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Double-layer ramp-metering model for incident congestion on expressway

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Abstract: In order to ensure stable traffic capacity and avoid incident congestion, a double-layer ramp metering model is proposed in this paper, based on coordination control theory, to predict and control the traffic flow at each on-ramp, when there is incident congestion on the expressway. The function of the lower model is to recognize where the incident congestion exists, based on an adaptive neural network with inputs of traffic flow, velocity and density. The outputs of the lower model are the number of section where the congestion occurs, the number of ramp which should be controlled, and real-time traffic flow information. These outputs should be transmitted to the upper model. The function of the upper model is to design the ramp-metering strategy based on nonlinear theory. The outputs of the upper model are a ramp-metering rate and traffic-flow state after ramp controlling on the expressway. The results of the simulation show that the double-layer ramp metering model could shorten the delay by about 25%, and the variance of the model results is 0.002, which could certify the control strategy is equitable.

Key words: traffic engineering; double-layer model; incident congestion; ramp metering; urban expressway

1 Introduction

Some traffic congestion is induced by traffic accidents, we call this "incident congestion". It is random and accidental, and impossible to predict where and when it might happen. As a result, it is difficult to disperse incident congestion. If it not dispersed in time, it can lead to paralysis of the road network (Liang 2005). In order to alleviate traffic jams and to elevate road capacity with sufficient service, many ramp-metering

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measures are used on the urban expressway. These are classified mainly into three: on-ramp metering, masterstroke control, and passageway control.

On-ramp metering is the most widely applied control measure, the objective of which is to control the number of vehicles entering the expressway, so as to keep the expressway working at a maximum traffic capacity (Papamichai and Papageorgiou 2008). When occasional jams occur on a certain section of the expressway, for instance, lanes are occupied as a result of a traffic accident, causing traffic capacity decline or jam, the congested sections should be controlled by taking effective measures to avoid the congestion spreading on a larger scale. Currently, the research on ramp metering has about 4 stages: local ramp metering; ramp-coordination metering; dynamic traffic assignment; and traffic channel integration control. The control method could be classified as: masterstroke control, line guide control, speed-limit control, and so on (Ghods et al. 2007).

Of these, local ramp metering is a static or dynamic control method for single on-ramp on freeway. For instance, a local feedback control law (ALINEA), advanced by Papageorgiou, is a typical feedback method for local ramp metering, and could disperse part of the congestion, but may induce congestion drifting. The road section that is moving maybe become a newly congested section (Kotsialos et al. 2004; Kotsialos et al. 2002). Ramp-coordination metering is a static or dynamic control strategy for nearby on-ramps on the freeway, which could carry out a static control method, based on linear plan theory, or carry out linear secondary feedback control, and nonlinear optimal control, based on dynamic optimal control theory (Kotsialos et al. 1999).

The calculation rule of these control methods is simple and cost is low, but it cannot cope with traffic incidents and disturbance. So, the control results are not so good (Yuan et al. 2009). Some researchers have analyzed how to implement ramp-linkage metering, such as Payne, Papageorgiou, and so on. These models could reflect the traffic flow state and optimize the whole road network. However, the results of ramp-linkage metering maybe mean that the waiting time for some drivers, waiting on a controlled on-ramp, is too long to endure, or the queue length is too long, which may disturb the well-balanced traffic flow state for intersected roads (Bellemans et al. 2006; Papageorgiou and Kotsialos 2002).

Ramp-channel metering is a territorial, integrated-control method. By combining ramp metering on the freeway and urban traffic information regional control, a selected control index could achieve the best. The purpose of it is to compensate the delay time on the controlled ramp by decreasing the traveltime on the freeway (Jang and Han 1994). By doing this, the whole travel time for the traffic system could decrease. So the effects of this method depend on the traffic-flow state of the freeway and alternative routes, and whether drivers would choose the alternative routes (Ma 1999).

In this paper, a double-layer ramp metering model is advanced, based on coordination control theory. The function of the lower model is to recognize where the incident congestion is based on the adaptive neural network, whose inputs are traffic flow, velocity and density. The outputs of the lower model are the number of section where the congestion occurs, the number of ramp which should be controlled, and the real-time traffic flow information. These outputs should be transmitted to the upper model. The function of the upper model is to design the ramp-metering strategy, based on nonlinear theory. The outputs of the upper model are the ramp-metering rate and the real-time traffic flow state after ramp controlling on the expressway.

2 Basic idea of ramp-metering for incident congestion on urban expressway

Considering that incident congestion is random and accidental, the required ramp-metering number is also random and accidental (Han and Jiang 2007). So the occurrence time and place of the incident congestion must be identified first, then it is possible to control and disperse them. On account of the purpose, a double-layer ramp-metering model is advanced, based on coordination control theory. The basic ideal of the model is shown in Fig. 1. This double-layer model should identify the congestion, and design a control strategy quickly and accurately. The final outputs of the model are the ramp-metering rate and the real-time traffic-flow state after ramp controlling on the expressway. Meanwhile, the control strategy must be equitable for each driver, because for most control methods, in order to make the traffic system optimal, the waiting time for each on-ramp is unequal. Some drivers would wait a long time as the corresponding ramp was closed (Kotsialos and Papageorgiou 2001). For these control strategies, in spite of the optimal system, a driver experiencing a too long delay is inequitable. So the equitableness for each driver is considered in the double-layer ramp-metering model.

