Research on coordinated control method of urban traffic based on neural network

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Abstract: Due to the complexity of data in urban traffic coordination and control, there is a lack of relevance between data nodes of existing coordination methods, which leads to urban traffic holdup and congestion. A coordinated urban traffic control method based on neural network is proposed. The traffic flow prediction model is constructed to predict and calculate the urban traffic flow, green signal ratio, phase and period. The coordinated control method based on neural network is used to fine-tune the traffic signal, green signal ratio, phase and cycle, so as to improve the traffic capacity at the intersection during the peak period, and finally realise the coordinated control of urban traffic. The simulation results show that the proposed method can effectively alleviate the traffic capacity at intersections, and the time required for the method to run the whole process is less, which indicates that the proposed method is effective and reliable.

Keywords: neural network; urban traffic control; signal light coordination; simulation.

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1 Introduction

The purpose of coordinated control of urban traffic is to ensure traffic safety. Due to the continuous development and progress of the times, various contradictions in urban transportation are emerging one after another, people's living standards are constantly improving, and the requirements for transportation are getting higher and higher (Mohebifard and Hajbabaie, 2018). This will enable researchers to apply new scientific and technological achievements to the traffic control system, thereby accelerating the development of coordinated control for urban traffic and promoting traffic intelligence. Traffic coordination control is mainly divided into two parts: induction control and signal control. The induction control mainly plans the best driving route according to the information such as the location and destination of the vehicle, and reports the information to the driver through broadcast. But the method is only indicative of the control mode, does not exist mandatory. Signal control is based on a reasonable control scheme to coordinate control through the signal light (Al-Smadi et al., 2018). Among them, signal control is a key issue in intelligent transportation. Signal control is more suitable for a single intersection. In fact, the intersection of urban roads is complicated. If you want to rely on signal control to achieve coordinated control of traffic, the effect is not very satisfactory, and it is difficult to achieve the coordination purpose (Dorgham et al., 2018).

Since the coordinated control of traffic plays an important role, many scholars are more committed to the coordinated control of urban traffic and have achieved many research results. Kumar (2019) proposed a traffic phase optimisation method based on multiple genetic algorithms.

According to the vehicle delay model created by the traffic building theory, taking the minimum average delay of the vehicle in the main trunk line of the city as the coordinated control evaluation index, and the coordinated control of the main trunk line of the city was studied. The genetic algorithm was used to optimise the phase design of urban trunk junction. The experiment proves that the operation of this method will cause great disturbance to urban traffic. Pang et al. (2018) proposed a multi-period coordinated control optimisation method for urban traffic flow in the main trunk line. Firstly, the boundary of the coordinated control was determined based on the correlation model of the main road intersections of the city, and then the historical traffic volume of the intersections that need to be coordinated was clustered and analysed, and the corresponding multi-period control strategy was obtained. Based on this, taking that the bandwidth of main lines is the maximum and the average delay of vehicles along the routes is the minimum as coordination objectives, an optimisation model for multi-period control of main lines was established. The multi-objective particle swarm optimisation algorithm was used to solve the created optimisation model, to find the best coordinated control scheme for the main line intersections in the city and the best switching time. This method has poor filtering broadband, which results in serious delay of vehicles at intersections. Dai et al. (2018) proposed a method for coordinated control of urban trunk lines based on macroscopic basic maps. The method divided the urban road network into several sub-areas, divided the traffic flow contained in each sub-area into internal flow and transfer flow, and analysed the two parts to create a multi-sub-area traffic flow model based on the macro basic map. The boundary constraints of traffic flow in each sub-area were determined, and then the boundary was adjusted. The boundary feedback controller was used to dynamically induce the transfer flow of each sub-area, and the iterative process was analysed to see if it met the boundary constraints. Finally, the coordination controller was made stability analysis. The method will lead to the total number of vehicles at the intersection exceeding the set value, and the phenomenon that the overall flow rate is large is difficult to control. Xu and Li (2018) proposed a coordinated control method for urban main trunk road junctions based on bidirectional filtering. The objective was to adjust the filter width to the maximum, and the main road entrance was regarded as a straight road. The filter coordination parameters of the straight road were calculated by mathematical solution method. In order to maximise the traffic capacity of the exit, a dynamic coordinated control model was established, and the phase time of the intersection was calculated and analysed. The optimal phase time and sequence were obtained to keep the urban trunk line running smoothly, so as to achieve the goal of coordinated control of urban traffic. This method is mainly applicable to regular roads and intersections, and it has poor adaptability to traffic conditions of roads with uneven intersection spacing.

