

## *Retraction*

# **Retracted: Urban Fine Management of Multisource Spatial Data Fusion Based on Smart City Construction**

### **Mathematical Problems in Engineering**

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### **References**

- [1] Y. Long, X. Zhang, and F. Gao, "Urban Fine Management of Multisource Spatial Data Fusion Based on Smart City Construction," *Mathematical Problems in Engineering*, vol. 2021, Article ID 5058791, 10 pages, 2021.

## Research Article

# Urban Fine Management of Multisource Spatial Data Fusion Based on Smart City Construction

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With the increase of the types of urban management objects, the intelligent management of the whole city has become a matter of concern in various countries, and it is also one of the indispensable links in urban development. In the construction of cities all over the world, the intelligent and scientific management system has been used innovatively. We provide excellent facilities for transportation development, information exchange, and resource progress. The research on urban fine management based on multisource spatial data fusion is proposed. Aiming at the traffic problems in urban fine management, this paper proposes a deep network architecture based on multisource data fusion. Multisource spatial data fusion technology is used to analyze urban traffic data. Deep network architecture is used to improve the precision management status of a smart city and the accuracy of traffic condition prediction. Then, the convolution neural network technology is explored in the data fusion technology strategy. The research results show that the framework has the ability to deal with heterogeneous data and urban big data and can effectively improve the traffic management state in the construction of a smart city and effectively solve the complexity of urban fine management and processing efficiency in the construction of a smart city.

## 1. Introduction

Urbanization construction is one of the means for each country to realize the development of the whole transportation industry and information industry [1]. It is also the primary responsibility of countries to expand urban development and demand. According to a large number of data, with the growth of the year, the resident population of each country has increased linearly [2]. The trend of quantity growth is also very obvious. The proportion of the population in the whole city has changed greatly compared with the historical years [3, 4]. With the increasing number and density of population, the construction and management of urbanization have become the focus of national attention. The transformation rate of population and urban resident ratio from rural to urban is also growing steadily [5]. With

the gradual completion of urban development, the object types of management content also appear in various forms. Facing the complexity of the relationship between the management objects, the whole urban management problem has become one of the important factors to change the development speed and the progress of science and technology [6, 7]. The concept of urban fine management began in Japan in the last century and gradually spread to the whole world. The purpose is to strengthen the internal management and planning of the city by changing the way of human life, the mode of transportation, and the overall quality of people [8]. It emphasizes the collaborative nature and unity of people, which is embodied in the responsibility, clarity, and regularization of city management. Fine urban management is different from the previous process, and each department should work accurately and carefully [9]. It is

reflected in the timeliness, high efficiency, and orderly management of the work. According to these requirements, the refined concept of urban management is improved [10]. Through the quantitative evaluation of urban development process, the standard of urban operation process is confirmed. Finally, the whole urban management system will be refined to meet people's needs in the construction of intelligent city [11].

With the pursuit of urban fine management, people are also concerned about the development of traffic road changes [12]. The management of the city is also inseparable from traffic planning, and the traffic problems under the multisource spatial data fusion have more excellent innovative development than the traditional planning road [13, 14]. According to the use of big data, the algorithm after multidata fusion also makes the management model have more performance. The judgment of the whole urban planning has more data support and experience support than before [15]. Now, in the construction of a smart city based on the multifusion of big data, the research and judgment of traffic roads can better reflect the status of this factor in the fine management of the whole city in the three-dimensional space [16, 17].

This paper mainly introduces the content and meaning of fine management in urban construction. Through multisource data analysis, how to obtain the whole city data is realized. According to the fusion of city data change and traffic data analysis, the role of the above factors in the city fine management is simulated. Then, according to the multisource spatial fusion technology, the influencing factors of traffic roads in urban management are analyzed, and the data definition and planning simulation of the whole experimental process are carried out. Finally, the role of the experimental results in urban fine management is analyzed.

## 2. Research on Traffic Road Technology in Urban Fine Management Based on Multisource Spatial Data Fusion

*2.1. Research on the Technology of Multisource Spatial Data Fusion in Road Traffic.* In the intelligent transportation system, map data, urban characteristic data, weather data, and GPS data are widely used in urban computing [18]. According to different data structures, we divide these types into point vector data information and network structure data information [19]. Point-based data mean that the data represent a point in the city map. For the data of the whole network structure, it is to capture the information distribution in the big data of the target city [20]. With spatial change and dynamic distribution, such changes can be divided into a variety of data structures. They are space static information data, space static and dynamic information data, and space dynamic information data [21].