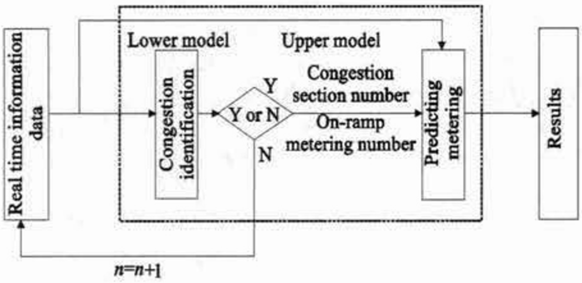

Fig. 1 Basic ideal of double-layer ramp-metering model

3 Dynamic traffic-flow of urban expressway

As shown in Fig. 2, on an urban expressway with N sections, the length of each road section is $\Delta_i\,(i=1,2,\cdots,N)$; and the samping period is T, after continuous time discrimination, $t=kT$, $k=0,1,\cdots,K$, KT is the ending time. Note the traffic volume of section i, traffic density and velocity are $q_i(k)$, $\rho_i(k)$, $v_i(k)$, respectively, and the traffic volumes at the entrance and exit are $r_i(k)$, $s_i(k)$, respectively.

The dynamic traffic model of the urban expressway is as follows ($i=2,\cdots,N-1$):

$$\rho_i(k+1)=\rho_i(k)+\frac{T}{\Delta_i}[q_{i-1}(k)-q_i(k)+r_i(k)-s_i(k)] \quad (1)$$

$$v_i(k+1)=v_i(k)+\frac{T}{\tau}[v(\rho_i(k)+\frac{T\xi}{\Delta_i}v_i(k))]\times[v_{i-1}(k)-v_i(k)]-\frac{uT[\rho_{i+1}(k)-\rho_i(k)]}{\tau\Delta_i[\rho_i(k)+\theta]} \quad (2)$$

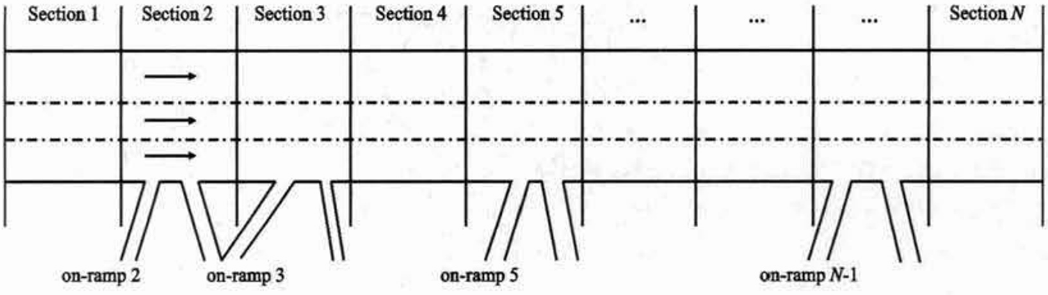

Fig. 2 Structure of expressway

$$v[\rho_i(k)]=v_f[1-(\frac{\rho_i(k)}{\rho_{\text{jam}}})^l]^m \quad (3)$$

$$q_i(k)=\alpha\rho_i(k)v_i(k)+(1-\alpha)[\rho_{i+1}(k)\times v_{i+1}(k)-r_{i+1}(k)]-s_i(k) \quad (4)$$

Eqs. (1)-(4) form the MACK model (Park and Kim 2004), where τ is a corrected parameter to adjust the weight of the second term in Eq. (2); ξ is a corrected parameter to adjust the weight of the third term in Eq. (2); μ is a corrected parameter, together with τ to adjust the weight of the fourth term in Eq. (2); θ is a corrected parameter, introduced to avoid that the fourth term in Eq. (2) is too big when $\rho_i(k)$ is very small; l, m are model parameters, estimated according to actually measured traffic data; ρ_{jam} is jam density; v_f is free driving speed; α is weighting coefficient.

As for the start and end of a section of the urban expressway, $i=1$ and $i=N$, the following could be obtained:

$$\rho_1(k+1)=\rho_1(k),\ v_1(k+1)=v[\rho_1(k)] \quad (5)$$

$$\rho_N(k+1)=\rho_N(k),\ v_N(k+1)=v[\rho_N(k)] \quad (6)$$

For the traffic flow, when $i=1$, Eq. (4) is still true, and when $i=N$, the following could be obtained:

$$q_N(k)=\alpha\rho_N(k)v_N(k) \quad (7)$$

In the entrance ramp control, in addition to the preceding equations, the queue length $p_i(k)$ obviously needs to be considered, so the following could be achieved:

$$p_i(k+1) = p_i(k) + T(d_i(k) - r_i(k)) \quad (8)$$

where $d_i(k)$ is the traffic need of ramp i at time k; T is designated as before.