The above methods are all fuzzy control methods, which can be combined with human thinking and experience to meet practical requirements. However, the quantisation factor of ordinary fuzzy control will change at any time. For the intricate road system of the city, fuzzy control alone can not guarantee the control effect and it will reduce the robustness of the control method. A neural network with better nonlinear mapping ability, self-learning and self-adaptive ability, generalisation ability and fault tolerance can solve the above problems. Therefore, a neural network-based method for urban traffic coordination control is proposed. The specific research structure is as follows:

1 The coordinated control technology of urban traffic is analysed.

2 Combining neural networks with urban traffic control, neural network is used to achieve coordinated control of urban traffic.

3 It is proved by the simulation experiment on the experimental platform that the method has high effectiveness, and the experimental results are highly consistent with the actual demand of urban traffic, which is in line with the coordinated control of urban traffic.

4 Conclusions.

2 Coordinated control method of urban traffic

2.1 Control analysis of urban traffic

2.1.1 Traffic control analysis

2.1.1.1 Signal phase

The signal phase refers to the green light duration and the traffic flow direction during the green light period in the moment when the signals at the intersection are unchanged. Phase is the basic unit of signal control. It can control the single-point signal by adjusting the green light duration of a phase, the yellow light duration, the full red duration of the signal light in the intersection, and the number of phases of a period (Goatin and Rossi, 2019). Generally speaking, after passing through N phases, an intersection returns to the initial phase and continues to period, then the intersection is controlled by N phases.

For the bidirectional coordinated control of urban trunk roads, there are two kinds of phase difference: the upstream phase difference $t_{p,u}^{j,j+1}$ and the downstream phase difference $t_{p,d}^{j+1,j}$ (Wu et al., 2018), and the calculation formula is:

$$t_{p,u}^{j,j+1}(k)=\frac{d_{j,j+1}}{v_{j,j+1(k)}} \tag{1}$$

$$t_{p,d}^{j+1,j}(k)=\frac{d_{j+1,j}}{v_{j+1,j(k)}} \tag{2}$$

where $j=1,2,\cdots,n-1,n$ represents the number of intersections on the urban traffic trunk, $d_{j,j+1}$, $v_{j,j+1(k)}$ respectively represent the length and speed of the upstream segment between the intersection j and $j+1$. $d_{j+1,j}$ and $v_{j+1,j(k)}$ represent the length and speed of the downstream segment between the intersections j and $j+1$. The formula shows that $d_{j,j+1}=d_{j+1,j}$.

2.1.1.2 Period

In the intersection signal control process, when the signal control device periods through the N phases and returns to the original phase to continue operation, the periodic phase number of the signal is N, and the signal period is the sum of the time of the N phases (Zheng et al., 2019a).

Assuming that there are N phases in a certain intersection and the duration of the phase is $Pt_i, i=0,1,2\cdots,N-1$, then the calculation formula of the signal period C is:

$$C=\sum_{i=0}^{N-1}Pt_i \tag{3}$$

The signal period C is adjusted according to the saturation X of the main trunk line. According to the traffic statistics, the optimal period duration C_{opt}, the minimum period duration $C_{\min}$ and the maximum period duration $C_{\max}$ of the main trunk line are obtained. According to traffic control, if the period length is too large, the saturation is low; the period length is too small, the saturation is large, and the optimum saturation is usually 0.9 (Lin et al., 2018).

The formula for calculating the saturation X is as follows:

$$X=\frac{\sum_{i=1}^{3}Q_i}{\sum_{i=1}^{3}\lambda_i S_i} \tag{4}$$

where Q_i, λ_i and S_i represent the flow rate, green signal ratio and saturation flow of the phase $i(i=1,2,3)$ in main trunk line, respectively.

2.1.1.3 Green signal ratio

The green signal ratio is the ratio of the duration and period of the effective green signal for traffic flow over a signal period. As long as the green signal ratio is adjusted, the goal of reducing the average delay of traffic flow can be achieved (Campos et al., 2018). The formula for calculating the green signal ratio λ is as follows:

$$\lambda=Ge/C \tag{5}$$

where Ge represents the effective green signal duration and C represents the signal period.

The green signal ratio of each phase is different, and is usually determined by the degree of saturation of each phase. Saturation reflects the degree of traffic congestion. The greater the phase saturation is, the larger the traffic flow of the phase is, and the longer the green light duration should be adjusted; otherwise, the green light duration of the phase is shortened (Kanmani and Narsimhan, 2018).

First, the minimum value C_{opt} and the maximum value C_{opt} of green light duration in each phase are determined based on the traffic data. The green signal of each intersection is calculated separately according to its real-time saturation. After each period is completed, it needs to be adjusted again. The next period runs according to the new green signal ratio. The calculation process is as follows.

