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SIMULATION AND COMPARISON OF TWO FUSION METHODS FOR MACROSCOPIC FUNDAMENTAL DIAGRAM ESTIMATION

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Abstract:

Accurate estimation of macroscopic fundamental diagram (MFD) is the precondition of MFD's application. At present, there are two traditional estimation methods of road network's MFD, such as the loop detector data (LDD) estimation method and the floating car data (FCD) estimation method, but there are limitations in both traditional estimation methods. In order to improve the accuracy of road network MFD estimation, a few scholars have studied the fusion method of road network MFD estimation, but there are still some shortcomings on the whole. However, based on the research of adaptive weighted averaging (AWA) fusion method for MFD estimation of road network, I propose to use the MFD's two parameters of road network obtained by LDD estimation method and FCD estimation method, and establish a back-propagation neural network data fusion model for MFD parameters of road network (BPNN estimation fusion method), and then the micro-traffic simulation model of connected-vehicle network based on Vissim software is established by taking the intersection group of the core road network in Tianhe District of Guangzhou as the simulation experimental area, finally, compared and analyzed two MFD estimation fusion methods of road network, in order to determine the best MFD estimation fusion method of road network. The results show that the mean absolute percent error (MAPE) of the parameters of road network's MFD and the average absolute values of difference values of the state ratio of road network's MFD are both the smallest after BPNN estimation fusion, which is the closest to the standard MFD of road network. It can be seen that the result of BPNN estimation fusion method is better than that of AWA estimation fusion method, which can improve the accuracy of road network MFD estimation effectively.

Keywords: *traffic engineering, macroscopic fundamental diagrams estimation, adaptive weighted averaging, back propagation neural network, data fusion, Vissim traffic simulation*

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1. Introduction

Urban traffic congestion has caused enormous challenges to urban transport. How to alleviate the problem of urban traffic congestion has become a key research direction. Many scholars have proposed various traffic control strategies, which have effectively relieved urban traffic congestion to a certain extent (Żochowska, 2014). However, as the traffic flow continues to increase, traffic congestion has intensified. Various traffic control strategies have become inapplicable. Recent studies have shown that macroscopic fundamental diagrams (MFD) provide a new idea for traffic management and control of road networks. Godfrey (1969) proposed the concept of MFD firstly, but it was not until 2007 that Daganzo (2007) and Geroliminis and Sun (2011) revealed the theoretical principle of MFD. They believe that MFD is the inherent objective law of road network, which reflects the internal relationship between the traffic operation status of road network and the cumulative number of vehicles objectively. It is also the general relationship between the weighted traffic flow and the weighted traffic density in road network.

The MFD of road network has been applied in oversaturated traffic network control, traffic status discrimination and congestion pricing, etc. but accurate estimation of MFD is the precondition of MFD's application. At present, there are two MFD estimation methods of traffic network, such as the loop detector data (LDD) estimation method and the floating car data (FCD) estimation method. The LDD estimation method is to install fixed detectors (such as coil detectors, video detectors, etc.) on road sections, then collect traffic data in real-time, and finally use an MFD-related theory to estimate the road network's MFD. The FCD estimation method is to install satellite equipment on taxis, buses and other floating cars, and then collect the trajectories of floating cars in real time, and estimate the road network's MFD by using the trajectory estimation method proposed by Edie (1963). Some scholars have studied the estimation methods of road network's MFD. For example, Courbon et al. (2011) compared three methods of MFD estimation (theoretical analysis, LDD estimation and FCD estimation), and analyzed the impact of traffic heterogeneity and fixed detector location on road network's MFD. Lu et al. (2013) estimated the MFD of road network by using two kinds of traffic data (the fixed detectors' data and the floating cars' data), and found that the statistical time interval of the data would affect the estimation results of the MFD of road network. Nagle and Gayah (2013) pointed out that when the coverage of floating cars should be known and more than 15%, and floating cars are evenly distributed in the road network, the FCD estimation method can be used to obtain the MFD of road network more accurate. Leclercq et al. (2014) simulated and compared two existing MFD estimation methods (LDD estimation method and FCD estimation method) by using two typical road networks, and pointed out that LDD method cannot estimate the weighted density of road network better, but the weighted traffic density estimated by FCD method and the weighted traffic flow estimated by LDD method can be used to estimate the MFD of road network better, even if the coverage of floating cars is less than 10%. Du et al. (2016) defined the weighted harmonic average of driving time and distance of a single floating car as the equivalent coverage of floating cars in view of the uneven coverage of floating cars, and then the FCD method is used to estimate the MFD of road network. Zhang et al. (2018) proposed an improved FCD estimation method based on variable permeability using floating car data and fixed detector data in view of the uneven coverage of floating cars. In fact, the fixed detector can only collect traffic data of some sections, and the sections without fixed detector cannot obtain traffic data. And if the coverage of floating car is low, the traffic data will be insufficient, the estimated MFD of the road network has a large error. Ambu et al. (2016) found that there were few papers combine the two estimation methods, and proposed a data fusion algorithm based on a large number of experiential experiments, which can fuse the estimation results of road network's MFD, but its application scope is limited. Jin et al. (2018) proposed a fusion method for estimating the MFD of road network based on the proportion of the length of road segment to the total length of road network by using traffic data collected by two kinds of fixed detectors, but the discreteness of traffic flow and the performance of detectors have great influence on the estimation results of this method. Lin et al. (2018) proposed a fusion method of MFD estimation based on adaptive weighted averaging (AWA estimation fusion method). This method used the MFD parameters estimated by 100% networked vehicles as calibration data, introduced dynamic errors, and used