In addition to the above equations, $r_i(k)$ should follow the conditions of the upper limit and the lower limit. At the same time, the minimum regulation rate limits $r_i(k) \geqslant r_{imin}$.

The queuing vehicles at the entrance ramp i should also not exceed the queuing capacity p_{imax}, so the following could result:

$$p_i(k) + T[d_i(k) - r_i(k)] \leqslant p_{imax} \Rightarrow$$

$$r_i(k) \geqslant d_i(k) - [p_{imax} - p_i(k)]/T \quad (9)$$

The maximum regulation rate limit is $r_i(k) \leqslant r_{imax}$. Obviously, the queuing length $p_i(k+1) \geqslant 0$, i. e., $p_i(k) + T[d_i(k) - r_i(k)] \geqslant 0$, can be converted to the following:

$$r_i(k) \leqslant d_i(k) + p_i(k)/T \quad (10)$$

Therefore, the limit of $r_i(k)$ is as follow:

$$\max\{r_{imin}, d_i(k) - \frac{1}{T}[p_{imax} - p(k)]\} \leqslant$$

$$r_i(k) \leqslant \min\{r_{imax}, d_i(k) + \frac{1}{T}p_i(k)\} \quad (11)$$

Status variables include $\rho_i(k)$, $v_i(k)$ and $p_i(k)$; the control variable is $r_i(k)$; and the output variables are $\rho_i(k)$ and $p_i(k)$.

Eqs. (1)-(4), (8) and (11) could be combined to describe the traffic-flow state on the urban freeway.

4 Double-layer ramp-metering model and solution

4.1 Lower model-congestion identification and solution

Although the incident congestion is random and accidental, there are some rules for the traffic-flow state in spatial and temporal distributions when incident congestion has formed. For temporal distribution, the traffic flow, velocity and density are mutational before and after the traffic accidents. For spatial distribution, the traffic flow and velocity decrease, and the density increases in the upper section when incident congestion has formed. The traffic-flow state in the lower section is opposite (Long 2009). These rules are shown in Figs. 3 and 4, in which, t_1 is the time when the traffic accident happens, and t_2 is the detection time for the upper section.

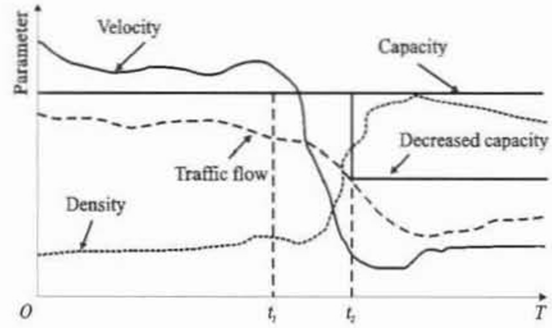

Fig. 3 Time distribution of incident congestion

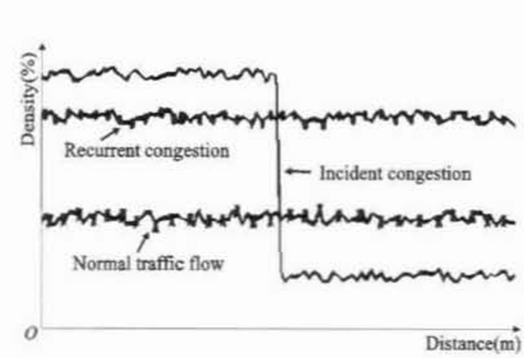

Fig. 4 Space distribution of incident congestion

Considering the structure of congestion rules was nonlinear, in order to identify the incident congestion, a Back Propagation neural network (BP neural network) was used to establish the lower model, because a BP neural network could draw near any nonlinear mapping, accurately (Wang et al. 1993). Some weaknesses of a BP neural network, such as the difficulty of constructing the network, a tendency towards a local optimal solution, and slow convergence speed, could be avoided by bringing in particle-swarm optimization.