Urban point of interest data, such as a restaurant or a shopping mall, is based on the data between points [22]. It is invariant in space and static in the time domain, so it belongs to space static body information data. The traffic network structure represents the road changes in the whole urban

planning and belongs to the information data in the network structure [23]. From the short-term time point of view, it is invariable in space and time and also belongs to the spatial static body information data. Weather data is collected through meteorological stations, and each meteorological station represents a point in geographical location [24]. Therefore, we attribute the weather data to point-based data, and the weather stations will not change after the completion of the layout. However, the weather state changes with time, so the weather data belongs to the combination of static and dynamic information data [25]. Real-time traffic data is the representation of the traffic state of the urban road system, which belongs to network-based data. The vehicle runs on the road system, so the road condition data is dynamic, so it also belongs to the combination of spatial static and dynamic information data. As a real-time road condition sensor, GPS data represents the change of vehicle driving state. It includes the longitude and latitude, driving speed, and direction data, which belongs to the point-based data. And the spatial division is dynamic. Trajectory data represents the vehicle's driving path in a certain period of time, which belongs to network-based data. And it is dynamic in the space division; these data are different from the data structure to the actual physical meaning. Therefore, it is impossible to fuse urban multisource data directly. We need to study this kind of situation based on intelligent spatial data fusion.

Urban traffic condition is a dynamic process in the time and spatial domains, which is influenced by many external factors. The impact of these external factors on traffic is shown in Figure 1.

Figure 1 is the result of the interaction of three basic elements: vehicle, road, and environment. The change of urban road conditions is not only directly affected by the traffic flow on the road network but also affected by the external environment. For example, heavy rain will reduce the driver's visual distance, resulting in slower vehicle speed. The end of a concert will lead to a lot of traffic flow into the road, leading to congestion and so on. Multisource data fusion allows us to analyze traffic from the perspective of vehicle and road and also needs to analyze road traffic from the external environment. The impact of the external environment on traffic is also a process of temporal and spatial changes. In the morning, more vehicles will flow into the road network in the residential area, while more vehicles will choose to leave the road network in the factory area. Therefore, at the same time, the vehicle travel modes in different functional areas are different from each other. Similarly, in the evening, there will be more vehicles pouring into the roads in the factory area. In residential areas, more people will choose to go home. Therefore, in the time domain, the travel mode of each region is also changing with time. Based on this motivation, we propose a method based on spatial data fusion. While considering the spatial and temporal changes of traffic-related data, the temporal and spatial changes of external factors are also taken into account. In order to improve the accuracy of road prediction, the two are fused in the feature layer. It is convenient for the management and planning of the whole city.

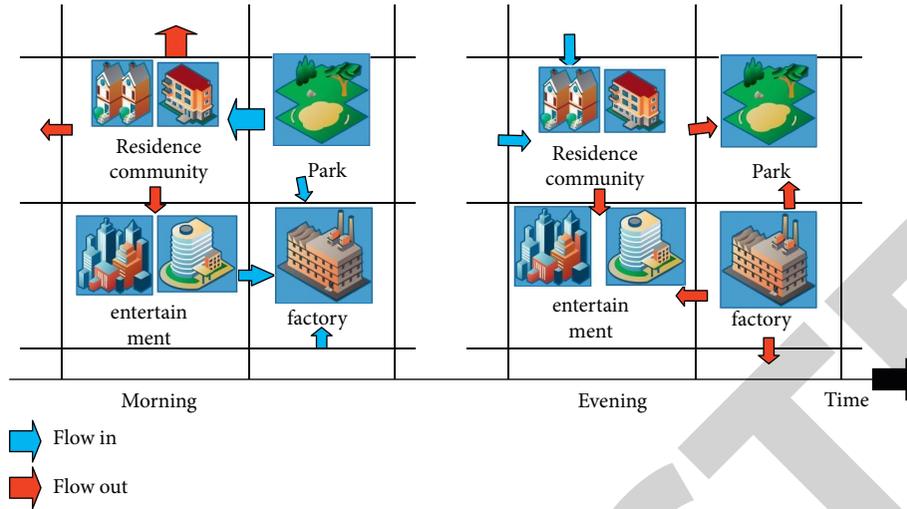


FIGURE 1: Spatiotemporal influence on traffic condition from external factors.