the adaptive weighted averaging method to fuse the MFD parameters estimated by LDD method and FCD method. And a traffic simulation model was established to verify the effectiveness of the algorithm. However, this method needs to prepare validation data, and sometimes the validation data is difficult to obtain, thus affecting the application of this method.
At present, only a few scholars have studied the fusion method of road network MFD estimation, and there are still some shortcomings on the whole, which need further study. Therefore, based on the research of AWA estimation fusion method (Lin and Xu, 2018), I propose to use the MFD's two parameters of road network (such as the weighted traffic flow and the weighted traffic density) obtained by LDD estimation method and FCD estimation method, and establish a back-propagation neural network data fusion model for MFD parameters of road network (BPNN estimation fusion method), and then compared and analyzed two MFD estimation fusion methods of road network by using traffic simulation technology, in order to determine the best MFD estimation fusion method of road network. In the aspect of algorithm validation, the micro-traffic simulation model of connected-vehicle network based on Vissim software is established by taking the intersection group of the core road network in Tianhe District of Guangzhou as the simulation experimental area. The LDD method and the FCD method are used to estimate the road network's MFD respectively, then two new MFDs of road network are obtained by data fusion by using AWA estimation fusion method and BPNN estimation fusion method respectively. In order to evaluate the effectiveness of various estimation methods, the network car data (NCD) method (i.e. special FCD estimation method) is used to estimate the MFD parameters of road network, because the data source of NCD estimation method comes from all the networked vehicles in the road network, its estimation result is the most accurate, so it is regarded as the standard MFD of the road network. And then, the mean absolute percent error (MAPE) of the parameters of road network's MFD obtained by LDD estimation method, FCD estimation method, AWA estimation fusion method, BPNN estimation fusion method and NCD estimation method are compared. Finally, the differences of the MFD of road network obtained by various estimation methods are compared by using the state ratio R and its' the difference value of the road network's MFD.

2. Methodology

2.1. LDD estimation method

LDD estimation method is to collect traffic density and traffic flow in real time through fixed detectors installed on various sections, and then to estimate the MFD of road network according to the relevant theory of MFD (Daganzo, 2007; Geroliminis and Sun, 2011). The formula is as follows:

$$\begin{cases} k^w = \dfrac{\sum_i k_i l_i}{\sum_i l_i} \\ q^w = \dfrac{\sum_i q_i l_i}{\sum_i l_i} \end{cases} \tag{1}$$

where k^w and q^w are the weighted traffic density (*veh/km*) and the weighted traffic flow (*veh/h*) respectively; l_i is the length of road section i (*km*); and k_i and q_i are the traffic flow of road section i *(veh/h)*, and the traffic density of road section i (*veh/km*) respectively.

According to the research results of Daganzo, 2007 and Geroliminis and Sun, 2011, road network's MFD presents a cubic function curve of one variable, which can be expressed as follows: $q^w(k^w(t)) = ak^w(t)^3 + bk^w(t)^2 + ck^w(t) + d$.

2.2. FCD estimation method

Edie (1963) proposed that when the trajectories of all the vehicles in the road network are known, the weighted traffic flow and the weighted traffic density of the road network can be calculated. The formulas are as follows:

$$k^w = \frac{\sum_{j=1}^{n} t_j}{T * \sum_{i=1}^{r} l_i} \tag{2}$$

$$q^w = \frac{\sum_{j=1}^{n} d_j}{T * \sum_{i=1}^{r} l_i} \tag{3}$$

where T(s) is the acquisition cycle; r is total number of sections of the road network; n(*veh*) is number of vehicles recorded during the acquisition cycle T; t_j(s)is the driving time of j-th vehicle during the acquisition cycle T; and d_j(m) is the driving distance of j-th vehicle during the acquisition cycle T.
However, it is difficult to obtain the trajectories of all vehicles in the actual road network, but some data of floating cars can be obtained by satellite vehicle equipments. Therefore, Nagle and Gayah (2014) pointed out that if floating cars are evenly distributed in the road network and the proportion of floating cars is known, the road network's MFD can be estimated by using the trajectory estimation method proposed by Edie (1963). The formula is as follows:

$$\hat{k}^w = \frac{\sum_{j=1}^{n'} t'_j}{\rho^* T * \sum_{i=1}^{r} l_i} \tag{4}$$

$$\hat{q}^w = \frac{\sum_{j=1}^{n'} d'_j}{\rho^* T * \sum_{i=1}^{r} l_i} \tag{5}$$

where $\hat{k}^w$ and $\hat{q}^w$ are the weighted traffic density (*veh/km*) and the weighted traffic flow (*veh/h*) of the road network obtained by the FCD estimation method respectively; ρ is the ratio of floating cars; n' is the number of floating cars during the acquisition cycle T (*veh*); t'_j is the driving time of *j-th* floating car during the acquisition cycle T(s); and d'_j is the driving distance of *j-th* floating car during the acquisition cycle T(m).