The average corrected traffic flow for phase $i(i=1,2,\ldots,n)$ in the period is calculated:

$$\tilde{Q}_i(k)=\alpha Q_i(k)+\beta\tilde{Q}_i(k-1)+\gamma\bar{Q}_i(k) \tag{6}$$

where $\tilde{Q}_i(k)$ and $\tilde{Q}_i(k-1)$ represent the corrected traffic flow of phase i at the k^{th} and $k-1^{\text{th}}$ signal periods, respectively; $Q_i(k)$ represents the actual traffic flow of phase i at the k^{th} signal period; $\bar{Q}_i(k)$ represents the historical average flow of phase i at the $k-1^{\text{th}}$ signal period; positive coefficients α, β, and γ are satisfied: $\alpha+\beta+\gamma=1$, the larger the value of α is, the higher the real-time performance is and the larger the values of β and γ are, the better the stability is.

The formula for calculating the effective green light duration is:

$$t_i=\lambda_i\left(C-Y_{all}-R_{all}\right) \tag{7}$$

where Y_{all} indicates the duration of the yellow light in the period, and R_{all} indicates the duration of the red light in the period. If $t_i<t_{i,\min}$, then $t_i=t_{i,\min}$, $t_{i,\min}$ represents the minimum value of the green signal duration of phase i, wherein the missing green signal duration can be supplemented proportional to other phases, the other formula for reducing the green light duration $t_{j,ded}$ is:

$$t_{j,ded}=\frac{\lambda_j}{\sum_{k=1,2,\ldots,n;k\neq i}\lambda_k}\left(t_{i,\min}-t_i\right) \tag{8}$$

If $t_i>t_{i,\max}$, then $t_i=t_{i,\max}$, $t_{i,\max}$ represents the maximum value of the green signal duration of phase i, and the remaining green signal duration is allocated to other phases in a certain proportion. The calculation formula of the remaining green signal duration $t_{j,add}$ obtained by other phases is:

$$t_{j,add}=\frac{\lambda_j}{\sum_{k=1,2,\ldots,n;k\neq i}\lambda_k}\left(t_{i,\max}-t_i\right) \tag{9}$$

In order to maintain coordinated control through the bandwidth, $t_{1,\min}$ and $t_{2,\min}$ should be adjusted appropriately.

d Adjustment of step

In the process of signal control of traffic, the main way is to adjust the phase duration. Since it is the control of urban traffic, the most important issue is the security issue (Liu et al., 2018). When adjusting the phase duration, you need to use a step-by-step approach and should be based on security issues. The adjustment of step size is the maximum phase length that can be adjusted when the phase duration is adjusted.

Supposing that a phase time length is Pt_i, and after adjusting its phase duration, the time length of the new phase is Pt_i', and the calculation formula is:

$$Pt_i' \in \left[Pt_i - \Delta t, Pt_i' + \Delta t\right] \tag{10}$$

2.1.2 Traffic control indicators

2.1.2.1 Delay

It refers to the fact that traffic flow on urban trunk lines can not be freely and quickly accessible, and the low-speed driving and parking are caused by various factors, resulting in the time loss of traffic flow on the main line. Delays can be divided into two categories: consistency delays and random over saturation delays (Ardalan et al., 2020).

The formula for calculating the average delay D is as follows:

$$D = D_1 + D_2 \tag{11}$$

where D_1 indicates consistency delay and D_2 indicates random over saturation delay.

2.1.2.2 Capacity

It refers to the maximum traffic load that the trunk line can support in every hour under different quality conditions, that is, the maximum traffic load that the trunk line can bear under the same conditions (Yao and Jiang, 2018).

Assuming that the basic load capacity of the main line is C (vehicle/hour), then the headway distance and the vehicle speed are theoretically used as the evaluation criteria, and the safety head spacing H (metre) obtained by using the vehicle flow to ensure the same speed V (Km/h) is used. The minimum value is determined:

$$C = 1{,}000\, V / H \tag{12}$$

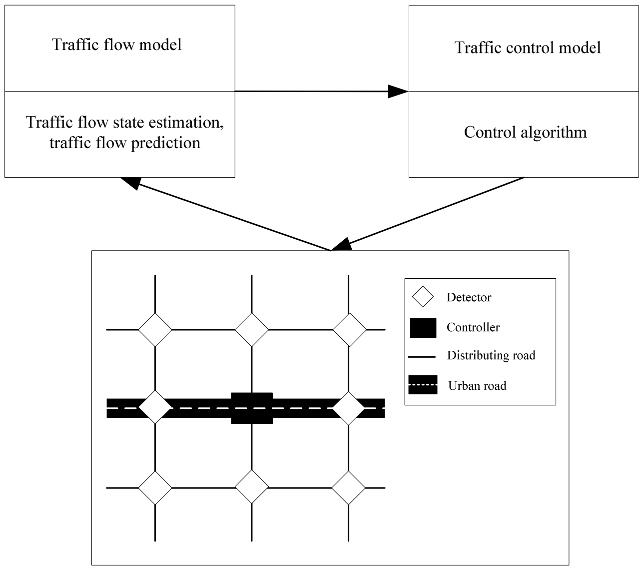
2.1.2.3 Queue length

It refers to the situation that the traffic flow is forced to stay at the intersection or a certain section, and the traffic flow is forced to stay. The number of vehicles waiting to pass through is often used to judge the traffic status of the intersection (Zheng et al., 2019b).