First of all, we build a data framework according to the network structure and use the technology of big data fusion analysis to form a tree diagram. In the process of analyzing the tree view, the flow status of the captured data is viewed. The variable calculation formula is as follows:

$$f(x) = \begin{cases} \lambda e^{-\lambda x}, & x > 0 \\ 0, & x \leq 0 \end{cases}. \quad (1)$$

According to the index formula, the feature points and dimension changes are expressed by time-series order. In the process of variable definition, the definition function is used to calculate the discrete state as follows:

$$H(x) = - \sum_{i=1}^n p(x_i) \ln p(x_i), \quad (2)$$

where  $p(x_i)$  represents the efficiency of the whole network analysis. If it is concentrated in a certain place in the overall dynamic change, the information data is 0. This kind of situation is determined by the distribution range of data sources. The analysis of window time in the whole data planning is calculated according to the following formula:

$$L_a(P, Q) = \frac{1}{1-\alpha} \ln \sum_{i=1}^n \frac{p_i^a}{q_i^{a-1}}. \quad (3)$$

The formula variable represents the function of distribution characteristic points. The data analysis based on the discrete situation is different from the result in formula (2). The dynamic change of road should be considered in the subsequent data intersection. Therefore, the formula for calculating the abnormal situation is as follows:

$$\beta L(\text{Current}, \text{Normal}) + (1-\beta) L(\text{Current}, \text{Previous}) > \text{Threshold}. \quad (4)$$

In the calculation of abnormal conditions, there is a period of normal time. It also includes the last period, the next period, and the scope of the period. For the

characteristics of parameter variables, we calculate them according to the weighted formula as follows:

$$\text{HostStatus} = \sum_i \text{Weight}_i^* \text{Service}_i, \quad (5)$$

where the two-way variable mainly refers to the relationship between the main body state weight coefficient and the index. The main body state weight is defined according to the following formula:

$$\text{AllHostStatus} = \sum_i \text{WeightHost}_j^* \text{HostStatus}_j. \quad (6)$$

Urban traffic prediction in the traffic network diagram is one of the core contents of smart transportation and smart city. The prediction results of the network graph directly affect the management and decision of road information in the whole urban planning. In order to predict traffic changes accurately and in real time, we build the traffic prediction on the road network map based on road sections. The formula is as follows:

$$G = (V, E, A), \quad (7)$$

where  $V$  refers to all road sections,  $E$  represents the neighbor relationship between nodes, and  $A$  is the weight connection matrix between nodes, representing the weight connection relationship between nodes.

We divide the multisource data used in urban traffic prediction into two categories: traffic direct correlation data and traffic indirect correlation data. The data directly related to traffic refers to the data that can measure the traffic signal on the road network map

$$X_G^t [X_G^t \in R^{N \times C}], \quad (8)$$

where  $N$  represents the total number of nodes and  $C$  refers to the type of traffic data signal, for example, traffic speed, traffic flow, and vehicle density. Indirect traffic-related data are external factors that affect the traffic state, such as weather factors, urban characteristic points, and so on. We

define it as  $F_G \in R^{N \times M}$ , where  $M$  represents the number of types of all external factors.

Then we create the planning management model according to the multisource data fusion technology. The formula for calculating variables is as follows:

$$\begin{aligned} \varphi_0(x) &= 1; \\ &\dots \\ \varphi_{n-1}(x) &= 2x\varphi_{n-2}(x) - 2(n-2)\varphi_{n-3}(x). \end{aligned} \quad (9)$$

The matrix formula affected by the excitation variables is as follows:

$$X = \begin{bmatrix} \varphi_0(x_1)\varphi_1(x_1)\dots\varphi_{n-1}(x_1) \\ \varphi_0(x_2)\varphi_1(x_2)\dots\varphi_{n-1}(x_2) \\ \dots \\ \varphi_0(x_n)\varphi_1(x_n)\dots\varphi_{n-1}(x_n) \end{bmatrix} \in R^{m \times n}. \quad (10)$$

