Optimizing the Perimeter Control for Urban Traffic Sub-region by BP Neural Network

Wenchao Liu and Wenxing Zhu*
Shandong University, Jinan, China
*zhuwenxing@sdu.edu.cn

Abstract. In this paper, we improve the effect of perimeter control for Urban Traffic Sub-region by optimizing signal timing in traffic sub-region. Firstly, we verify the influence of different signal timing on the shape of macroscopic fundamental diagram (MFD) by simulation. Then, we use BP neural network to model the mapping relationship between signal timing and MFD maximum volume (saturated traffic volume of sub-region). In perimeter control based on MFD, the larger the saturated traffic volume, the more vehicles passing through the sub-area. When the output of the BP neural network model reaches the maximum value, the signal timing of the road network is the best one. Comparing the perimeter control effects of different signal timings, we find that the larger the saturation traffic, the larger the traffic in the boundary control and the smaller the vehicle delay.

1. Introduction

With the advancement of urbanization and the increase of car ownership, single point control and main stem control can no longer solve the increasingly serious traffic congestion problem. In view of the over-saturated state of urban regional traffic, the perimeter control strategy has a good adjustment effect. Perimeter control strategy is a kind of urban traffic sub-region control strategy based on macroscopic fundamental diagram (MFD). It can improve the traffic situation in sub-region by adjusting the number of vehicles entering and leaving sub-region to maximize the traffic volume. MFD can intuitively describe the relationship among average traffic flow, average density and average speed in homogeneous traffic network, which provides a theoretical basis for macro-network regulation [1-3].

In 2007, Daganzo proved the existence of MFD through theory, and pointed out that MFD is the inherent attribute of road network and does not depend on OD distribution of road network [4]. Buisson et al. used French highway and urban road traffic data to prove that heterogeneity has a greater impact on the shape of macro-basic maps [5]. Geroliminis et al. found that MFD also exists in inhomogeneous networks, and the shape of MFD is affected by signal control [6]. The shape of MFD determines the maximum traffic volume that can be reached in the sub-region, i.e. saturated traffic volume. That is to say, different signal timing correspond to different saturated traffic volumes for the same traffic sub-area.

In order to obtain the maximum saturated volume, we use BP neural network to model the saturated traffic volume in the sub-region with the input of signal timing. We establish three BP neural network models with one hidden layer, two hidden layers and three hidden layers, and the validity of the models were compared and analyzed. The BP neural network with three hidden layers is used to find out the maximum saturated traffic volume in the sub-region and the corresponding signal timing.
scheme, that is, the optimal signal timing. Bang-Bang perimeter control is carried out under the optimal signal timing, and the results are compared with those under other non-optimal signal timing. The results show that the effect of perimeter control can be optimized by maximizing saturated traffic volume.

2. The Influence of Signal Control on MFD
This paper is based on the simulation data of VISSIM, which is a simulation software suitable for macro traffic simulation. We build a 4×4 road network, as shown in the Figure 1. All traffic signals are fixed with a period of 100 seconds, in which the main road adopts three phase signal control and the rest is two phase signal control. So the dimension of the signal timing vector is 5.

![Figure 1. Sub-area network](image)

We use different signal timing to simulate traffic and draw MFD of road network. The simulation results and MFD curves are shown in the Figure 2. Comparing these figures to determine whether different signal timing will affect the shape of MFD.

The red curve in the graphs represent the relationship between the cumulative number of vehicles in the road network and the traffic volume of the sub-region. It is fitted by a cubic function. When the state of the road network is at the vertex of the curve, the road network is saturated[7]. The cumulative number of vehicles corresponding to saturated state is the critical number of vehicles, and the corresponding traffic volume is the saturated traffic volume. As can be seen from Figure 2, the MFDs are different under each signal timing. They have different saturated traffic volume and critical cumulative number of vehicles. In order to determine the mapping relationship between signal timing and saturated traffic volume, we use BP neural network to model saturated traffic volume.

![Figure 2](image)

(a) (b)
3. Saturated Traffic Volume Modeling in Traffic Subarea

Using BP neural network to model the peak flow of MFD, i.e. saturated traffic volume of the sub-region, and the input of the model is signal timing. We establish three BP neural network models with one hidden layer, two hidden layers and three hidden layers, and the validity of the models were compared and analyzed.

3.1. BP Neural Network Model

Back propagation neural network is a concept proposed by Rumelhart and McClelland in 1986. BP neural network can learn and store the nonlinear mapping relationship between input and output. Here we use it to model the saturated traffic volume. The input of the model is the signal timing vector of the sub-region. It modifies the weights and thresholds of the network through the reverse propagation of errors, so that the errors between the predicted values and the real values are continuously reduced. When the error reaches the set value or the number of iterations reaches the maximum value, the training stops and the modeling is completed. The structure of BP neural network is shown in the Figure 3.

\[
\mathbf{a}_j = f\left(\sum_i x_i w_{ij} + b_j \right)
\]
where $x_i$ and $a_j$ are the input of the neural network and the output of the hidden layer neuron $j$, respectively; $w_{ij}$ is the weight of $x_i$ to $a_j$, and $b_j$ is the bias; $f$ is an activation function. In the process of error back propagation, we use loss function to measure the error between predicted value and real value, and use gradient descent method to update the weights of the network, which makes the predicted value of the network as close as possible to the real value. As iteration proceeds, the value of loss function decreases. The loss function used in this modeling is MSE (mean square error).

$$MSE = \frac{1}{m} \sum_{i=1}^{m} (y_{pi} - y_{ni})^2$$ (2)

where MSE and MAE are mean square error and mean absolute error respectively; $m$ is the number of output nodes; $y_{pi}$ is the predicted value of BP neural network and $y_{ni}$ is the true value.

