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SHORT TERM ROAD NETWORK MACROSCOPIC FUNDAMENTAL DIAGRAM PARAMETERS AND TRAFFIC STATE PREDICTION BASED ON LSTM

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***Abstract*:**
Macroscopic Fundamental Diagram (MFD) is widely used in traffic state evaluation due to its description of the macro level of urban road network. This study focuses on the discrimination and short-term prediction of macro traffic states in urban road networks, using MFD combined with FCM clustering for state partitioning to characterize different macro states of the road network. To predict the MFD state, this paper builds two LSTMs to perform short-term predictions on two important parameters in MFD: road network weighted flow q^w and road network weighted density k^w. The parameters of the first three statistical intervals and the predicted time period are used as inputs to output the MFD parameters for the predicted time period. To ensure that the two LSTM structures and hyper-parameters settings can achieve the best prediction performance for MFD, the parameter optimization process of both should be included in the same search framework for hyper-parameters search. Therefore, this paper uses GA algorithm combined with multi-objective particle swarm optimization algorithm as the solving algorithm, with the accuracy of solving two MFD parameters and the accuracy of MFD point positioning as the hyper-parameters solving objectives. The study was validated using actual road network data from Hong Kong, and the results showed that the method proposed in this paper has an MRE prediction error of less than 7.8% for the two parameters of MFD, and can predict the future temporal trend of the two parameters, demonstrating the feasibility of MFD related predictions. The model's prediction of the overall shape and change trajectory trend of MFD is consistent with reality, and some test sets in MFD state prediction show high accuracy, the overall accuracy is 81.45%. To verify the effectiveness of the multi-objective search algorithm, typical LSTM models and RNN models were used for comparison. The experiment proved that the model used in this study performed better in error control and state prediction. This study explores and practices a short-term prediction method for road network MFD parameters, MFD status, and their changing trends. Provided path reference for urban road network prediction, traffic control status, and MFD related research.

Keywords: *multi-objective optimization; macroscopic fundamental diagram; LSTM; traffic prediction*

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1. Introduction

Real time and accurate recognition and prediction of road network traffic status are key to traffic control and guidance implementation. Urban roads have a network structure, with internal elements directly or indirectly connected to each other. With the rapid development of urban motorization, the road system is gradually becoming saturated, regional traffic problems are becoming increasingly prominent. Therefore, for traffic management and services, it is also necessary to maintain a global perspective, starting from the overall situation of the entire road network, and analyzing traffic bottlenecks from a macro perspective.

For the road network system, traditional evaluation indicators such as speed, traffic capacity, traffic density, etc., due to their aggregation characteristics, are difficult to fully characterize the operational status of the road network, and predictions based on this are even more difficult to achieve effectiveness. At the same time, the proposal and application of the Macroscopic Fundamental Diagram (MFD) provide new ideas and basis for a deeper understanding of the characteristics and evolution process of regional road network traffic flow, and for the study of regional traffic control methods. MFD analyzes the road network at the macro level using road network detection data, reflecting the universal functional relationship and internal objective laws between average flow and average density in the road network. This functional relationship only depends on the road network and control strategies and the road network itself, and is independent of specific traffic demand (He Zhengbing et al. 2014). Based on this characteristic, MFD is widely used in the evaluation of road network traffic status, as well as in the field of sub area boundary control based on road network state partitioning (Peng Wang et al. 2021). Predicting and mastering the MFD parameters and their forms in the future time period will be crucial for the macro state of road network traffic and implementing control measures.

2. Literature review

For the study of MFD, Godfrey (1969) first proposed its physical model, but it was not until 2007 that scholars such as Daganzo (2007; 2011) and Geroliminis (2011) elaborated on the theoretical principles of MFD. They proposed that MFD objectively reflects the intrinsic relationship between the operating status of the road network and the cumulative number of vehicles, and is also a universal relationship between the weighted flow of the road network and the total traffic volume, and established a relationship formula. MFD research mainly focuses on MFD modeling and influencing factors, MFD traffic state discrimination, and traffic control applications.