2.3. AWA estimation fusion method

AWA estimation fusion method takes the MFD parameters of the road network obtained from FCD estimation of 100% networked vehicle data under the environment of vehicle networking as test data, introduces dynamic errors, and uses adaptive weighted average method to fuse the MFD parameters of the road network obtained from LDD estimation method and FCD estimation method respectively. The specific process is as follows:

(1) The MFD parameters of the road network obtained by LDD estimation method and FCD estimation method before *t-1* time are input.
(2) The absolute relative error of the MFD parameters obtained by the estimation method is calculated by taking the MFD parameters obtained by 100% networked vehicles as the actual data. The formulas are as follows:

$$e_{ar,i}(t-1) = \left| \frac{y(t-1) - y_i(t-1)}{y(t-1)} \right| \tag{6}$$

where $e_{ar,i}(t-k)$ is the absolute relative error of the MFD parameters obtained by *i-th* estimation method in *t-k* period, *i*= 1 represents the LDD estimation method and *i* = 2 represents the FCD estimation method; $y(t-1)$ is the actual data of *t-1* period; $y_i(t-1)$ is the estimated data of MFD parameters of the road network obtained by *i-th* estimation method in *t-1* period.

(3) The dynamic error is calculated, and the formula is as follows:

$$e_{d,i}(t-1) = \\ = \frac{1}{k}\left[e_{ar,i}(t-1) + e_{ar,i}(t-2) + \cdots + e_{ar,i}(t-k) \right] \tag{7}$$

where $e_{d,i}(t-1)$ is the dynamic error of the MFD of the road network obtained by *i-th* estimation method in t period; k is the k period before t period.

(4) The initial weighting factor is determined, and the formula is as follows:

$$w_i^*(t) = \frac{1}{e_{d,i}(t-1)} \tag{8}$$

where $w_i^*(t)$ is the initial weighting factor of *i-th* estimation method in t period.

(5) The weighting factor is normalized, and the formula is as follows:

$$w_i(t) = \frac{w_i^*(t)}{\sum_{i=1}^{n} w_i^*(t)} \tag{9}$$

$$\sum_{i=1}^{n} w_i(t) = 1 \tag{10}$$

where $w_i(t)$ is the weighting factor of the MFD parameters of the road network obtained by *i-th* estimation method at t period.

(6) The parameters of MFD obtained by LDD and FCD estimation at *t* period are calculated.
(7) The fusion value is calculated according to the MFD parameters estimated at t period and the normalized weighting factor.

$$\hat{y}(t) = \sum_{i=1}^{n} w_i(t) y_i(t) \tag{11}$$

where $\hat{y}(t)$ is the fusion value of road network's MFD in t period; $y_i(t)$ is the estimated data of MFD parameters of the road network obtained by *i-th* estimation method in *t* period.

(8) The results are output and the fusion values of MFD parameters of the road network in *t* period are obtained.

2.4. BPNN estimation fusion method

A back propagation neural network（BPNN）is a multilayer prefeedback-type network, which is the most widely used artificial neural network. It consists of an input layer, a hidden layer and an output layer. Its learning algorithm is a global approximation method, which has good generalisation ability (Ma, 2017). If a BP neural network model is used to perform data fusion of the weighted traffic flow and the weighted traffic density calculated respectively by the LDD and FCD estimation methods, more accurate weighted traffic flow and weighted traffic density of the road network can be obtained and used to estimate the road network's MFD more accurate. The two key parameters of road network's MFD are the weighted traffic flow and the weighted traffic density. Therefore, two identical BPNN estimation fusion models are designed respectively for the weighted traffic flow and the weighted traffic density of the road network. The specific steps are as follows:
(1) Input and Output Data
For the road network weighted traffic flow fusion model, the input data mainly include the road network weighted traffic flow (q_{LDD}) obtained by the LDD estimation method, the road network weighted traffic flow (q_{FCD}) obtained by the FCD estimation method and the number of road network floating cars (n_{FCD}). Accordingly, the neural network input layer has three parameters, and the output layer is the weighted traffic flow of the integrated road network ($\bar{q}$).
For the road network weighted traffic density fusion model, the input data mainly include the road network weighted traffic density (k_{LDD}) obtained by the LDD estimation method, the road network weighted traffic density (k_{FCD}) obtained by FCD estimation method and the number of road network floating cars (n_{FCD}). Thus, the neural network input layer has three parameters, and the output layer is the weighted traffic density of the integrated road network ($\bar{k}$).
(2)Number of Network Layers
The BP neural network includes at least three layers, namely the input, hidden and output layers. The hidden layer can be more than one, but a larger number of hidden layers increases the network complexity and training time. Generally, a three-layer network with one hidden layer can meet most application requirements. Therefore, in this study, each of the two models has three network layers.
(3)Number of Neurons
The number of neurons in the hidden layer can be obtained by the following empirical formula (Nagle and Gayah, 2014):

$$N_{BP} = \sqrt{m_{BP} + n_{BP}} + c \tag{12}$$

where N_{BP} is number of neurons in the hidden layer; n_{BP} is number of neurons in the input layer; m_{BP} is number of neurons in the output layer; and *c* is experience constant, with value ranging from 0 to 10.