4.1.1 Model establishment

The inputs of the lower model include the followings: traffic flow ratio of time t to time $t-1$ for upper section; traffic velocity ratio of time t to time $t-1$ for upper section; density ratio of time t to time $t-1$ for upper section; traffic flow radio of time t to time $t-1$ for lower section; traffic velocity ratio of time t to time $t-1$ for lower section; density ratio of time t to time $t-1$ for lower section; ratio of density to velocity for upper section; and the ratio of density to flow for upper section. These inputs are written as $X = (x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8)$, which are shown in

Eq. (12). The outputs are congestion state ($y_1 = 1$) and no congestion state ($y_2 = 1$), which could be written as $Y=(1,0)$. If $Y=1$, there is traffic incident congestion, and the lower model should output the number of road section where congestion happens, as well as the required ramp-metering number.

$$\begin{cases} x_1 = q_t/q_{t-1}, & x_2 = v_t/v_{t-1}, & x_3 = o_t/o_{t-1} \\ x_4 = q_t'/q_{t-1}', & x_5 = v_t'/v_{t-1}' \\ x_6 = o_t'/o_{t-1}', & x_7 = o_t/v_t, & x_8 = o_t/q_t \end{cases} \tag{12}$$

where q_t is the traffic flow for upper section at time t; v_t is the traffic velocity for upper section at time t; o_t is the density for upper section at time t; q_{t-1} is the traffic flow for upper section at time $t-1$; v_{t-1} is the traffic velocity for upper section at time $t-1$; o_{t-1} is the density for upper section at time $t-1$; q_t' is the traffic flow for lower section at time t; v_t' is the traffic velocity for lower section at time t; o_t' is the density for lower section at time t; q_{t-1}' is the traffic flow for lower section at time $t-1$; v_{t-1}' the traffic velocity for lower section at time $t-1$; o_{t-1}' is the density for lower section at time $t-1$.

The structure of the lower model is described as "3 +1". "3" means the typical 3-layer BP neural network, and "1" means a transport layer to the upper model. As shown in Fig. 5, if $Y=0$, the output of the lower model is null; if $Y=1$, the dot product function would be activated, and the required ramp-metering number would be calculated and transported to the upper model as input data. The range of needed ramp-metering number is $[l-h_1, l+h_2]$, in which l is the nearest ramp number at the upper section, and h_1, h_2 are the adjustment coefficients of the ramp-metering area which are decided by the actual traffic network.

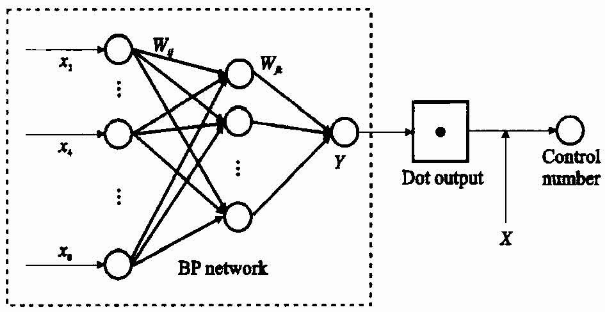

Fig. 5 Structure of lower model-incident congestion identification

4.1.2 Solution

An S-function is used as an activated function for hidden neurons, and a linear transfer function is used as an activated function for output neurons.

$$f(x) = 1/(1+1/e^x) \tag{13}$$

$$p(x) = \alpha x + \beta \tag{14}$$

where x is the input; α, β are parameters.

The initial value of the weight and number of hidden neurons were solved by particle-swarm optimization, as shown in reference (Liu 2009). In order to accelerate the convergence speed, a momentum was introduced to amend study step λ, based on the traditional BP algorithm (Gu and Ai 2007).

$$W(k+a) = W(k) + \alpha(k)[1-\eta D(k) + \eta D(k-1)] \tag{15}$$

$$\begin{cases} \alpha(k) = 2^k \alpha(k) = -1 \\ \lambda = \mathrm{sign}[D(k)D(k-1)] \end{cases} \tag{16}$$

where $\alpha(k)$ is the study ratio at time k; η is the momentum factor used to inhibit oscillation.

4.2 Upper model-ramp metering model and solution

4.2.1 Model establishment

The urban expressway's traffic control system has multiple indexes assessment. With respect to avoiding occasional jams spreading on a larger scale, the traffic capacity of the un-congested sections should be used sufficiently, as much as possible. Through the traffic guidance, the congestion is controlled to prevent large-scale and rapid spreading. Assuming the expected density of each section is ρ_{si}, where $\rho_{si} = \rho_{cri}$, which is the key density when the expressway's traffic capacity reaches its maximum, the expected queuing length of the ramp should be metered $\rho_{si} \leqslant \lambda$ where λ is a constant. When occasional congestion occurs on a section of expressway, the objectives for ramp control should be as follows: one is to ensure the un-congested sections are used at their maximum traffic capacity; the other is to control the queuing length of the ramp as short as possible (Wu et al. 2007). Therefore, we set the following function:

$$J(k_0) = \sum_{k=k_0}^{k_0+N_p-1} [\sum_{i\in\Phi_s} (\rho_i(k)-\rho_{cri})^2 + \alpha_p \sum_{m\in\Phi_0} \rho_m^2(k)] + \alpha_r \times \sum_{k=k}^{k_0+N_c-1} \sum_{m\in\Phi_0} [r_m(k)-r_m(k-1)]^2 \tag{17}$$

where N_p, N_c are the predicted time domain and control domain; Φ_s is the section set; Φ_0 is the ramp set; and α_p, α_r are the weighting coefficients. The first term is to make the density of expressway as close to the key density as possible, to enable its traffic capacity to reach its maximum. The second term $p_{si}=0$, the queuing length, should be kept as small as possible. The third term is to restrain the high-frequency oscillation of the control variable $r_i(k)$ (ramp flow rate).