2.1.3 Structure of traffic control system

The control system determines the control strategy based on the real-time status of the city trunk. The structure of control system consists of two parts, as shown in Figure 1.

Figure 1 Traffic control system



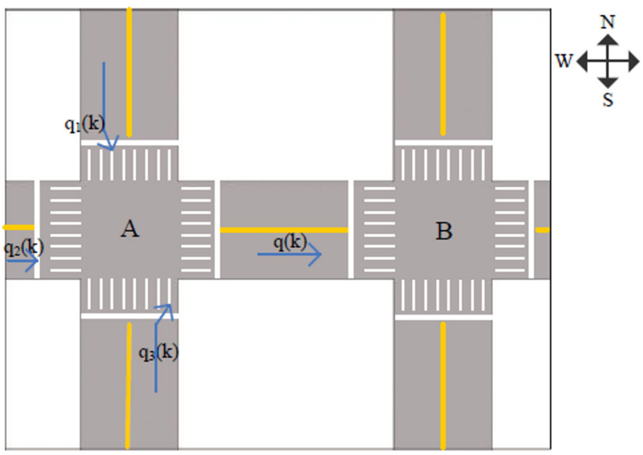
2.2 Neural network prediction model

Figure 2 shows the traffic flow relationship between the two typical adjacent intersections in the main trunk line of the city. Among them, $q_1(k)$, $q_2(k)$ and $q_3(k)$ respectively indicate that the traffic flow from north to south and turns left, the traffic flow from west to east and the traffic flow from south to north in intersection A, respectively. In the traffic flow in the period $((k - 1)T, k^T]$, $q(k)$ represents the traffic flow of the observation point between the intersections A and B during that time period, where $k = 1, 2, \cdots$. As seen from Figure 2, there is a nonlinear relationship among the traffic flow $q(k + 1)$ of the observation point during the period, the traffic flow $q(k)$ of the previous period and the traffic flow $q_1(k)$, $q_2(k)$ and $q_3(k)$ of the section entering the previous period of the intersection A. The expression is:

$$q(k+1) = f\left(q_1(k), q_2(k), q_3(k), q(k)\right) \tag{13}$$

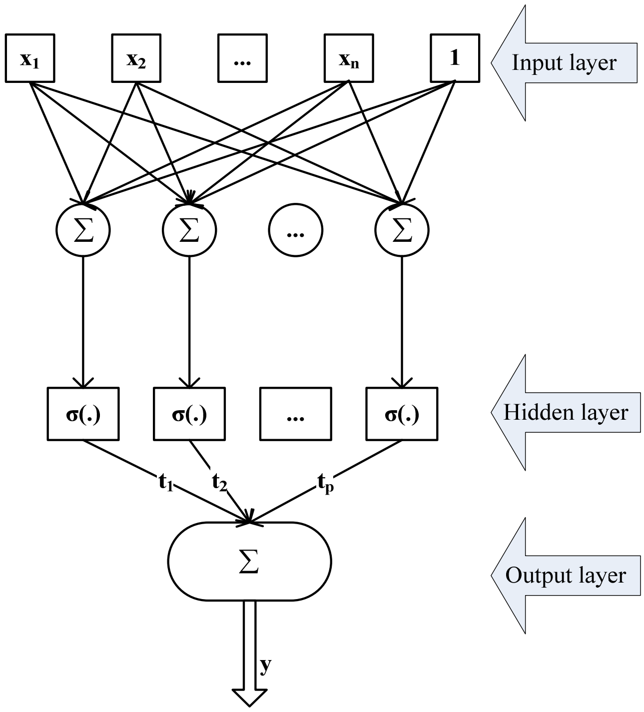
where $f(\cdot)$represents a nonlinear function.

Figure 2 Traffic flow relationship between adjacent intersections (see online version for colours)



The above traffic flow control is analysed, and the neural network traffic flow prediction model is proposed. The schematic diagram of the neural network is shown in Figure 3.

Figure 3 Schematic diagram of the neural network (see online version for colours)



Neural network has many interconnected neural networks. To a certain extent, it can simulate human brain cells, neural structure and thinking characteristics according to specific methods to obtain the ability similar to human thinking mode. Depending on the complexity of the system, it can achieve the purpose of processing information by adjusting the relationship between a large number of internal nodes, and the complexity of the algorithm is relatively high Low, more suitable for the information processing of the more difficult conventional mathematical methods (Jing et al., 2018).