The output variable formula is as follows:

$$Y = \begin{pmatrix} y_1 \\ y_2 \\ \dots \\ y_m \end{pmatrix} \in R^m. \quad (11)$$

The error calculation formula for prediction data processing is as follows:

$$\begin{aligned} E &= \frac{1}{2} \sum_{i=1}^m \left[ y_i - \sum_{j=0}^{n-1} w_j \varphi_j(x_i) \right], \\ w &= (X^T X)^{-1} X^T Y. \end{aligned} \quad (12)$$

Traffic prediction based on multisource data fusion: the observed value formula of traffic conditions in the first several periods of a given number of nodes is as follows:

$$\chi = (X_G^{t-P+1}, X_G^{t-P+2}, K, X_G^t) \in R^{P \times N \times C}. \quad (13)$$

The calculation formula of future observation data is as follows:

$$Y = (X_G^{t+1}, X_G^{t+2}, K, X_G^{t+Q}). \quad (14)$$

A mapping function variable between the above formula and the input data, namely,

$$Y = f(\chi, F_G). \quad (15)$$

**2.2. Research on Multisource Spatial Data Fusion Technology Architecture.** Aiming at the problem of urban fine management in the construction of a smart city, we first explore the complexity of traffic conditions formed by various factors. Traffic system, terrain characteristics, urban characteristics, and weather data all need to be calculated in traffic condition information processing. Facing the above problems, we propose to use multisource spatial data fusion technology to analyze traffic conditions. The architecture of multisource data fusion is

shown in Figure 2. The structure mainly includes two branches and a fusion module. The first branch is the graph convolution neural network, which is composed of several spatiotemporal convolution modules. It is mainly used to process the data directly related to traffic and extract its spatiotemporal feature map. The second branch is used to deal with indirect traffic-related data, mainly including two parts. The first part is spatial embedding by temporal revolution (Seton). It embeds traffic indirect data and time factors in space and time, respectively, and then convolutes the space-embedding vector with the obtained time-embedding vector to obtain the low-level spatiotemporal representation. The second part is the feature transformer module, which is used for further feature extraction of low-level spatiotemporal representation. A higher-level feature map is obtained to match the spatiotemporal feature map extracted by graph convolution neural network. The last one is the feature fusion module, which fuses the feature images of the two branches in the feature layer and then gets the final output through the output layer. Next, we will introduce each module in detail.

We will show the information of traffic sections in the form of a network diagram. Road network graphs based on the link can effectively depict its spatial topology. We use a graph convolution neural network to process the data directly related to traffic. The network structure comes from traffic work. This work uses the data directly related to fixed-length traffic to predict the future traffic situation. The formula is as follows:

$$\hat{Y} = g(X_G^{t-P+1}, X_G^{t-P+2}, K, X_G^t), \quad (16)$$

where  $\hat{Y}$  represents the output of the predicted value. When the spatial convolution algorithm is composed of multiple modules, we can regard it as a multilevel model. The module is used to process the input data and feature extraction. The final predicted value  $\hat{Y}$  is calculated according to the time-space relation dependence.

We take the output of the second spatiotemporal convolution module as the feature map. From the perspective of mapping, the process can be shown in Figure 3. The formula is defined as follows:

$$FM^g = f_g(X_G^{t-P+1}, X_G^{t-P+2}, \dots, X_G^t). \quad (17)$$

Although Como operator has achieved good performance improvement in the image classification task in traffic prediction, there are a variety of data that affect the traffic state, and the traffic prediction task has its particularity, that is, in addition to direct traffic-related factors, external factors will also affect the urban traffic. The external factors are represented by indirect traffic-related data. Firstly, we divide all indirect traffic-related data into several independent fields, such as weather data, entertainment places, shopping places, education areas, and so on. For each node variable, its external factors are recorded as vectors as follows:

$$F_v = \{f_{fiel d1}, f_{fiel d2}, K, f_{fiel dm}\}, \quad (18)$$

where  $f_{fiel dj}$  represents the field of each layer. For all nodes, the external factors can be written as  $F = \{F_1, F_2, \dots, F_n\}$ .