So Eqs. (1)-(4), (8), (11), (17) structure the prediction control model and the control objective could be reached by mineralizing the target function $J(k_0)$.

4.2.2 Single-step nonlinear prediction control algorithm

Considering the established ramp-metering system is a typical affine nonlinear system, and the affine nonlinear system could be written as follows:

$$X_{k+1}=Y(X_k)+G(X_k)U_k \tag{18}$$

$$Y_k=DX_k \tag{19}$$

$$X_k=(\rho_1(k), v_1(k), \cdots, \rho_N(k), v_N(k), p_1(k), \cdots, p_N(k)) \tag{20}$$

$$U_k=(r_1(k), \cdots, r_N(k)) \tag{21}$$

$$Y_k=(\rho_1(k), \cdots, \rho_N(k), p_1(k), \cdots, p_N(k)) \tag{22}$$

Note that if the road section i has entrance ramps, the vectors X_k and Y_k don't contain $p_i(k)$, and the vector U_k contains no $r_i(k)$. $Y(X_k)$, $G(X_k)$ are the function matrices as shown in Eqs. (1), (2) and (8), and D is the identity matrix.

One-step prediction results of the model at time k could be calculated as follows:

$$\begin{aligned} Y_{k+1|k}&=DY(X_{k|k})+DG(X_{k|k})U_{k|k}= \\ &[DY(X_{k|k})+DG(X_{k|k})U_{k+1}]+DG(X_{k|k})\times \\ &\Delta U_{k|k}=G_0(X_{k|k}, U_{k-1})+DG(X_{k|k})\Delta U_{k|k} \end{aligned} \tag{23}$$

where $Y_{k+1|k}$ is the predicted value output from the system when the time k corresponds to the coming time $k+1$; $\Delta U_{k|k}=U_{k|k}-U_{k-1}$; $G_0(X_{k|k}, U_{k-1})$ is the part formed with known information in the output prediction of the system; $DG(X_{k|k})\Delta U_{k|k}$ is the part formed with the increment of the controlled unknown variable, and can be solved in the future output prediction in the system.

The control objective could be reached by minimizing the following objective function:

$$\begin{aligned} J_k=J(k_0)&=\sum_{k=k_0}^{k_0+N_p-1}\Big[\sum_{i\in\Phi_s}(\rho_i(k)-\rho_{i\max})^2+ \\ &\alpha_p\sum_{m\in\Phi_s}p_m^2(k)\Big]+\alpha_r\sum_{k=k_0}^{k_0+N_c-1}\sum_{m\in\Phi_s}[r_m(k)-r_m(k-1)]^2= \\ &\frac{1}{2}\|Y_{k+1|k}-W_{k+1}\|_Q^2+\|\Delta U_{k|k}\|_P^2= \\ &\frac{1}{2}\Delta U_{k|k}^T H\Delta U_{k|k}+\frac{1}{2}F_1\Delta U_{k|k}+\frac{1}{2}\Delta U_{k|k}^T F_2+\frac{1}{2}J_0 \end{aligned} \tag{24}$$

$$H=(DG(X_{k|k}))^T Q(DG(X_{k|k}))+P \tag{25}$$

$$F_1=(G_0(X_{k|k}, U_{k-1})-W_{k+1})^T QDG(X_{k|k}) \tag{26}$$

$$F_2=(DG(X_{k|k}))^T Q(G_0(X_{k|k}, U_{k-1})-W_{k+1}) \tag{27}$$

$$F=F_2=F_1^T \tag{28}$$

$$W_{k+1}=(\rho_{cr1}, \rho_{cr2}, \cdots, \rho_{crN}, 0, \cdots, 0) \tag{29}$$

where W_{k+1} is the locus vector of the set value at time $k+1$; $N_p=N_c=1$; Q is the output value weighting matrix; P is the control increment weighting matrix. During the actual ramp control, it is needed to consider the influence of multiple constraints on optimization control. In addition to Eq. (6), we have the output value constraint condition $0\leqslant p_i(k)\leqslant p_{i\max}$.

The performance index J_k and corresponding constraint conditions are optimized based on the situation at time k. The optimization control rate $\Delta U_{k|k}$ can be obtained, and $U_k=U_{k-1}+\Delta U_{k|k}$ is controlled in real time at time k. This optimization control process above should be repeated at time $k+1$.