In the two models, $n_{BP}=3, m_{BP}=1$ and c = 7 (Ma, 2017),so the number of hidden layer neurons in both models is 9. The structural diagrams of the BP neural networks of both models are presented in Figure 1 and Figure 2.
(4)Activation Function Selection
I used the sigmoid transfer function as the network activation function as follows (Ma, 2017):

$$f(x) = \frac{1}{1+\exp(-x)}, x \in (-\infty, +\infty), f(x) \in (0,1) \tag{13}$$

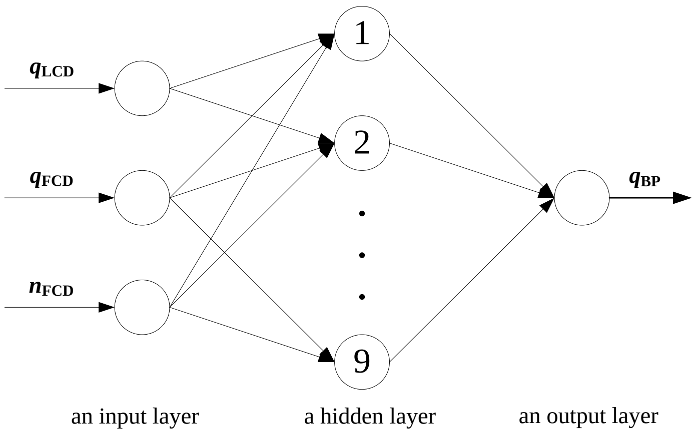

Fig. 1. Structure of weighted traffic flow fusion model of road network

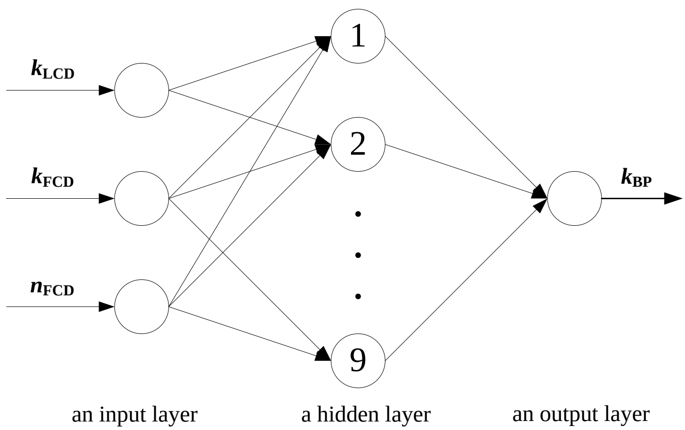

Fig. 2. Structure of weighted traffic density fusion model of road network

2.5. MFD difference analysis

The differences of road network's MFD obtained by LDD estimation method, FCD estimation method, AWA estimation fusion method, and BPNN estimation fusion method are evaluated by using the mean absolute percent error (MAPE) of the parameters of road network's MFD and the state ratio of road network's MFD based on road network's MFD obtained by the NCD estimation method (i.e. the FCD estimation method when the floating car coverage is 100%).

(1)The mean absolute percent error (MAPE)

The mean absolute percent error (MAPE) of the parameters of road network's MFD refers to the mean absolute percent error value of road network's MFD parameters obtained by various estimation methods compared with NCD estimation method. Its formula is as follows:

$$\begin{cases} \text{MAPE}_{EM}\text{-k}^{w} = \dfrac{1}{m}\displaystyle\sum_{i=1}^{m}\left|\dfrac{(k_{NCDi}^{w}-k_{EMi}^{w})}{k_{NCDi}^{w}}\right| \\ \text{MAPE}_{EM}\text{-q}^{w} = \dfrac{1}{m}\displaystyle\sum_{i=1}^{m}\left|\dfrac{(q_{NCDi}^{w}-q_{EMi}^{w})}{q_{NCDi}^{w}}\right| \end{cases} \tag{14}$$

where m is the number of data statistics intervals; i is *i-th* statistical interval time; k_{NCDi}^{w} and q_{NCDi}^{w} are the parameter of road network's MFD obtained by

NCD estimation method in *i-th* statistical interval time, i.e. the weighted traffic density (*veh/km*) and the weighted traffic flow (*veh/h*); k_{EMi}^{w} and q_{EMi}^{w} are the parameters of road network's MFD obtained by some estimation methods (such as LDD estimation, FCD estimation, AWA estimation fusion, and BPNN estimation fusion) in *i-th* statistical interval time, i.e. the weighted traffic density (*veh/km*) and the weighted traffic flow (*veh/h*).

(2)The state ratio(R)
The distance ratio between the MFD parameters and their critical state parameters at any time is defined as the traffic state ratio (R). If the state ratio of road network's MFD is the same in each statistical interval, then the road network's MFD is exactly the same, and its formula is as follows (Jin et al., 2018):

$$\begin{cases} R_{un} = \dfrac{\sqrt{(k_t^w - k_c^w)^2 + (q_t^w - q_c^w)^2}}{\sqrt{k_c^{w2} + q_c^{w2}}}, k_t^w \le k_c^w \\ R_{co} = \dfrac{\sqrt{(k_t^w - k_c^w)^2 + (q_t^w - q_c^w)^2}}{\sqrt{(k_j^w - k_c^w)^2 + q_c^{w2}}}, k_t^w > k_c^w \end{cases} \tag{15}$$

where R_{un} and R_{co} are the non-congestion state ratio and the congestion state ratio of the parameters of road network's MFD; k_t^w and q_t^w are the parameters of road network's MFD at t-time, i.e. the weighted traffic density (*veh/km*) and the weighted traffic flow (*veh/h*); k_c^w and q_c^w are the critical state parameters of road network's MFD, i.e. the critical weighted traffic density (*veh/km*) and the critical weighted traffic flow (*veh/h*); and k_j^w is the weighted congestion density of road network (*veh/km*).