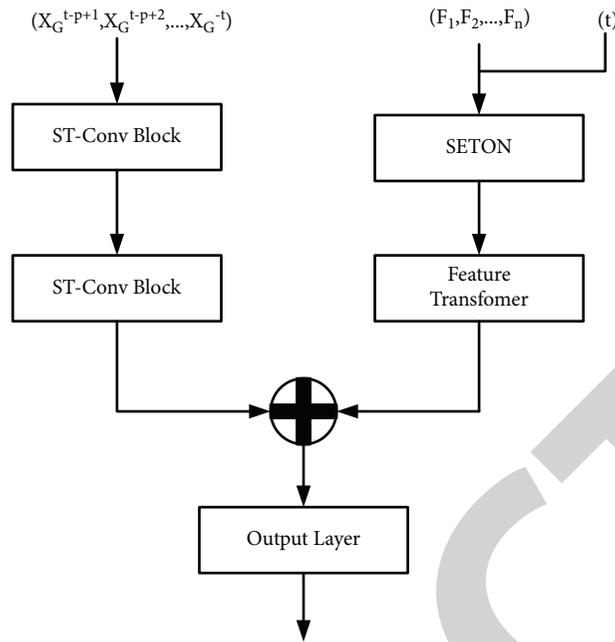


FIGURE 2: Multisource data fusion architecture.

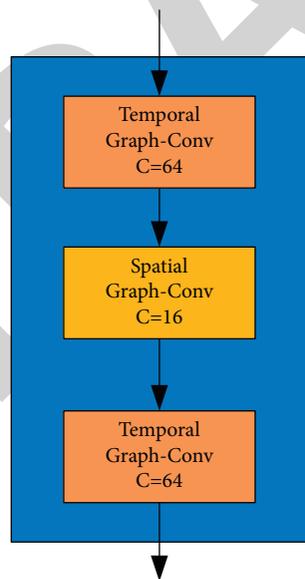


FIGURE 3: ST-Conv block.

The time-domain convolution module embedded in space is used to obtain the spatiotemporal representation of external factors. The spatiotemporal embedding representation module includes three parts: spatial feature embedding, temporal feature embedding, and spatiotemporal feature fusion, as shown in Figure 4.

Spatial feature embedding is used to solve the problem of different external factors, such as different lengths, different categories, and different numbers, and the external factors are embedded to obtain the same length spatial feature

representation, each of which is represented by a length unit vector. Time-domain feature embedding is used to capture the change of spatial features in the time domain. It is a three-dimensional vector, and the third dimension is the length of the period. A representation of time-domain features can be obtained by time-domain embedding. The fusion of space-time features is to treat the representation of time-domain features as convolution kernel and convolute the spatial representation to obtain the representation of low-level spatial and temporal features.

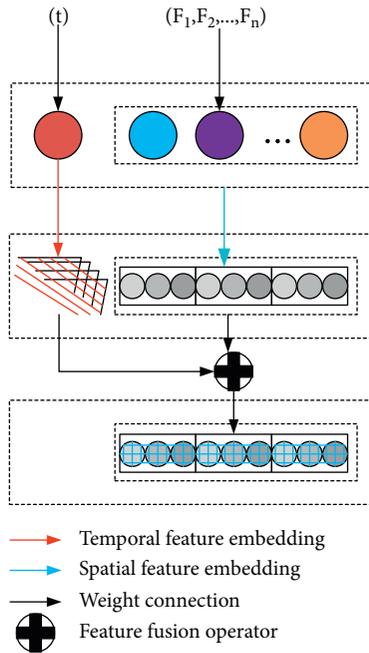


FIGURE 4: SETON architecture.

### 3. Result Analysis of Traffic Road Research Based on Multisource Data Fusion Technology in Urban Fine Management

**3.1. Analysis of Experimental Results of Traffic Detection and Overall Performance in Urban Fine Management.** The prediction of traffic congestion diffusion is to predict the node state, which can be seen as a two-classification prediction process. The state distribution of traffic congestion is uneven. Here, we use a variable value to measure it. The comparison methods of traffic congestion state prediction can be divided into two categories. The first category is time-series prediction. Firstly, the traffic congestion degree is predicted, and then the congestion state is directly determined by the definition of congestion. We choose several popular methods.