For the acquisition and drawing of MFD, the mainstream estimation methods are loop detector detection method (Nagle, A. S. et al. 2015) and floating car estimation method (Andrew. et al. 2018). In recent years, there are also literatures (Shou-Feng, L. U. et al. 2014; Jin Sheng. et al. 2018; Lin,X. et al. 2018,a; Y Ji. et al. 2018) using data fusion technology for multi-source data modeling. In terms of influencing factors of MFD, Xu Feifei et al. (2013) demonstrated through simulation experiments that road network traffic control strategies such as bus lanes and prohibition measures have a significant impact on the form of MFD. Jiang Yongdong et al. (2018) studied the impact of detection vehicle occupancy and traffic congestion on the accuracy of macroscopic basic map estimation, and proposed the optimal detection vehicle occupancy rate. Xu Jianmin et al. (2018) analyzed the sensitivity of the MFD curve to the proportion of large vehicles and proposed corresponding vehicle conversion coefficient calculation methods for different traffic states. Qingchang Lu et al. (2023) studied the impact of the penetration rate of intelligent connected vehicles on the MFD of expressways.

The research on the control application of MFD focuses on road network state detection and discrimination, boundary control, and auxiliary traffic control decision-making. Heng Ding et al. (2018) quickly identified the status of the expressway network by clustering real-time collected MFD data. Chen Wen (2019) modeled MFD using a three-stage trapezoid and proposed evaluation methods for road network carrying capacity, stability, and efficiency, which were applied in various structural road networks. LU et al. (2020) proposed four evaluation indicators based on the concept of MFD to evaluate the effectiveness of regional signal control schemes in road networks: maximum throughput, critical accumulation, grid accumulation, and homogeneity. Lei Yu et al. (2022) combined MFD with a traffic operation index model and proposed a solution method for the optimal traffic index of theoretical efficiency. They searched for the point with the highest road network efficiency in MFD and divided the traffic state of the road network by speed. Haiyan Jiang et al. (2022) constructed a traffic flow state analysis algorithm model that considers the complex linkage of multiple macro traffic flow parameters, and introduced a new macro traffic flow parameter "travel efficiency" as the basic element of MFD. The experiment proved that its image is the same as a typical MFD. Ruxue Li et al. (2021) proposed an optimal pricing strategy based on the distance traveled by users in the boundary, combined with MFD theory, and solved it using a bilevel programming model. Bing Li et al. (2022) aimed to overcome the limitations of existing methods for evaluating traffic impact on single intersections, and established MFD evaluation methods for traffic organization within different evaluation ranges such as single points, main roads, and regions.

The research on traffic state prediction has always been a hot topic in the field of transportation. At present, the field of predicting traffic conditions such as speed and flow is relatively mature, and there is rich research work in object modeling, algorithm design, and algorithm optimization. In the early research process, models that processed time series became the mainstream method for traffic prediction, such as historical averaging (Liu J, 2004) and Kalman filtering (Okutani I, 1984). These methods are all weighted processing of historical information, and their advantages are simple structure and easy calculation; The disadvantage is low accuracy and insufficient ability to fit nonlinearity. With the development of machine learning models, many researchers have begun to attempt to apply machine learning and deep learning methods to traffic state prediction.

Sun (2006) designed a network combining Bayesian and Gaussian mixture models to achieve traffic state prediction, which outperformed other models in the same period. Neto (2009) proposed an online SVR model for short-term prediction of highway traffic flow, which can achieve real-time updates of model parameters. However, the drawback is that it may face insufficient computing power in large-scale data scenarios. Yi (2017) trained a deep neural network on the TensorFlow platform to predict traffic conditions and achieved good prediction results. Shengrui Zhang (2023) established a traffic state model based on the traffic volume and occupancy rate of highway sections, and proposed a short-term traffic congestion prediction model that integrates FCM (Fuzzy C-means algorithm) clustering algorithm and RBF neural network, with a congestion state recognition rate of over 95%. Zhou (2002) used RNN to predict traffic congestion and achieved excellent results. However, due to the simple structure of RNN, it cannot handle time series with multiple steps, and its effect on medium - and long-term traffic state prediction is not significant. In order to solve the gradient vanishing and exploding problems of RNN in long sequence learning, Jurgen Schmidhuber (1997) improved RNN into Long Short Term Memory Network (LSTM), which was further improved by K. Cho (2014) to a Gated Recurrent Unit (GRU) network.