5 Simulations

5.1 Settings of simulations

Assume a one-way urban expressway with three lanes, 2.5 km in length, divided into 5 sections, each section's length is $\Delta_i=0.5$ km, road sections 2, 3 and 5 include one entrance ramp and one exit ramp, respectively, which are shown in Fig. 6. Assume the traffic volume of main line entrance $q_0=1000$ veh/h/lane. The need for each ramp within the time period under discussion is constant, such as $d_2=900$ veh/h, $d_3=d_5=1000$ veh/h, $v_f=97.3$ km/h, $\rho_{\text{jam}}=74$ veh/km/lane, and critical density $\rho_{cr}=37$ veh/km/lane with the corresponding traffic capacity $q_m=1800$ veh/h/lane. The exit ramp traffic volume S_i is in direct proportion to the traffic volume of this road section. Initial densities of the five sections are 24, 26, 21, 46, 27 veh/km/lane, respectively. Assume section 4 has a traffic jam and set the sampling period $T=1$ min, $N_p=1$ min, $N_c=1$ min, and $\alpha_p=\alpha_r=1.30$ times, one-step prediction control is conducted, i. e., $K=30$. Weightings of on-ramps in the influence area of the bottleneck are that the value of on-ramp 2 is 0.3, values of on-ramp 3 and on-ramp 5 are 0.5(Fig. 7).

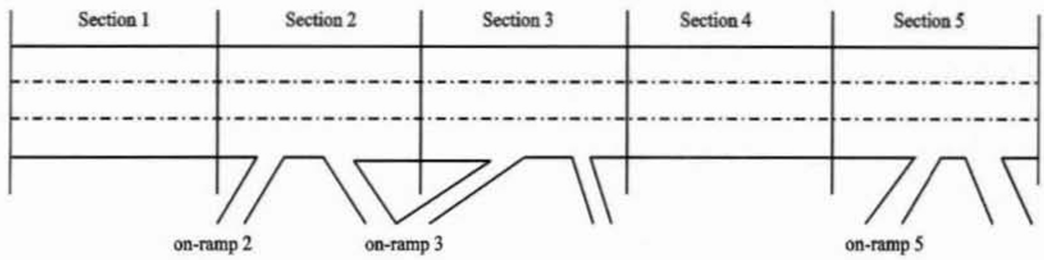

Fig. 6 Structure of urban expressway in simulation

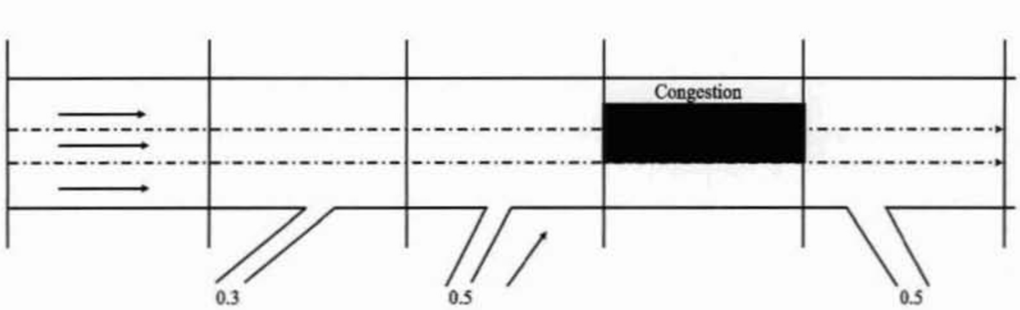

Fig. 7 Weighting factor distribution among on-ramps in influence area of bottleneck

5.2 Results of simulation

The ramp-metering model in this paper has double layers; the lower is to identify congestion; the upper is to design a control and disperse strategy. So the effectiveness of congestion identification is tested first, and then its validity is examined.

5.2.1 Testing of congestion identification

600 traffic data were chosen randomly as testing data, of which, 400 data were used for network training, and 200 data were used for network testing. The number of hidden layer nodes is set at 18 after training. As shown in Fig. 8, 334 study steps are needed to reach an expectant error and make it smooth and steady in a traditional BP neutral network. When particle-swarm optimization was introduced to calculate the number of hidden layer nodes and their weights and a momentum was introduced to adjust study step in traditional BP neutral network, there were only 132 steps needed to reach expectant error and make it smooth and steady. The results prove that the correctional BP neutral network could identify incident congestion more quickly. In the 200 testing data, 105 data are incident congestion data. The model could identify 100 incident congestion data correctly, so the accuracy of congestion identification is 95.2%.

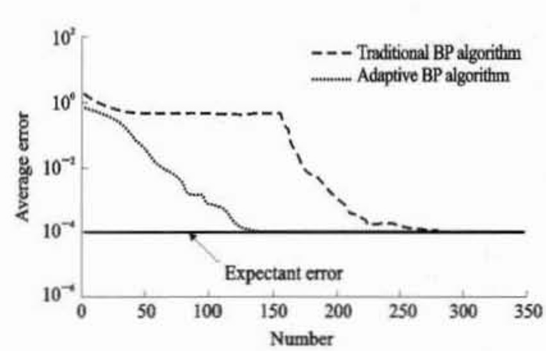

Fig. 8 Rate of convergence on traditional BP network and self-adaption BP network

5.2.2 Ramp-metering result analysis

By analyzing simulation results, the average value of the queuing delay decreases by 24.3%. So the double-layer ramp metering model, based on the results of congestion identification and real-time traffic information from the lower model, could adjust traffic flow on the ramp, eliminate incident congestion, and prevent congestion diffusion again. Take the incident congestion in section 4 as an example to describe the traffic flow state in detail.