The modeling steps are as follows[9-11]:

1. Determine the network structure. The number of neurons in input layer and output layer is determined according to the dimension of input and output. The number of neurons in hidden layer is determined by heuristic method.
2. Initialize the network. Initialization of weights and thresholds in networks.
3. Forward transmission of information. The input vector is computed layer by layer to get the predicted value.
4. Reverse propagation of errors. The errors are computed by gradient descent method to get the change of weights, which are updated from the end of the network.
5. Determine whether the termination conditions are met. The termination condition is that the number of iterations reaches the upper limit or the error is small enough. If the condition is satisfied, the modeling stops, otherwise it goes back to step (3).

3.2. Analysis of Modeling Result

After testing, it is found that the BP neural network with one hidden layer, two hidden layers and three hidden layers has the best prediction effect when its structure is 5-12-1, 5-12-5-1 and 5-12-1-4-1, respectively. Three models are tested with simulation data, and the test results are shown in the Figure 4.

According to the figures, the prediction result of BP neural network of 5-12-1-4-1 is the closest to the real value, which is more reliable than the other two models. So we use BP neural network model with three hidden layers to find the best signal timing vector to maximize the saturated traffic volume. Here we can use genetic algorithm to optimize or traversal search. After optimization, it is found that the optimal timing vector is $[35, 13, 43, 51, 43]$, the corresponding maximum saturated traffic volume is 877 veh/Ts, and Ts is the sampling period.
4. Optimized boundary control
Perimeter control is a regional vehicle number control technology based on MFD. When the number of vehicles in the area exceeds the critical number of vehicles, the number of vehicles entering the sub-area will be reduced through the signal lights at the boundary intersection. When the number of vehicles in the area is less than the critical number of vehicles, the number of vehicles entering the sub-area will be increased. In this way, the number of vehicles in the area can be maintained near the critical value, and the traffic volume in the area can also be maintained near the saturated traffic volume. Therefore, during the implementation of boundary control, the larger the saturated traffic volume, the more vehicles passing through the road network. In the third chapter, we use the BP neural network model to find the signal timing which maximizes the saturated traffic volume is [35, 13, 43, 51, 43].

We use Bang-Bang control strategy to verify whether the optimized signal timing vector can improve the effect of boundary control. The signal timing vector and its corresponding saturated traffic volume are shown in the Table 1. The first group in the table is the optimal timing vector and the maximum saturated traffic volume.

| signal timing vector(s) | saturated traffic volume(veh) |
|-------------------------|-----------------------------|
| [35,13,43,51,43]        | 877                         |
| [30,17,44,56,38]        | 810                         |
| [38,30,23,55,39]        | 695                         |
| [40,39,12,58,36]        | 511                         |

The effect of the Bang-Bang control under four timing vectors is shown in the Figure 5. Figure 5.(a) shows the variation of sub-area flow with simulation time in each signal cycle, and Figure 5.(b) shows the variation of vehicle average delay with simulation time in each signal cycle.

As can be seen from Figure 5, compared with the Bang-Bang control under the other three signal timing vectors, the traffic volume in the Bang-Bang control under the optimized signal timing vector is larger and the vehicle delay is smaller. This proves that the optimized sub-region signal timing vector can improve the effect of boundary control based on MFD.

5. Conclusion
In this paper, we use BP neural network to model the saturated traffic volume in the sub-region with the input of signal timing. The simulation data show that the BP neural network with three hidden layers can well reflect the mapping relationship between signal timing and saturated traffic volume. With the help of BP neural network model, we get the signal timing which maximizes the saturated
traffic volume, and call it the optimal signal timing. It is found that compared with other signal timing, the optimal signal timing can increase the traffic volume of sub-region and reduce the delay of sub-region.

References
[1] Gan Q J 2014 Macroscopic modeling and analysis of urban vehicular traffic J. Dissertations & Theses - Gradworks
[2] Knoop V L, Hoogendoorn S P and Van Lint J W C 2013 The impact of traffic dynamics on macroscopic fundamental diagram (poster) J. Civil Engineering & Geosciences pp 236-250
[3] Shraiber A, Haddad J 2014 Robust control design for a perimeter traffic flow controller at an urban region C. Control Conference
[4] Dangzo C F 2007 Urban gridlock:Macroscopic modeling and mitigation approaches J. Transportation Research Part B pp 0-62
[5] Buisson C, Ladier C 2009 Exploring the Impact of Homogeneity of Traffic Measurements on the Existence of Macroscopic Fundamental Diagrams J. Transportation Research Record: Journal of the Transportation Research Board pp 123-136
[6] Ludovic L, Nikolas G 2013 Estimating MFDs in simple networks with route choice J. Transportation Research Part B pp 468-484
[7] Wu C Y, Li M, Jiang R, Hao Q Y and Hu M B 2018 Perimeter control for urban traffic system based on macroscopic fundamental diagram J. Physica A pp 231-242
[8] Sadeghi B H M 2000 A BP-neural network predictor model for plastic injection molding process J. Journal of Materials Processing Technology pp 411-416
[9] Xiao Z, Ye S J and Zhong B 2009 BP neural network with rough set for short term load forecasting J. Expert Systems with Applications pp 273-279
[10] Jin W, Li Z J and Wei L S 2000 The improvements of BP neural network learning algorithm C. 5th International Conference
[11] Baoan Y, Hai J I 2001 A Study of Commercial Bank Loans Risk Early Warning Based on BP Neural Network J. Systems Engineering-theory & Practice