·ha: the historical average prediction method uses the average of all historical records in a certain period as the prediction value. For example, the prediction node V is on Monday 6:00 am–6:15 am. For traffic conditions, we calculate the average value of all the corresponding time historical data of node V and directly use it for prediction.

The spatiotemporal correlations of STC are fitted by the correlations among the nodes.

The diffusion model can be used to predict the congestion state directly.

It is a linear threshold model. The activation mode of LT is that when the information around the inactive node reaches a certain threshold, it will be congested. At the same time, the active node is allowed to influence the non-congested node many times. In this experiment, the threshold is set to 0.5.

The IC is an independent cascade model, and each congestion node cannot switch back to the noncongestion

state. In the propagation process, noncongested nodes can receive information from congested nodes and choose whether to become congested nodes with a certain probability. Moreover, this process can only be triggered once, and the activation between nodes is independent of each other.

In order to analyze the role of each part of our model, we modify the traffic congestion diffusion model:

TCD ni: the congestion diffusion model does not consider the influence of traffic flow

TCD no: online learning is removed during parameter learning

TCD ne: remove the part of multisource data fusion in the traffic flow model

TCD: traffic congestion diffusion model

Through congestion diffusion prediction, we forecast the node congestion status of different regions in the period of 6:00 am–10:00 pm. We randomly selected five regions in Shenzhen, namely Shekou, Futian, Bao'an, Luohu, and Buji. Table 1 shows the prediction performance of different methods in different regions. It can be seen from the table that the TCD model has the best performance, with the highest value of 89.67% and the average value of 87.66%. LT and IC have the worst performance because they only predict from the perspective of diffusion, but the root cause of actual traffic congestion diffusion is the influence of traffic flow, rather than a simple linear relationship. Compared with IC and LT, the performance of the following methods has been partially improved, but it is lower than STC, because these methods regard congestion diffusion as a time-series prediction problem and do not consider how the traffic flow influence spreads in the network. Therefore, traffic congestion diffusion should consider not only the propagation behavior of traffic flow but also the continuous evolution process of traffic congestion. Among the variants of the TCD model, the performance of TCD ni is the worst, which indicates that the influence of traffic flow plays an important role in the whole model, followed by the performance of TCD no and TCD ne. Therefore, the dynamic prediction process of traffic congestion diffusion needs to consider both the influence of external factors and the dynamic change information of the nearest neighbor period.

**3.2. Analysis on Diffusion and Duration of Traffic Congestion in Smart City Construction.** Traffic congestion diffusion is a process of congestion state change in the time and spatial domains. In order to analyze the performance of the congestion diffusion model in different periods and different regions, we make a more fine-grained analysis of its performance. We focus on three periods: early peak (8:30–10:30), lunch break (12:00–14:00), and late peak (17:30–19:30). We choose two types of areas: downtown (Shekou, Futian, and Luohu) and suburban (Baoan and Buji). Figure 5 shows the performance of the TCD model in different periods and different regions, where the horizontal axis represents the region name and the vertical axis represents the prediction accuracy. From the figure, we can see that the performance

TABLE 1: Performance comparison.

Methods	Shekou	Futian	Baoan	Luohu	Buji
LT	0.7372	0.8167	0.7826	0.8294	0.7670
IC	0.7869	0.8168	0.7921	0.8581	0.8107
HA	0.8463	0.8359	0.8065	0.8589	0.8299
ARIMA	0.8559	0.8432	0.8144	0.8611	0.8392
STC	0.8549	0.8494	0.8178	0.8671	0.8318
TCD ni	0.8735	0.8809	0.8301	0.8843	0.8446
TCD no	0.8770	0.8835	0.8384	0.8878	0.8372
TCD ne	0.8776	0.8868	0.8392	0.8890	0.8506
TCD	0.8830	0.8967	0.8464	0.8954	0.8515