The neural network shown in Figure 3 is a common feedforward neural network consisting of S function neurons whose neurons output an S-type nonlinear function with all input weights and a certain threshold (Mistele et al., 2019). The S function $\sigma(\cdot)$ is a non-decreasing function and satisfies $\sigma(-\infty) = 0$ and $\sigma(\infty) = 1$, and its expression is:

$$\sigma(x) = \frac{1}{1+e^{-cx}} \tag{14}$$

where c represents a constant for the determination of the shape of the S function.

Information transmission in feedforward neural networks is one-way transmission (Zeng et al., 2018). As shown in Figure 3, the neural network contains P neural processing units, and uses a single hidden layer input and output mode, wherein the weighted sum of the hidden layer output values is the output y, and the expression is:

$$y = \sum_{j=1}^{p} t_j \sigma\left(\sum_{i=1}^{n} w_{ij} x_i + w_{n+1,j}\right) \tag{15}$$

where t_j and w_{ij} represent adjustable weights.

Supposing that the input vector $X = [x_1, \cdots, x_n]^T$, the connection weight vector $\theta = [w_{11}, \cdots, w_{n+1,p}, t_1, \cdots, t_p]$, then the relationship between input and output can be expressed by:

$$Y = N(X;\theta) \tag{16}$$

Let y_p denote the output value of the unknown system:

$$y_p = F(X;n) \tag{17}$$

where $F(\cdot,\cdot)$ represents the uncertainty function, and the error between y_p and y is calculated as follows:

$$e = y - y_p = N(X;\theta) - F(X;n) \tag{18}$$

The goal of neural network learning is to adjust the weight θ, so that it satisfies $e \to 0$, i.e., $y \to y_p$. At this time, formula (16) can describe the output and input characteristics of formula (17). The weight θ is adjusted by optimisation means to make the cost function e minimum.

Usually, formula (13) is written as:

$$q(k+1) = \lambda q(k) + g\left(H(k)\right) \tag{19}$$

where

$$H(k) = \left[q_1(k), q_2(k), q_3(k), q(k)\right]^T, |\lambda| \leq 1$$

denotes an arbitrary constant, and $g(\cdot)$denotes a nonlinear function, and the condition $g(\cdot) = f(\cdot) - \lambda q(k)$ is satisfied.

The neural network is able to recognise the nonlinear function $g(\cdot)$ such that the predicted value $\tilde{q}_n(k+1)$ of the neural network is infinitely close to the actual predicted value $q(k + 1)$. When using the following method, assuming that $N_g(\cdot;\ \theta_g)$ can infinitely approximate the neural network of the nonlinear function $g(\cdot)$, where θ_g represents the weight vector. Then the weight $\theta_g(k)$ model corresponding to the time $(k + 1)T$ can be used to derive the estimated value of the traffic flow:

$$\tilde{q}_n(k+1) = \lambda q(k) + N_g\left(H(k);\theta_g\right) \tag{20}$$

The estimated error is:

$$e(k) = \tilde{q}_n(k+1) - q(k+1) = N_g\left(H(k);\theta_g\right) - g\left(H(k)\right) \tag{21}$$

The connection vector is adjusted according to the following adjustment rules:

$$u(k+1) = \theta_g(k) - \frac{\gamma_0}{\beta_0 + \left\|\xi(k)\right\|^2}\xi(k)e(k) \tag{22}$$

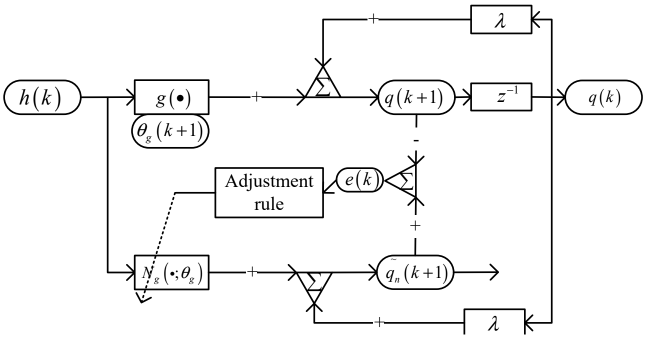
$$\theta_g(k+1) = \begin{cases} u(k+1) \left|u(k+1)\right| \leq M_\theta \\ \dfrac{M_\theta}{\left|u(k+1)\right|} u(k+1) \left|u(k+1)\right| \geq M_\theta \end{cases} \tag{23}$$

where $0 < \gamma_0 < 2$, $\beta_0 > 0$ and $M_\theta > 0$ represent design parameters, and:

$$\xi(k) = \frac{\partial^T N_g\left(h(k);\theta_g(k)\right)}{\partial\theta_g(k)} \tag{24}$$

Through the above-mentioned traffic flow prediction algorithm based on neural network and adjustment of parameters, the neural network prediction model is obtained, as shown in Figure 4.