At present, many research works have applied LSTM and GRU models to traffic state prediction tasks, and have achieved good results. S. Shao (2016) explored the application of LSTM model in short-term traffic state prediction in the paper; Y. Li (2017) proposed a differential convolutional GRU for traffic state prediction. Yanqi Ma (2021) took Shenzhen transportation as the research object and constructed a road network system based on basic vehicle data and road coordinates. Using the LSTM algorithm to predict vehicle speed and road density, and based on this prediction result, calculating the traffic flow state TSI, quantitatively rating the traffic state. Di Liang (2019) used road travel speed and speed variance as indicators to predict traffic parameters based on LSTM. The predicted travel speed and current speed variance were used as feature parameters and input into the traffic state recognition model to predict the traffic state. The prediction accuracy reached 98.67%; Jia Wei (2020) selected two traffic parameters, namely traffic flow and average driving speed, and proposed an LSTM-RBF prediction combination model to obtain the prediction results of traffic flow and average driving speed. Obtain the evaluation results of traffic operation status level. Ying Liang (2022) used GPS data to construct a traffic state model based on vehicle speed and speed variance, and also used FCM clustering and LSTM-SVR model for prediction. Some new technologies, such as using spatiotemporal feature vectors (Bofan Yao et al. 2021), reinforcement learning theory (Xiaoyuan Feng et al. 2023; Muyao Tang et al. 2022), probability graph models (Ruo Jia et al. 2021), and deep learning networks (Yongle Liu. 2022) for traffic state prediction, have also been applied by scholars.

In summary, as an important macroscopic parameter of the road network, MFD has been validated and applied in its ability to characterize the state of the road network. However, currently, most predictions of the traffic state of the road network still focus on traffic flow parameters such as flow, speed, travel time, and occupancy rate. There are still few predictions and applications related to MFD parameters. On the one hand, obtaining long-term MFD data requires a large scale of detector coverage, and at the same time, there are many influencing factors and large data fluctuations in road network MFD, which are the difficulties of MFD prediction. In recent years, Long Short Term Memory Networks (LSTM) have shown strong capabilities in processing sequential data, providing new possibilities for predicting short-term MFD parameters and their states. This paper aims to explore the short-term road network MFD prediction method based on LSTM, providing theoretical support and practical guidance for MFD research and actual traffic management.

Starting from the basic characteristics of MFD, Chapter 3 mainly discusses the modeling and clustering theory of MFD in this paper. Chapter 4.1 describes the short-term prediction method in this paper - LSTM theory, and discusses how this study predicts the final MFD using two LSTMs. In Chapter 4.2, a multi-objective optimization framework based on GA-MOPSO was proposed to optimize prediction accuracy. In Chapter 5, multiple experiments were conducted using actual data, including MFD category classification, MFD basic parameter prediction, MFD state prediction, and comparison of predictions from different models. Chapter 6 is a summary.

3. MFD model construction and state clustering

3.1. Description of Macro Basic Diagram

As the basic attribute of the road network, there is a corresponding MFD for any road network form. Taking the relationship model between the weighted traffic flow in the road network and the weighted traffic density established by Daganzo, the typical mathematical representation of MFD is as presented in Eqs. (1).