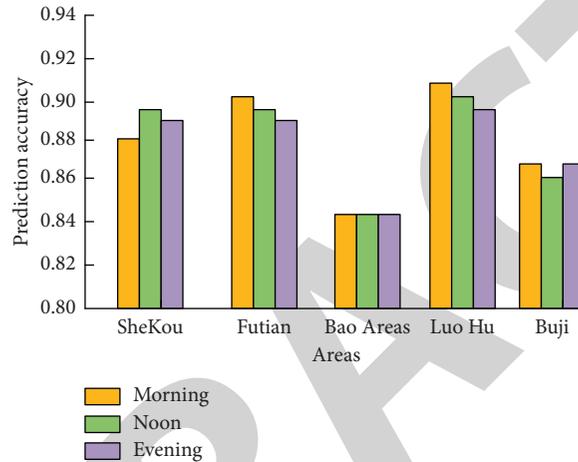


FIGURE 5: TCD performance analysis both in the spatial and temporal domains.

of TCD in downtown areas is better than that in suburban areas. In downtown areas, the performance of Futian and Luohu is the best. From the time point of view, except for the Shekou area, other areas have the best performance in the morning peak period. On the contrary, the Shekou area has the best performance during the lunch break.

TCD model can be used not only for short-term prediction but also for long-term prediction. Figure 6 shows the performance of TCD in long-term prediction, where the horizontal axis represents the length of prediction time for the future. The left vertical axis represents the error between the predicted congestion degree and the actual congestion degree, and the right vertical axis represents the predicted value of the congestion state. With the growth of prediction time, the prediction error of congestion degree increases rapidly and then tends to be flat. Similarly, the prediction performance of the congestion state decreases rapidly and then becomes flat. Therefore, TCD has no problem of error explosion growth in long-term prediction, which is mainly because the overall change of urban traffic is basically consistent, and our model can capture the overall change trend of urban traffic.

Figure 7 shows the relationship between the net traffic inflow and the overall trend of urban traffic change. The horizontal axis represents the time, and the left and right vertical axes represent the number and net inflow of all congestion nodes in the city. From the figure, we can see that

when the number of congested nodes increases, the value of net inflow is positive. On the contrary, when the number of congested nodes decreases, the net inflow is negative. On the whole, our traffic flow model can capture the overall trend of traffic congestion in the whole city. The calculated value of the traffic flow model and its related variables is 91.2%, which is why the TCD model has better performance in long-term prediction.

Offline learning can learn the average trend of traffic congestion changes in historical data, while online learning has a smaller time span and is more sensitive to short-term dynamic changes. Therefore, too large online learning weight will make the model parameters fall into an overfitting state, which will reduce the prediction performance of future traffic congestion diffusion. Thus, the online learning process is removed, resulting in the model cannot adapt to the rapid dynamic changes of traffic congestion. Therefore, we do a grid search for online learning parameters; the search range is  $[0,1]$ ; and the step size is 0.0. The comparison of its impact on congestion diffusion prediction and expected impact is shown in Figure 8. The horizontal axis represents the online learning weight parameters, and the vertical axis represents the error between the predicted value and the real value of crowding degree on the test set. We can see that when the online learning weight value is 0.38, the performance gets the best value.

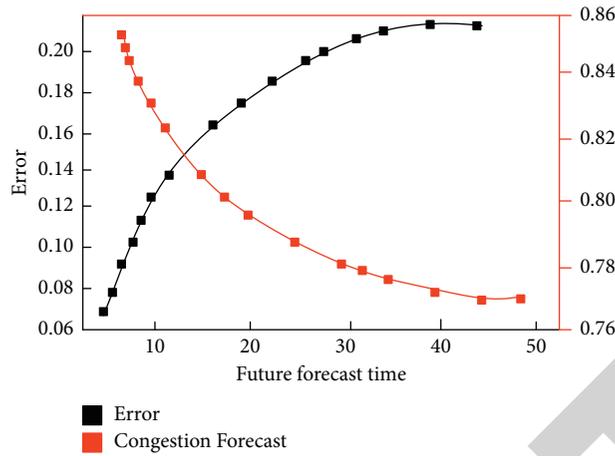


FIGURE 6: TCD performance on long-time traffic prediction.

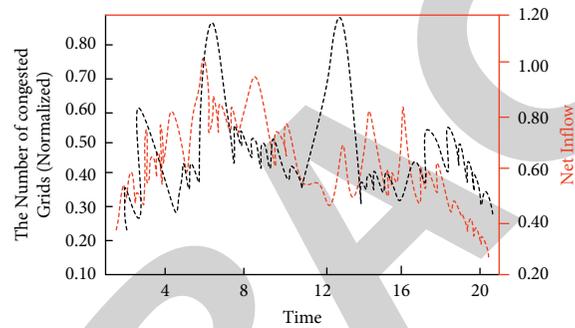


FIGURE 7: Traffic flow model has the ability to capture the traffic dynamics.