Figure 4 Neural network prediction model

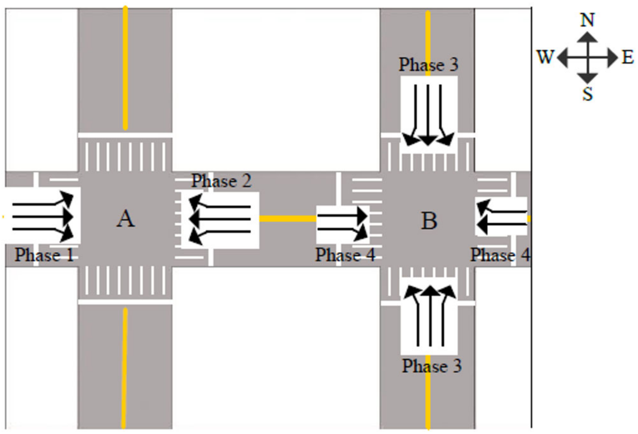


If there is a linear relationship between $N_g(\cdot;\theta_g)$ and θ_g and corresponds to θ_g' of the unknown parameter, $g(\cdot)$can change the parameter to the same form as $N_g(\cdot;\theta_g)$, then it will satisfy the requirement of $e_i(k) \to 0$ when $k \to \infty$.

2.3 Coordinated control of urban traffic flow

In order to achieve coordinated control of urban traffic, the phase is first set, as shown in Figure 5 (phase 4 is the coincident phase of phase 1, 2), and then according to the common signal period C, the upstream phase difference $t_{p,u}^{j,j+1}$ and the downstream phase difference $t_{p,d}^{j+1,j}$ of the road segment mentioned above, the opening times of the phases 1 and 2 are determined.

Figure 5 Diagram of phase setting (see online version for colours)



Assuming that the upstream direction intersection starts from phase 1, and the opening time t_u^1 is 0s, the opening time t_u^j of the phase 1 in other intersection is avoided by the upstream phase difference of the link, and the opening time is expressed as:

$$t_u^j = \sum_{k=2}^{j} t_{p,u}^{k-1,k} - mC;\ m = 1,2,\cdots;\ j = 2,3,\cdots n \tag{25}$$

where the value of m should satisfy the condition of $0 < t_u^j < C$.

Assuming that the opening time t_d^n of the phase 2 of the downstream direction intersection n is ts, and the opening time t_d^j of the phase 2 of the other intersections should be avoided with the downstream phase, and the starting time is expressed as:

$$t_d^j = t + \sum_{k=j}^{n-1} t_{p,d}^{k,k+1} - lC;\ l = 1,2,\cdots;\ j = n-1,\cdots 2,1 \tag{26}$$

In the formula: the value of l should satisfy the condition of $0 < t_d^j < C$.

Supposing that $t_u^{j,g}$ and $t_d^{j,g}$ respectively represent the green signal duration of phase 1 and 2 of intersection j, respectively. According to the idea of the control system, an optimal control parameter t is needed, first satisfying the performance index J_1, and satisfying the basic performance index J_2:

$$J_1 = \min\left(\sum_{j=1}^{m}\left|t_u^j - t_d^j\right| > a^j\ ?1:0\right)$$

$$a^j = \begin{cases} t_d^{j,g} & if\ t_d^j > t_u^j \\ t_u^{j,g} & else \end{cases} \tag{27}$$

$$J_2 = \max\left(\sum_{j=1}^{m}\left|t_u^j - t_d^j\right|\right) \tag{28}$$

Figure 6 Flow chart of calculation of control system data (see online version for colours)

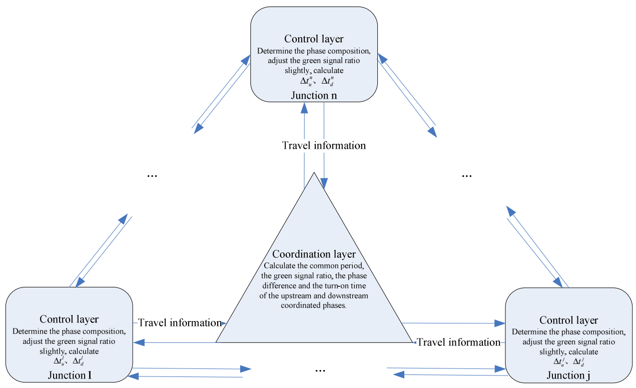


Figure 6 is a flow chart of control data calculation, the main process is:

1 The central coordination controller can calculate the signal period, phase difference and green signal ratio by analysing the traffic information and real-time traffic status for a period of time, and calculate the opening times of phases 1 and 2 based on this.