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

Where q_i, l_i, k_i are the traffic flow of the *i* road the length of the *i* road, and the traffic density of the *i* road. The MFD curve can be modeled as a ladder diagram, which includes rising, stationary, and falling segments. The curve can also be fitted as a quadratic or cubic polynomial, as shown in Fig 1. Although the relationship curve between flow density speed parameters is similar to that of a road segment, MFD reflects not a single road segment but the overall state of the transportation network. The flow and density of the entire road network, as well as the outflow volume and the total number of vehicles in the area, all exhibit a parabolic shape. That is, when the total number of vehicles in a region reaches a fixed value, the outflow volume of the road network reaches its maximum; If the number of vehicles continues to increase, the outflow will rapidly decrease. This provides a basis for using MFD to control traffic in road networks, especially in uniformly congested areas. Therefore, MFD can be used for global management and control of urban transportation networks.

3.2. FCM based road network traffic state division

Clustering the collected and drawn MFD is a common method for dividing the road network status. This paper needs to identify and divide the MFD status through clustering. Fuzzy C-means algorithm (FCM) is a clustering method that is based on objective optimization. Through iteration, the weighted sum of distances between samples and the center of the fuzzy cluster is minimized, and the objective is set as shown in Eqs. (2).

$$\min\{\mathrm{J_m}(\mathrm{U}, \mathrm{v_1}, \mathrm{v_2} \ldots \mathrm{v_c})\} = \sum_{j=1}^{n} \sum_{i=1}^{c} (\mu_{ij})^m (d_{ij})^2 \tag{2}$$

In the formula, *U* is the membership degree between each data point and the corresponding cluster center; V_c is the *i*-th fuzzy clustering center, $\mu_{ij} \in [0,1]$ represents the membership degree of the *j*-th data point belonging to the *i*-th cluster center; d_{ij} is the Euclidean distance between the *i*-th cluster center and the

j-th data point; $m \in [1,\infty]$ is a weighted index, and as m increases, the fuzziness of clustering increases; And Eqs. (2) satisfies $\sum_{i=1}^{c} \mu_{ij} = 1, \forall j = 1,2\ldots\ldots n$.
The specific steps of the FCM algorithm are:
Step 1: Given the number of clustering categories c, the fuzzy weighting index m, set the iteration stop threshold, the number of iterations of the algorithm is b_{max}, and initialize the membership matrix.
Step 2: Calculate the fuzzy clustering center.

$$u_i^{(b)} = \frac{\left[\sum_{j=1}^{n} (\mu_{ij}^{(b)})^m \cdot x^j\right]}{\left[\sum_{j=1}^{n} (\mu_{ij}^{(b)})^m\right]}, \quad i = 1,2\ldots\ldots,c \tag{3}$$

Step 3: Update the fuzzy clustering membership matrix U (b+1).

$$\mu_{ij}^{(b+1)} = \left[\sum_{k=1}^{c} \left(d_{ij}^{(b+1)} - d_{kj}^{(b+1)}\right)^{\frac{2}{m+1}}\right]^{-1}, \quad k = 1,2\ldots,c \tag{4}$$

4. Short term prediction method for MFD parameters

4.1. LSTM prediction model

As mentioned earlier, in order to obtain the MFD of the road network, at least two parameters, the weighted traffic flow q^w and the weighted traffic density k^w of the road network, are required to determine the points of the current road network state in Fig 1, and thus clarify the traffic state. That is to say, the problem of predicting the macro traffic state of the road network is essentially a problem of how to predict the two parameters q^w and k^w. Both parameters are macro parameters calculated from the traffic characteristics of each component of the road network, and their calculations are independent, making it difficult to synchronize them as prediction output items. Therefore, independent LSTMs are used for prediction separately.
The update rules are as follows:

$$\begin{cases} f_t = \sigma(W_f \cdot [h_{t-1}, x_{t-1}] + b_f) \\ i_t = \sigma(W_i \cdot [h_{t-1}, x_{t-1}] + b_i) \\ o_t = \sigma(W_o \cdot [h_{t-1}, x_{t-1}] + b_o) \end{cases} \tag{5}$$