The results of prediction metering are shown in

Figs. 9-11, whose values are the on-ramp metering ratios. Since the traffic congestion is in the downstream road section, the traffic volume of on-ramp 5 is greater than that of on-ramp 2 and on-ramp 3. When the downstream congestion is eased, the upstream main line volume should be controlled in case that the volume is too much and causes traffic jams again. Comparing the results of Figs. 12, 13, the traffic congestion on the expressway dissipates after about 15 min, a 25% time shorter than that without control, which is about 20 min for dissipation. Moreover, the vehicle flow density of the road section changes smoothly, which is good for traffic safety. So the constraint parameter of the ramp-metering ratio introduced to the objective function in the double model is effective, which could smooth the change curve of the ramp-metering ratio, and in favour of eliminating incident congestion smoothly.

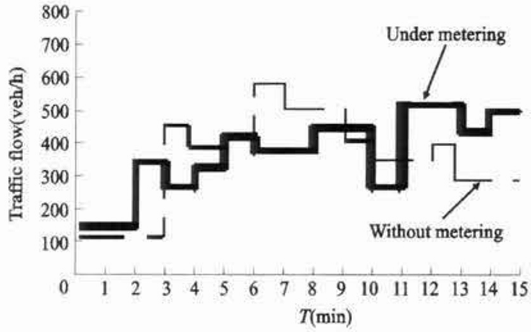

Fig. 9 Metering ratio of on-ramp 2

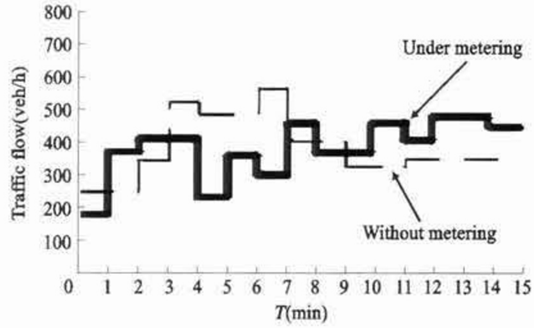

Fig. 10 Metering ratio of on-ramp 3

It is necessary to check out the equity for waiting drivers to avoid some waiting too long. Assume the queuing and waiting time of ramp m is $t_m(k) = \dfrac{p_m(k)}{d_m(k)}$, and the average waiting time of all ramps $\bar{t}(k) = \dfrac{1}{n}\sum_{m\in\Phi_0} t_m(k)$. So the variance of average wait-

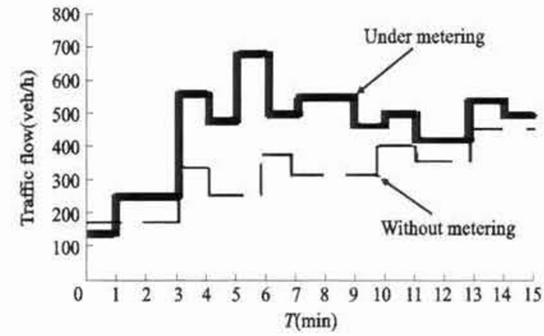

Fig. 11 Metering ratio of on-ramp 5

ing time of all ramps $Var(k) = \dfrac{\sum_{m\in\Phi_0}[\bar{t}(k) - t_m(k)]^2}{n}$, where n is the number of entrance ramps. The variance of the whole system is $Var = \dfrac{1}{K}\sum_{k=0}^{K-1} Var(k)$. The smaller the variance, the better the equity (Wu et al. 2007). We can obtain the variance of this control method, $Var = 0.002$ and $Var = 0.010$ for no control. As a result, equity increases.