2 Set l = 0.

3 The intelligent signal controller of intersection is based on the signal period, the opening time $\tilde{t}_u^j$ and $\tilde{t}_d^j$ of phase 1 and 2 calculated by central controller, and the actual phase composition is determined according to the real-time traffic condition. The effective green signal light duration of each phase is fine-tuned, and the turning time Δt_u^j and Δt_d^j of phase 1 and 2 to the left direction are calculated. Then coordinated control is operated, to upload the traffic information acquired in the period to the central controller.

4 Let $l = l + C$, and check whether $l = 8C$ is established, if the equation is established, proceed to the next step, otherwise return to step (3).

5 The coordination layer estimates the saturation of the main intersections in the next period of time based on the traffic data detected over a period of time and the green signal ratio of each intersection, and uses the neural network algorithm to calculate the period C of the next period of time. The saturation of the main intersection is close to the normal value of 0.9. At the same time, the upstream and downstream speeds $v_{j,j+1}$ and $v_{j+1,j}$ in the next period of time are estimated. The opening times $\tilde{t}_u^j$ and $\tilde{t}_d^j$ of the upstream and downstream coordinated phases of each intersection are calculated. Return to the second step and repeat it until the saturation is close to the normal value, and finally achieve coordinated control of urban traffic.

3 Simulation experiments and results

In order to verify the effectiveness of the coordinated control method of urban traffic based on neural network, an experimental platform is built in the TCMS traffic control software, and JAVA software programming is used to simulate the experiment. The experimental data is selected from the intersection of urban trunk line in a city to monitor the road conditions. Supported by the national plan project 'Smart Traffic Coordination Control Technology', on the Thursday of April 25, 2019, the peak of the traffic flow, in cooperation with the traffic police detachment of the city, a new traffic coordination control system is created in the city, which is mainly used to control the implementation of the scheme and display dynamic traffic guidance on the ITS screen. It is necessary to install annular vehicle detectors at all intersections and main sections for real-time monitoring of traffic information, and to upload the information to the central control centre using a dedicated network for storage in the information base. According to the traffic police's command behaviour, 50 sets of data are randomly collected as the initial sample of the neural network. The intersection map is shown in Figure 7.

Figure 7 Intersection map (see online version for colours)

Figure 8 Traffic flow observation point at the intersection (see online version for colours)

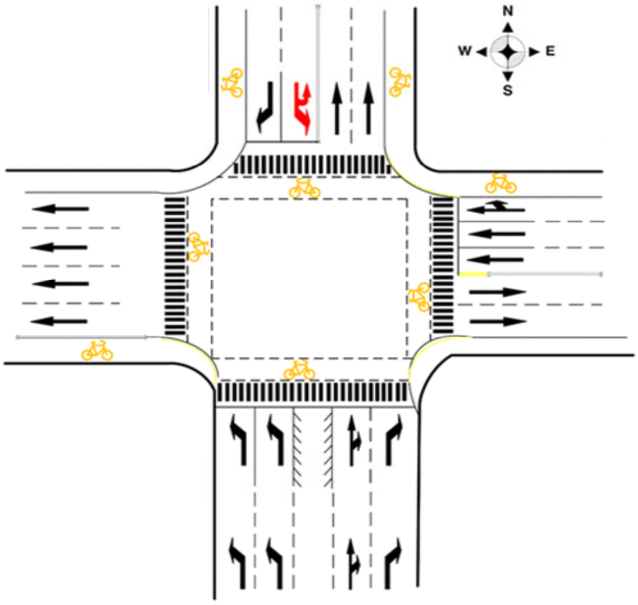
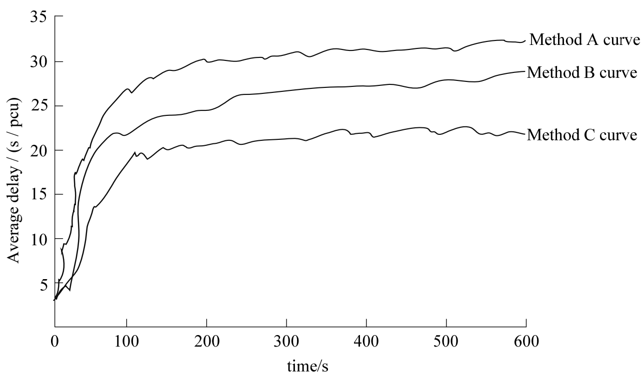


Figure 8 shows the location of the observation points of the traffic coordination control system for city's urban trunk line. The section is a two-way 8-lane road. The observation point detects and records the data 24 hours, and gathers the data every 10 minutes to get the traffic flow in each cycle.