$$\begin{cases} \tilde{C}_{t-1} = tanh(W_f \cdot [h_{t-1}, x_{t-1}] + b_t) \\ C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_{t-1} \end{cases} \tag{6}$$

$$\mathrm{h_{t-1} = o_t - 1 \cdot tanh(C_{t-1})} \tag{7}$$

In the formula, f_t, i_t, and o_t represent the forget gate unit, input gate unit, and output gate unit of each LSTM unit, respectively; W_f, W_i, W_o are the weights of recursive connections; h_1, h_2, h_3... h_t are hidden layer states; X_t is the input information; b_f, b_i, b_o, and b_t are the biases of the function, respectively; $\tilde{C}_{t-1}$ and C_t are the output layers of the hidden layer, which are critical states.

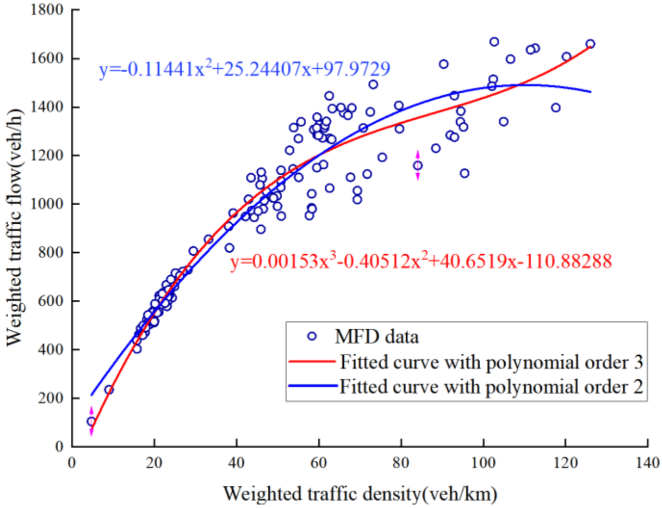


Fig. 1. Typical MFD morphology and its fitting effect (Lin, X, 2022)

It can be seen that the entire LSTM unit selectively stores critical state values based on forgetting and memory ratios on the basis of RNN, and obtains output results. Taking advantage of the selective memory advantage of LSTM, this paper uses it for predicting the parameters of q^w and k^w. The q^w and k^w of the previous three time series, as well as the proportion T of the time period to be predicted, are used as inputs for the prediction algorithm to predict the subsequent q^w and k^w. The structure is as presented in Fig. 3.

The calculation of T is shown in Eqs. (8), Δt represents the statistical time interval of 10 minutes. T is actually the time position of the time interval throughout the entire time period (The time period is 8:00-20:00, 12 hours). The introduction of T adds time input to the model prediction, enabling the model to better balance the temporal characteristics of MFD parameters.

$$\mathrm{T} = \frac{(\mathrm{t} + \Delta \mathrm{t})/\Delta \mathrm{t}}{12 * (60/\Delta \mathrm{t})} \tag{8}$$

