,

$$f(C,g) = min\sum_{n=1}^{N}\left(\alpha_t \frac{D_n^{(C,t)}}{D_n^0} + \beta_t \frac{H_n^{(C,t)}}{H_n^0} + \gamma_t \frac{N_n^{(C,t)}}{N_n^0}\right) \tag{5}$$

where $D_n^{(C,t)}$, $H_n^{(C,t)}$, and $N_n^{(C,t)}$ respectively represent the vehicle delay time, vehicle queuing times, and vehicle queuing length at the intersection; D_n^0, H_n^0, and N_n^0 respectively represent the initial vehicle delay time, vehicle queuing times, and vehicle queuing length at the intersection; α, β, γ represent the weight values of the control indicators. Further, the calculation rule for $D_n^{(C,t)}$, $H_n^{(C,t)}$, and $N_n^{(C,t)}$ is,

$$\begin{cases} D_n^{(C,t)} = \sum d_i = \sum\left(\dfrac{C(1-\lambda_i)^2}{2(1-y_i)} + \dfrac{1-\lambda_i}{2q_i} - \dfrac{q_i C}{2s_i g_i (s_i g_i - q_i C)}\right) \\ N_n^{(C,t)} = \sum N_i = \sum \dfrac{\lambda_i s_i t}{4}\left(y_i - 1 + \sqrt{(y_i - 1)^2 + \dfrac{12\left(y_i - 0.67 - \dfrac{s_i g_i}{600 \times 3600}\right)}{\lambda_i s_i t}}\right) \\ H_n^{(C,t)} = \sum h_i = \sum \dfrac{0.9 q_i C}{3600}\left(\dfrac{1-\mu_i}{1-y_i} + \dfrac{e^{\frac{-1.33(1-x)\sqrt{s_i q_i}}{x}}}{2(1-x) q_i C}\right) \end{cases} \tag{6}$$

The calculation rule for the weights is,

$$\begin{cases} \alpha_i = 2(1-Y)\sqrt[7]{s_i}\, y_i \big/ \left(y_i + y_{ip}\right) \\ \beta_i = \dfrac{1-Y}{0.9}\sqrt[7]{s_i} \\ \gamma_i = 2Y\sqrt[7]{s_i} \end{cases} \tag{7}$$

where d_i, N_i, h_i respectively represent the vehicle delay time, vehicle queue length and vehicle parking rate of signal phase i; y_i indicates the flow ratio of signal phase *i*; s_i indicates saturated flow of signal phase i; q_i indicates the actual flow of signal phase *i*; y_{ip} represents the pedestrian flow ratio of signal phase *i*.

3.3 PSO algorithm for solving objective function

Particle swarm optimization (PSO) is an intelligent optimization algorithm, which is easy to understand, with few parameters, high precision and fast convergence. The PSO can search for multiple objectives simultaneously, iterating to find the optimal value, including particle best (Pbest) and global best (Gbest).

When there are n particles seeking an advantage in a d-dimensional search space, the rule for the velocity change of the particles can be expressed as,

$$v_{id}^{k+1} = wv_{id}^{k} + c_1 r_1 \left(Pbest_{id} - x_{id}^{k}\right) + c_2 r_2 \left(Gbest_{d} - x_{id}^{k}\right) \quad (8)$$

The rule for the change of position of a particle can be expressed as,

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k} \quad (9)$$

where x_{id}^{k} and v_{id}^{k} represent the d-dimensional position and velocity components of particle *i* at the *k*-th iteration; c_1 and c_2 denote learning factors; r_1 and r_2 represent arbitrary number satisfying uniform distribution in [0, 1]; w represents inertia weight; $Pbest_{id}$ and $Gbest_{d}$ indicate the best position of the current particle and the current best position of the population, respectively.

4. CASE ANALYSIS

4.1 Simulation parameters

According to the calculation methods mentioned above, simulation parameter presets were required, and the specific parameter settings are shown in Table 2.

Table 2 Simulation parameter presets

Parameters	Parameter setting	Parameters	Parameter setting
Traffic rules	Right hand principle	Simulation accuracy	5 Time steps/simulation second
Vehicle type	Cars and buses	Simulation speed	10 simulation seconds/s
Lane saturation traffic	2000veh/h	Simulation duration	3600 simulation seconds

In addition to this, the base traffic information is mandatory before the simulation process, as given in Table 3.

Table 3 Statistics of traffic flow at the intersection of Lu Tai Avenue-Shi Ji Road (veh/h)

Entrances	Straight (cars, buses)	Right (cars, buses)	Left (cars, buses)
East entrance	1250 (1084, 166)	236 (205, 131)	350 (303, 47)
West entrance	993 (861, 132)	124 (108, 16)	244 (212, 32)
South entrance	927 (804, 123)	211 (183, 28)	176 (153, 23)
North entrance	812 (704, 108)	195 (169, 26)	183 (159, 24)

The signal timing optimization scheme is shown in Table 4.

Table 4 Signal Timing Optimization Solution

Signal phase	Phase 1	Phase 2	Phase 3	Phase 4
Signal duration/s	28	34	49	61
Signal phase	Phase 5	Phase 6	Phase 7	Phase 8
Signal duration/s	28	34	49	61

4.2 Analysis of simulation results

The specific simulation process is implemented in software VISSIM for the intersection of Lu-tai road and Shi-ji road. The simulation demonstration of the intersection of Lu-tai road and Shi-ji road is shown in Figure 3.

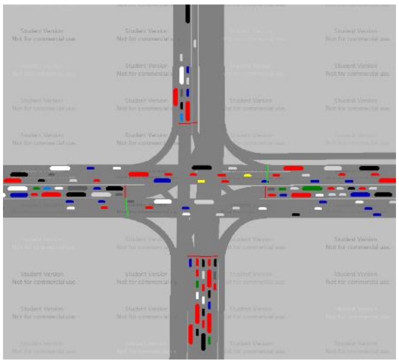

Figure 3 Intersection simulation demonstration

The operational effectiveness of the intersection is evaluated by calculating the average value of all simulations, shown in Table 5.

Table 5 The simulation experiment data of Lu-tai road and Shi-ji Road intersection

Evaluation indicators	Current simulation	Optimization simulation	Improved results
Average vehicle delay (*s*)	60.94	52.07	14.56%
Queue length (*m*)	92.13	80.65	12.46%
Queuing frequency	0.78	0.69	11.54%

According to Table 4, the optimized simulation is better than the current state simulation since the average vehicle delay changed from 60.94s to 52.07s, with a reduction of 14.56%. The queue length changed from 92.13m to 80.65m, with a reduction of 12.46%. The queuing frequency changed from 0.78 to 0.69, with a reduction of 11.54%. These statistics show that the signal timing control scheme based on the flow level prediction data can improve the traffic capacity and green light utilization of intersections.

5. CONCLUSION

In this study, a long-short term memory (LSTM) neural network-based signal control method was constructed. And a novel signal control method was proposed to control the intersection traffic flow. Traffic flow data from Zibo Public Security Bureau were retrieved for model calibration. And a comprehensive comparison was implemented between the conventional signal control method and the signal control method proposed in this study. Three evaluation parameters including average vehicle delay, queue length, and queuing frequency were calculated. The results showed that the signal control method built in this study is superior. The signal timing method proposed in this study has better control effect and is recommended for practical intersection flow control. In the subsequent research, we will build a better traffic flow prediction model to improve the prediction performance and thus propose a better signal control method.

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