Figure 9 Comparison of average delay of vehicles



Firstly, the traffic phase optimisation method based on multiple genetic algorithms, the coordinated control method of urban trunk line based on macroscopic basic map and the method of this paper are simulated, and the experimental results are compared. The experimental results are shown in Figure 9 and the comparison results are shown in Table 1. In order to make the experimental results clearer, the above three methods are respectively represented as: Method A, Method B and Method C.

Table 1 Comparison of experimental results of different methods

	Average delay of vehicles/(s / pcu)	*Time consuming of single experiment/s*
Method A	124.13	3.16
Method B	83.45	8.27
Method C	55.29	1.03

By analysing Figure 9 and Table 1, it can be seen that after the coordinated control of the proposed method, the vehicle's average delay of this section is lower than that of the other two methods. Compared with Method A, the average vehicle delay is reduced by 68.84s/pcu, and the experimental time is reduced by 2.13s. Compared with Method B, the vehicle delay is reduced by 28.16s/pcu, and the experimental running time is reduced by 7.24s. It can be explained that the proposed method can control traffic flow well, effectively reduce vehicle delay, and has shorter running time and better coordination control effect.

Secondly, the experiment is carried out again by the above methods, and the average driving time of the vehicle on the main road is collected. The total duration of the simulation experiment is 10 h, and the interval is 4 ks, that is, 40,000 simulation steps. The intersection traffic collected by the experiment is shown in Table 2 and Table 3. The average running time of the vehicle and the traffic capacity of the intersection are shown in Table 3.

Table 2 Traffic flow of intersection

Intersection direction		*Intersection 1*	*Intersection 2*	*Saturated flow*
East exit	Turn left	125	204	1350
	Go straight	702	480	1500
	Turn right	217	76	1350
North exit	Turn left	84	100	1350
	Go straight	553	527	1500
	Turn right	104	103	1350
West Exit	Turn left	153	141	1350
	Go straight	491	624	1500
	Turn right	281	308	1350
South exit	Turn left	209	219	1350
	Go straight	531	285	1500
	Turn right	114	207	1350

Note: Unit: ($veh \cdot h^{-1}$)

By analysing Table 2 and Table 3, it can be seen that compared with Method A, the vehicle travel time of the proposed in this section is shorter, the overall average travel time is reduced by 24.24%, and the intersection capacity is increased by 16.72%; compared with Method B, the average travel time of the proposed in this section is reduced by 18.04% overall, and the road crossing capacity is increased by 13.72%. This shows that the operation of the proposed method can effectively improve the traffic efficiency of urban traffic.

Table 3 Comparison of experimental results of different methods

		Time /ks										
		4	*8*	*12*	*16*	*20*	*24*	*28*	*32*	*36*	*40*	*Mean value*
Average travel time in the upstream direction/s	Method A	246.8	252.4	248.7	250.2	246.3	241.1	255.6	247.5	251.9	253.7	249.4
	Method B	250.0	258.6	249.3	257.5	255.8	249.7	245.6	251.2	244.4	247.8	251.0
	Method C	204.1	201.5	211.8	203.3	209.5	210.3	207.9	199.2	200.4	204.7	205.3
Average travel time in the down direction/s	Method A	298.4	308.3	288.7	295.1	291.5	305.8	295.6	300.2	293.3	299.5	297.6
	Method B	256.6	258.1	249.4	255.2	257.7	244.5	261.9	250.3	265.7	246.4	254.6
	Method C	207.2	211.8	207.5	215.4	197.8	213.1	204.7	212.3	217.1	203.6	209.1
Intersection capacity/pcu	Method A	2,249	2,302	2,169	2,322	2,238	2,314	2,189	2,258	2,177	2,305	2,252
	Method B	2,314	2,346	2,297	2,391	2,337	2,285	2,401	2,312	2,287	2,359	2,333
	Method C	2,619	2,684	2,670	2,789	2,756	2,684	2,693	2,708	2,735	2,699	2,704

4 Conclusions

Studying an effective coordinated control method of urban traffic is of great practical significance for avoiding various traffic accidents and traffic detention caused by traffic jams. To this end, in this paper, a coordinated control method of urban traffic based on neural network is proposed. Based on the analysis of the existing coordinated control methods and the results of the analysis of green signal ratio, signal period and phase, a coordinated control method based on neural network is established to fine-tune the green signal ratio, signal period and phase, so as to achieve the goal of coordinated control of urban trunk traffic. The simulation experiment proves that this method is of great significance for coordinated control of congested road sections and intersections and reducing traffic problems such as traffic detention.

Many advanced traffic coordination control methods can no longer be used in actual traffic. This is because researchers only focus on control methods and ignore the factors of actual random variation. Therefore, in the next study, it should be more important to be linked to the actual situation, while at the same time reducing costs as much as possible, in line with actual needs.

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