The difference of the state ratio of road network's MFD is defined as Δ. If the shape of road network's MFD is more similar, the value of Δ is smaller. On the contrary, if the shape difference of road network's MFD is greater, the value of Δ is larger. Its formula is as follows (Jin et al., 2018):

$$\Delta_t = \begin{cases} R_{un}^{EM} - R_{un}^{NCD} \\ R_{co}^{EM} - R_{co}^{NCD} \end{cases} \tag{16}$$

where R_{un}^{NCD} and R_{co}^{NCD} are the non-congesttion state ratio of road network's MFD and the congestion state ratio of road network's MFD when NCD estimation method is used; R_{un}^{EM} and R_{co}^{EM} are the non-congestion state ratio of road network's MFD and the congestion state ratio of road network's MFD when some other estimation methods are used, such as LDD estimation method, FCD estimation method, AWA estimation fusion method and BPNN estimation fusion method.

3. Experimental analysis

3.1. Experimental basic data

In the aspect of algorithm validation, the core road network intersection group of Tianhe District in Guangzhou is taken as the simulation experimental area (Lin, 2019), which includes 8 three-dimensional intersections, more than 60 plane intersections and more than 100 entrances and exits, as shown in Figure 3. The peak hour traffic data at most intersections are collected by detectors. The traffic flow data of individual intersections without detector are investigated by manual investigation.

3.2. Experimental procedure

The experiments to verify the performances of the two models consist of the following steps:
(1) Based on the basic data of road network, a microscopic traffic simulation model of connected-vehicle network based on Vissim software is established. The detector is set in the middle of each road section. In the traffic composition, 15% of the vehicles are set as floating cars, and the trajectory data of each network vehicle are collected as test data. Because the investigated traffic flow data are peak hour traffic flow, in order to simulate the change process of traffic flow, from the peak period of 32400 seconds, the traffic flow at each boundary entrance of the road network decreases by 13.5% every 3600 seconds until the low peak period of 3600 seconds.
(2) The real-time traffic data are collected by fixed detectors of each section, including traffic density and traffic flow. The period of data acquisition is 120 seconds. According to LDD estimation method, the weighted traffic flow (q_{LDD}^{w}) and the weighted traffic density (k_{LDD}^{w}) of road network are calculated. A total of 270 groups of parameters of road network's MFD are obtained. According to the NCD

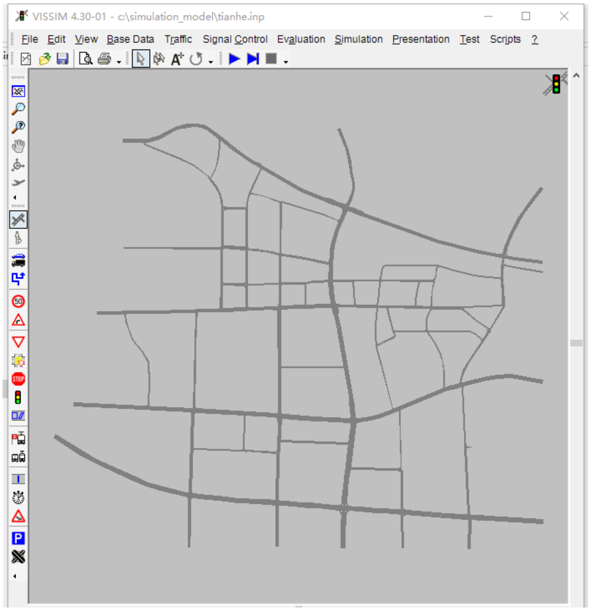

Fig. 3. Layout of Tianhe District core road network (Lin, 2019)

estimation method, the weighted traffic density (k^{w}_{NCD}) and the weighted traffic flow (q^{w}_{NCD}) of the road network are calculated every 120 seconds, and 270 sets of parameters of road network's MFD are obtained. According to the FCD estimation method, the weighted traffic density (k^{w}_{FCD}) and the weighted traffic flow (q^{w}_{FCD}) of road network is calculated every 120 seconds, and 270 sets of parameters of road network's MFD are obtained.

(3) According to the flow of AWA estimation fusion method (Lin et al., 2018), data fusion of the above-mentioned LDD estimation method and FCD estimation method is carried out in Matlab software. Finally, the fusion values of the weighted traffic flow and the weighted traffic density of the MFD network are obtained.

(4) The two BPNN fusion models are realized by using the Neural Network Toolbox of MATLAB software. The q^{w}_{LDD} , q^{w}_{FCD} and n_{FCD} data in the first 100 cycles are used as the training samples for the road network weighted traffic flow fusion model. The q^{w}_{NCD} data in the first 100 cycles are used as the test sample to train the road network weighted traffic flow fusion model. The k^{w}_{LDD} , k^{w}_{FCD} and n_{FCD} data in the first 100 cycles are used as the training samples for the road network weighted traffic flow fusion model. The k^{w}_{NCD} data in the first 100 cycles are used as the test sample to train the road network weighted traffic density fusion model. Finally, data fusion is performed on 270 data cycles using a trained neural network model.

(5) The MFD_{FCD} obtained by FCD estimation method, the MFD_{LDD} obtained by LDD estimation method, the MFD_{AWA} obtained by AWA estimation fusion method, the MFD_{BP} obtained by BPNN estimation fusion method and the MFD_{NCD} obtained by NCD estimation method are generated respectively. The parameters of MAPE and R are used to evaluate the difference of road network's MFD obtained by the above estimation methods compared with road network's MFD_{NCD}.