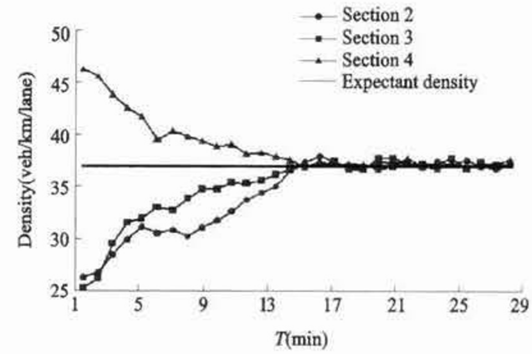

Fig. 12 Density change under control

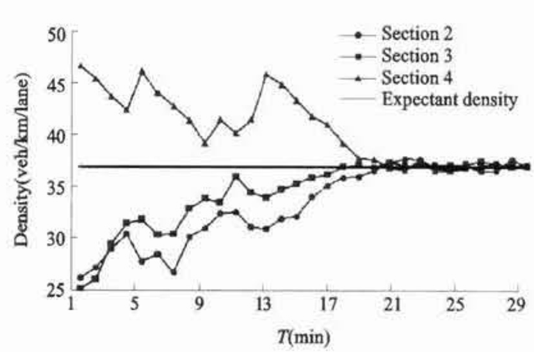

Fig. 13 Density change without control

6 Conclusions

In order to ensure stable traffic capacity and avoid incident congestion, a double-layer ramp-metering model is proposed in this paper, based on coordination control theory. The function of lower model is to recognize where the incident congestion occurs, based on an adaptive neural network, with inputs of traffic flow, velocity and density. The outputs of the lower model are the number section where the congestion occurs, the number of which should be controlled, and the real-time traffic-flow information. The accuracy of congestion identification is 95.2%. Then the upper model is established to design a ramp-metering strategy, based on nonlinear theory, which is linked to the lower model by setting the output data as its input data. The outputs of upper model are ramp-metering rate and real-time traffic-flow state, after ramp controlling on the expressway. The results of the simulation show that the double-layer ramp-metering model could decrease the delay by about 25%, and the variance of the model results is 0.002, which could certify that the control strategy is equitable.

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References

Bellemans, T., De Schutter, B., De Moor, B., 2006. Model predictive control for ramp metering of motorway traffic: a case study. Control Engineering Practice, 14(7): 757-767.

Ghods, A. H., Kian, A., Tabibi, M., 2007. A genetic-fuzzy control application to ramp metering and variable speed limit control. IEEE International Conference on Systems, Man and Cybernetics, Montreal.

Gu, Danzheng, Ai, Qian, 2007. Application of adaptive neural network in dynamic load modeling. Proceedings of the Chinese Society for Electrical Engineering, 27 (16): 31-36.

Han, Xianglin, Jiang, Changhuan, 2007. A modified coupled map car-following model based on application of intelligent transportation system and control of traffic congestion. Acta Physica Sinica, 56(8): 4383-4392.

Jang, Zifeng, Han, Xiling, 1994. The cooperation control of variable speed control (VSC) and on-ramp control in intermediate density of freeway traffic flow. Journal of Xi'an Highway Transportation University, 14(4): 58-62.

Kotsialos, A., Papageorgiou, M., 2004. Nonlinear optimal control applied to coordinated ramp metering. IEEE Transactions on Control Systems Technology, 12(6): 920-933.

Kotsialos, A., Papageorgiou, M., Mangeas, M., et al., 2002. Coordinate and intergraded control of motorway networks via non-linear optimal control. Transportation Research Part C, 10(1): 65-84.

Kotsialos, A., Papageorgiou, M., 2001. Efficiency versus fairness in network-wide ramp metering. IEEE Intelligent Transportation Systems Conference Proceedings, Oakland.

Kotsialos, A., Papageorgiou, M., Messmer, A., 1999. Optimal coordinated and integrated control motorway traffic control line. Proceedings of the 14th International Symposium on Transportation and Traffic Theory, Jerusalem.

Liang, Xinrong, 2005. Studies on intelligent freeway control methods. PhD thesis, South China University of Technology, Guangzhou, China.

Liu, Jianhua, 2009. The research of basic theory and improvement on particle swarm optimization. PhD thesis, Central South University, Changsha, China.

Long, J. C., 2009. Studies on congestion propagation properties and dissipation control strategies of urban road traffic. PhD thesis, Beijing Jiaotong University, Beijing, China.

Ma, Shoufeng, 1999. Study of control and guidance in intelligent transportation system. PhD thesis, Tianjin University, Tianjin, China.

Papageorgiou, M., Kotsialos, A., 2002. Freeway ramp metering: an overview. International Conference on Intelligent Transportation Systems, Dearborn, MI, USA.

Papamichai, I., Papageorgiou, M., 2008. Traffic-responsive linked ramp-metering control. International Conference on Intelligent Transportation Systems, United States.

Park. J. H., Kim, S. H., 2004. Direct adaptive output-feedback fuzzy controller for a nonaffine nonlinear system. IEEE Proceedings: Control Theory and Applications, United States.

Wang, Guangsheng, Wang, Pingyang, Hu, Zhaoyi, 1993. Fuzzy control based on BP neural network. Electric Power Technology, 5(1): 17-21.

Wu, J., McDonald, M., Chatterjee, K., 2007. A detailed evaluation of ramp metering impacts on driver behaviour. Transportation Research Part F, 10(1): 61-75.

Yuan, Yufei, Daamen, W., Hoogendoorn, S., et al., 2009. Coordination of agent-based control in a freeway network. International Conference on Control and Decision, Guilin, China.