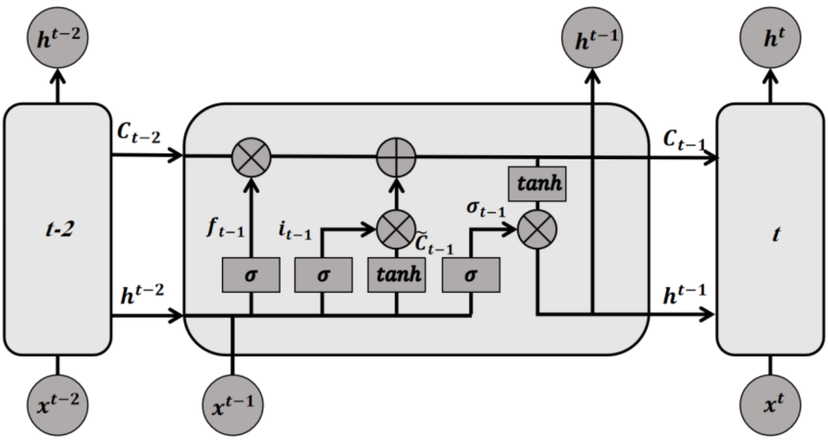


Fig. 2. Typical LSTM framework diagram

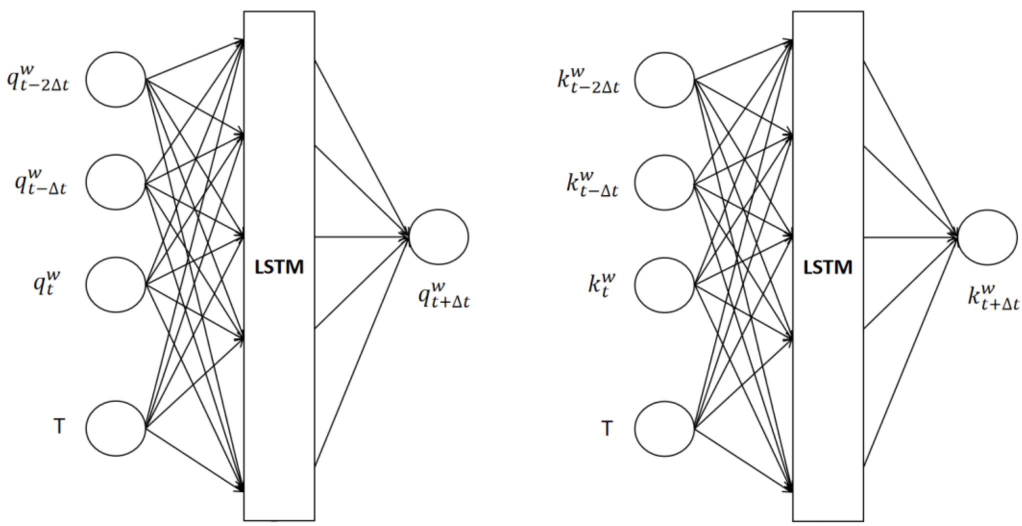


Fig. 3. Two sets of LSTM structures

The specific training steps for the LSTM model are as follows:
Step 1: Create two LSTMs with the prediction of q^w and k^w parameters as the objective, and determine the loss function. The two LSTMs in this paper use mean relative error (MRE) as the loss function. The calculation formula is as follows:

$$\mathrm{MRE} = \frac{1}{\mathrm{n}} \cdot \sum_{\mathrm{i}=1}^{\mathrm{n}} \left| \frac{\mathrm{x_p(i) - x(i)}}{\mathrm{x(i)}} \right| \tag{9}$$

In the formula, n is the number of samples, X_p is the predicted value of the i-th sample, and X is the actual value. Meanwhile, mean absolute error (MAE) will also be introduced as an experimental evaluation indicator to evaluate numerical errors, and its calculation formula is as follows.

$$\mathrm{MAE} = \frac{1}{\mathrm{n}} \cdot \sum_{\mathrm{i}=1}^{\mathrm{n}} \left| \mathrm{x_p(i) - x(i)} \right| \tag{10}$$

Step 2: Initialize each parameter. To achieve the desired accuracy of the model, the parameters need to be continuously updated until the loss function converges and the model training is completed. This paper uses the Adam optimization algorithm to optimize the parameters.
Step 3: Use test data to make predictions on the trained LSTM.
The setting of the number of hidden layers and the number of neurons in each hidden layer of LSTM is still a research difficulty, and can only be adjusted through trial and error in practice. The update step size of each iteration in the learning rate is a hyperparameter, and if the value is too large, it can easily cause turbulence in the results, while if it is too small, it can slow down the convergence speed. The specific value needs to be obtained through multiple experiments within the empirical value range.
On the other hand, although the prediction process of q^w and k^w parameters is independent, their values will jointly determine the state of MFD. If the model is trained with the goal of minimizing the errors of q^w and k^w parameters separately, they may not ultimately achieve better performance in MFD prediction. This paper considers synchronously training the LSTM model with q^w and k^w parameters within the same framework, And establish a multi-objective optimization model with MFD state prediction as one of the objectives.
In order to quickly find the above parameter settings and improve the model's generalization performance, the GA-MOPSO algorithm will be used for parameter search in this paper.