3.3. Analysis of experimental results

(1) The MAPE of the parameters of road network's MFD

The statistical data of k^{w}_{NCD} , k^{w}_{LDD} , k^{w}_{FCD} and k^{w}_{BP} are compared and analyzed, as shown in Figure 4.The statistical data of q^{w}_{NCD} , q^{w}_{LDD} , q^{w}_{FCD} and q^{w}_{BP} are compared and analyzed, as shown in Figure 5.

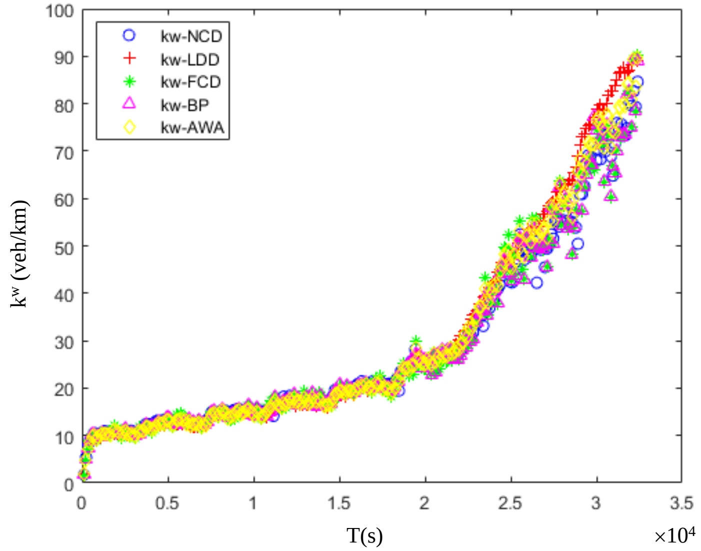

Fig. 4. Comparison of the road network weighted traffic densities obtained by various estimation methods

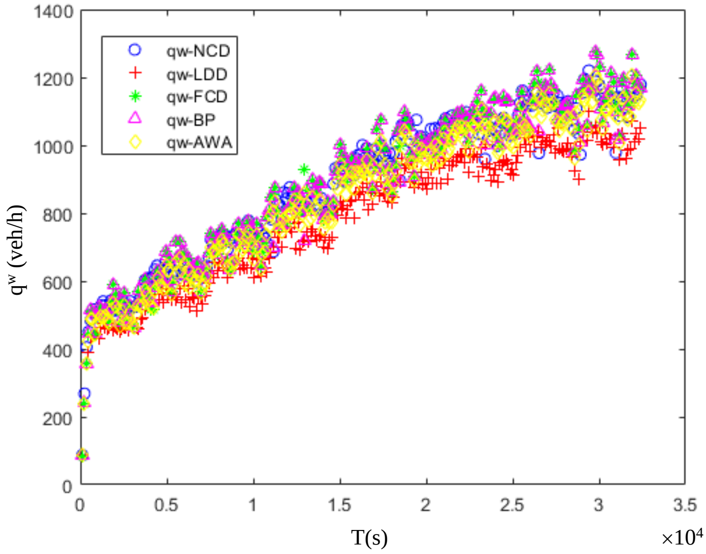

Fig. 5. Comparison of the road network weighted traffic flow obtained by various estimation methods

As shown in Figures 4 and 5, it can be seen that the parameters of road network's MFD obtained by FCD estimation method vary greatly, because the coverage of floating car is set at 15%, which has some errors compared with NCD estimation results. The parameters of road network's MFD obtained by LDD estimation method and NCD estimation method change slightly, and the trend of change is basically the same. However, the parameters of road network's MFD obtained by LDD estimation method are slightly smaller than those obtained by NCD estimation method, because when the fixed detector collects traffic data, a small number of vehicles have not passed the fixed detector. Through statistical analysis, the MAPE of q^w_{LDD}, q^w_{FCD} and q^w_{BP} compared with q^w_{NCD} and the MAPE of k^w_{LDD}, k^w_{FCD} and k^w_{BP} compared with k^w_{NCD} are shown in Table 1.

Table 1. The MAPE of the parameters of the road network's MFD obtained by other estimation methods relative to q^w_{NCD} and k^w_{NCD}

	q^w_{LDD}	k^w_{LDD}	q^w_{FCD}	k^w_{FCD}	q^w_{BP}	k^w_{BP}
MA	11.3	6.7	4.3	4.9	3.9	3.5
PE	1%	2%	0%	7%	5%	9%

As shown in Tables 1, the MAPE of q^w_{LDD} and k^w_{LDD} are the largest compared with q^w_{NCD} and k^w_{NCD}, which are 11.31% and 6.72% respectively, followed by those of q^w_{FCD} and k^w_{FCD}, which are 4.3% and 4.97% respectively. After AWA estimation fusion, the MAPEs of q^w_{AWA} and k^w_{AWA} are 4.63% and 4.38%, respectively. After BP neural network data fusion, the MAPE of q^w_{BP} and k^w_{BP} are 3.95% and 3.59%, which are closest to q^w_{NCD} and k^w_{NCD}.

With the use of various estimation data, road network MFD_{FCD} based on FCD estimation, road network MFD_{LDD} based on LDD estimation, MFD_{AWA} based on AWA fusion estimation, MFD_{BP} based on BP neural network data fusion estimation and road network standard MFD_{NCD} based on network vehicle trajectory can be generated, as shown in Figure 6.