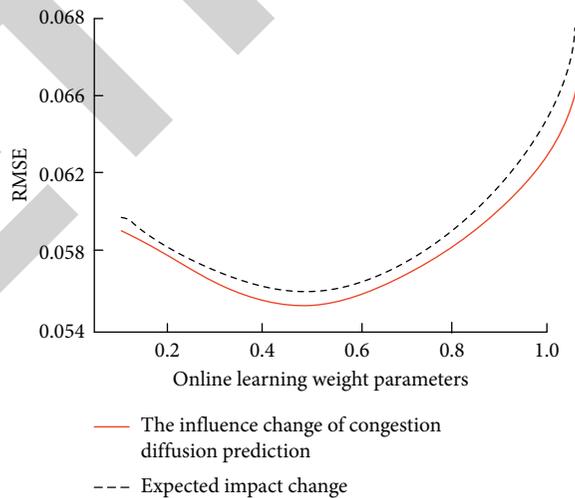


FIGURE 8: Performance variation with online learning weight.

The relationship between traffic flow and congestion degree determines the threshold of traffic congestion state. We learn the parameter in a data-driven way. We increase the parameter from 0.1 to 3.5 in steps of 0.1. The change trend of the training data set in the offline learning stage is checked and compared with the expected trend, as shown in Figure 9. The horizontal axis represents the value of

parameter  $a'$ , and the vertical axis represents the error between the predicted value and the real value.

As can be seen from Figure 8, the change curve of congestion diffusion impact is lower than the expected change but gradually approaches the expected change curve. This shows that this method can obtain the best performance node. Figure 9 shows the comparison between the data

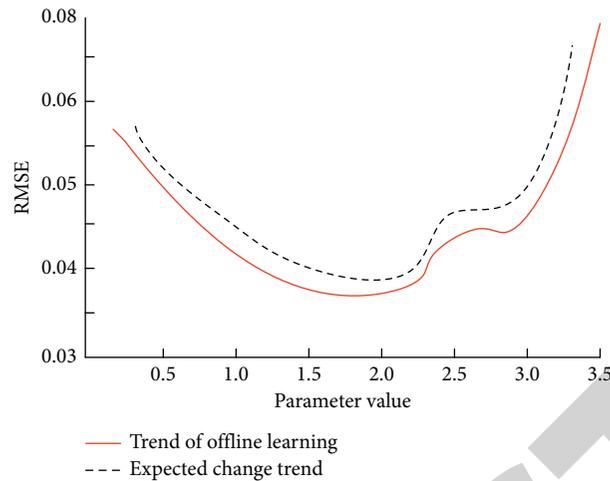


FIGURE 9: Performance variation with  $a'$ .

change trend and the expected trend in the offline learning and training stage. When the threshold is 2.1, the fitting ability of the model is the best. Similarly, we can calculate that the threshold of traffic congestion is 0.65.

#### 4. Conclusion

Based on multisource data fusion technology, this paper adopts the deep learning method. This paper proposes a deep multisource data fusion architecture based on the strategy of fusion in branch transformation to improve the accuracy of real-time traffic prediction. Firstly, we deeply study the fusion strategy of the branch-to-branch transformation in the convolutional neural network and propose a Como operator. The deep network structure to enhance VGG and ResNet network is found. At the same time, we explore the data mismatch problem in heterogeneous multisource data fusion. Different branches process different data with different network structures and simultaneously extract the spatiotemporal characteristics of all kinds of data in the traffic dynamic change information. The feature representation of the two branches is fused in the feature layer, and then the final output is obtained through the output layer. The advantages of multisource data in the process of smart city refined management of traffic prediction are effectively played, and the accuracy of prediction is improved. In the design of network structure, parameter sharing mechanism and data-embedding method are applied so that our multisource data fusion method can have very good scalability in parameter quantity and avoid the problem of overfitting.

#### Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

#### Conflicts of Interest

The authors declare that there are no conflicts of interest.

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