As shown in figure 6, the data points of MFD_{LDD}, MFD_{BP} and MFD_{NCD} are changed slightly, and the data points of MFD_{FCD} is changed greatly. The parameters of road network's MFD obtained by various estimation methods increase gradually with the passage of simulation time. When k^w starts from 28 *veh/km*, the q^w tends to a higher stable value. The data points of each estimated road network's MFD are fitted, and the critical weighted traffic density k_c and the critical weighted traffic flow q_c are calculated. Finally, the percent errors (PE) of k_c and q_c for each estimated road network's MFD are obtained, compared with the standard values of $k_{c(NCD)}$ and $q_{c(NCD)}$, as shown in Table 2.

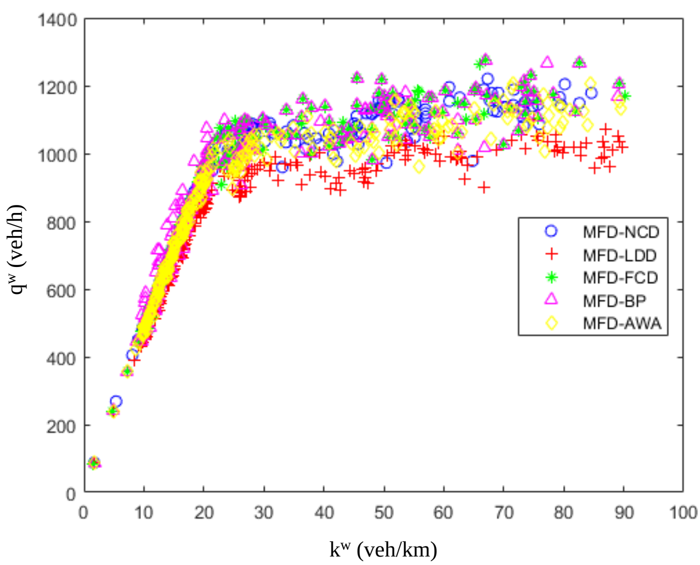

Fig. 6. The two dimensional MFD of road network obtained by various estimation methods

Table 2. The fitting function and the critical value of each estimated road network's MFD

	Fitting function	k_c (*veh/km*)	q_c (*veh/h*)	*PE* compared with $k_{c\ (NCD)}$	*PE* compared with $q_{c\ (NCD)}$
MFD_{NCD}	$y= 0.00990x^3 - 1.5525x^2 + 77.591x - 115.92$	41.32	1138	-	-
MFD_{LDD}	$y = 0.0066x^3 - 1.1343x^2 + 60.747x - 16.487$	42.66	1023	3.24%	-10.11%
MFD_{FCD}	$y = 0.0085x^3 - 1.4035x^2 + 73.689x - 86.645$	43.23	1163	4.62%	2.20%
MFD_{AWA}	$y = 0.0081x^3 - 1.3367x^2 + 69.962x - 65.072$	42.89	1116	3.80%	-1.93%
MFD_{BP}	$y = 0.0086x^3 - 1.4033x^2 + 72.864x - 73.59$	42.81	1138	3.61%	0%

As shown in Table 2, compared with the parameter k_c of MFD_{NCD}, the percent error of the parameter k_c of MFD_{FCD} is the largest, the percent error of the parameter k_c of MFD_{AWA} is smaller, followed by the parameter k_c of MFD_{BP}, and the percent error of the parameter k_c of MFD_{LDD} is the smallest, which are 4.62%, 3.8%, 3.61% and 3.24% respectively. Compared with the parameter q_c of MFD_{NCD}, the percent error of the parameter q_c of MFD_{LDD} is the largest, the parameter q_c of MFD_{FCD} is smaller, followed by the parameter q_c of MFD_{AWA}, and the percent error of the parameter q_c of MFD_{BP} is the smallest, which are -10.11%, 2.20%,-1.93% and 0% respectively. It can be seen that the optimal estimation method cannot be determined, and further analysis is needed.

(2) The state ratio and difference values of road network's MFD

The state ratio R and difference values of road network's MFD obtained by each estimation method are analyzed statistically, and the results are shown in Figure 7 and Figure 8.

As shown in Figure 7 and Figure 8, the state ratio and difference values of road network's MFD obtained by FCD estimation method are changed relatively larger. The state ratio and difference value of road network's MFD obtained by LDD estimation method, AWA estimation fusion method and BPNN estimation fusion method are more stable. The average absolute value($\overline{|\Delta|}$), the maximum absolute value($|\Delta|_{max}$) and the minimum absolute value($|\Delta|_{min}$) of the difference value of the state ratio of each road network's MFD are calculated, as shown in Table 3.

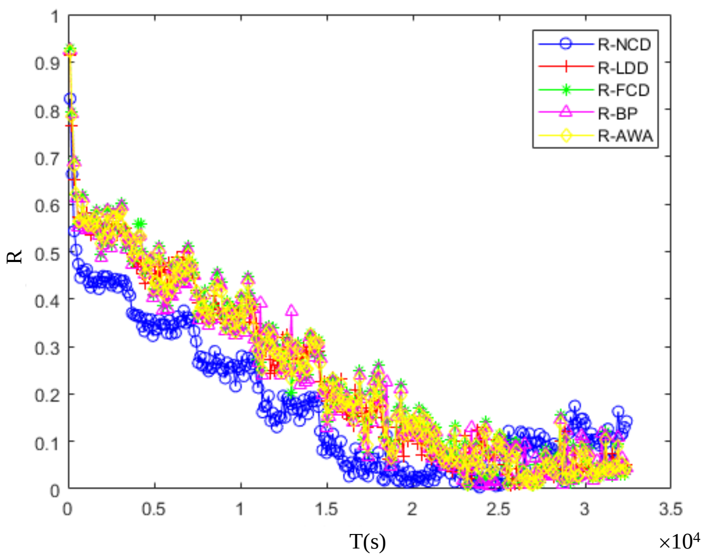

Fig. 7. The state ratio of road network's MFD obtained by each estimation method

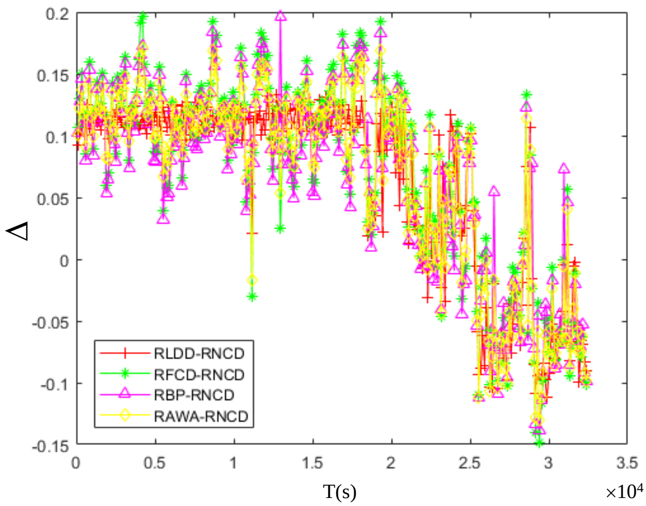

Fig. 8. The difference of the state ratio of road network's MFD obtained by various estimation methods compared with NCD estimation method

Table 3. The difference of the state ratio of road network's MFD obtained by various estimation methods compared with NCD estimation method

	MFD_{LDD}	MFD_{FCD}	MFD_{AWA}	MFD_{BP}
$\overline{\|\Delta\|}$	0.0908	0.0950	0.0934	0.0907
$\|\Delta\|_{max}$	0.1334	0.1968	0.1712	0.1961
$\|\Delta\|_{min}$	0.0015	0.0006	0.0003	0.0046

As shown in Table 3, compared with the MFD_{NCD}, the $\overline{|\Delta|}$ of the state ratio of MFD_{FCD} is the largest, which is 0.0950. The $\overline{|\Delta|}$ s of the state ratio between MFD_{LDD}, MFD_{AWA} and MFD_{BP} are smaller, but MFD_{BP} is closer to MFD_{NCD}, and its $\overline{|\Delta|}$ is 0.0907. Therefore, it can be seen that the road network's MFD obtained by BPNN estimation fusion method is more accurate.

4. Conclusions

Since the discovery of MFD, it has been widely concerned by scholars. Some scholars have studied the application of MFD in road network zoning, oversaturated network control, road network traffic status discrimination, road network congestion pricing, etc. However, accurate estimation of road network's MFD is the premise of MFD's application. At present, both LDD estimation method and FCD estimation method can estimate the MFD of road network, but both methods need certain applicable conditions. For example, LDD estimation method needs to set fixed detectors on the main sections of road network, while FCD estimation method needs to know the coverage of floating cars and the floating cars are evenly distributed in the road network.

In the past, only a few studies used data fusion technology to estimate road network's MFD, but there are some shortcomings in the existing methods of road network MFD estimation fusion. Therefore, I propose a fusion method for MFD estimation of road network based on BPNN, and use traffic simulation technology to compare and analyze the estimation results of AWA estimation fusion method and BPNN estimation fusion method, so as to determine the better fusion method. According to the results of empirical analysis, the following conclusions are drawn:

(1) According to the arrangement of MAPE of MFD parameters in road network, the MAPE of LDD estimation method's result is the largest, the MAPEs of FCD estimation method's result and AWA estimation fusion method's result are the smaller, and

the MAPE of BPNN estimation fusion method's result is the smallest, It shows that the BPNN estimation fusion method is the best way to estimate the MFD parameters of the road network.

(2) From the fitting function and critical value of MFD estimated by various methods, it is shown that compared with the parameter k_c of MFD_{NCD}, the percent error of MFD_{FCD}'s parameter k_c is the largest, the percent error of MFD_{AWA}'s parameter k_c is smaller, followed by MFD_{BP}'s parameter k_c, and the percent error of MFD_{LDD}'s parameter k_c is the smallest. Compared with the parameter q_c of MFD_{NCD}, the percent error of MFD_{LDD}'s parameter q_c is the largest, the percent error of MFD_{FCD}'s parameter q_c is smaller, followed by MFD_{AWA}'s parameter q_c, and the percent error of MFD_{BP}'s parameter q_c is the smallest. It can be seen that the optimal estimation method cannot be determined, and further analysis is needed.

(3)According to the analysis results of the state ratio R of MFD in road network, the $\overline{|\Delta|}$ of MFD_{FCD}'s R is the largest, while the $\overline{|\Delta|}$ of the state ratio of MFD_{LDD}, MFD_{AWA} and MFD_{BP} are smaller, but the $\overline{|\Delta|}$ of MFD_{BP}'s R is the smallest, which indicates that it is closer to MFD_{NCD}.

In summary, BPNN estimation fusion method effectively combines LDD estimation method and FCD estimation method to estimate road network's MFD more accurate, which lays a foundation for the subsequent application of MFD.

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