4.2. A multi-objective optimization algorithm based on GA-MOPSO

The optimization objective of the model is to accurately predict the parameters q^w and k^w as much as possible, as well as the accuracy of the point positions determined by the state of MFD, namely q^w and k^w. It is a typical multi-objective optimization problem with 3 objectives. The mathematical expression of the optimization objective is as follows:

$$\begin{aligned} &\min g(x) = \left(g_1(x), g_2(x), g_3(x)\right) \\ &g_1(x) = \frac{1}{n}\sum_{i}^{n}\left(k_i^w - \widetilde{k_i^w}\right)^2 \\ &g_2(x) = \frac{1}{n}\sum_{i}^{n}\left(q_i^w - \widetilde{q_i^w}\right)^2 \\ &g_3(x) = \frac{1}{n}\sum_{i}^{n}\sqrt{\left(q_i^w - \widetilde{q_i^w}\right)^2 - \left(k_i^w - \widetilde{k_i^w}\right)^2} \end{aligned} \tag{11}$$

q_i^w、$\widetilde{q_i^w}$、k_i^w、$\widetilde{k_i^w}$ represents the predicted and actual values of q^w and k^w for the i-th sample, respectively. Due to the different dimensions and significant numerical differences of the parameters q^w and k^w, the values in $g_3(x)$ are normalized values, which means that the parameters need to be divided by the maximum historical data value.
The parameters to be solved are the number of layers of the two LSTMs corresponding to q^w and k^w, with a range of [1,3], and the number of neurons in each layer, with a range of [10,60]. The dropout parameter of the LSTM model, dropout operation is to discard a certain proportion of neuron outputs in the LSTM, forcing the model to learn different feature combinations, which can reduce overfitting problems. The value range is [0.1, 0.2]. In addition, the learning rate of LSTM is also the parameter to be solved, which refers to the magnitude of the adjustment made to the model parameters. It is a hyperparameter with a range of [0.01, 0.1]. In summary, the parameters to be solved in this framework are the

number of layers, the number of neurons in each layer, dropout parameters, and learning rate of the two LSTM models.

The objective function model includes the three objectives mentioned above, and the parameters to be solved are the structures and hyperparameters of two LSTMs. The objective functions, parameters to be solved, constraints, etc. are closely related and involve two independent LSTM solutions, which are non-linear relationships. Therefore, non dominated sorting and intelligent algorithms are suitable for solving. This paper combines the Multi Objective particle Swarm Optimization (MOPSO) with Genetic Algorithm (GA) operations, which is a fast non dominated multi-objective optimization algorithm based on Parto solutions with selection, crossover, and mutation strategies on the basis of the original particle swarm algorithm. Ultimately, the most advantageous solution set in multi-objective optimization is determined. The solution process is as follows.

Step 1: Read the training set, initialize the size of the particle swarm and initial solution set, set the maximum number of iterations and convergence conditions;

Step 2: The particle swarm updates its values based on the model structure and hyperparameters, and calls LSTM for two training sessions to output the predicted q^w and k^w parameters, and obtain the corresponding objective function values;

Step 3: Sort the historical solutions of each particle in a non dominated manner. The solution set at the top of each particle is denoted as *pbest*, and the solution set at the top of all particle historical rankings is denoted as *gbest*;

Step 4: Update the position and velocity of each particle as presented in Eqs. (12):

$$\begin{aligned} V_i &= V_i \times w + C \times r \times (pbest_i - x_i) \\ &\quad + C \times r \times (gbest - x_i) \\ x_i &= x_i + V_i \end{aligned} \tag{12}$$

In the formula, w is the inertia factor, C is the learning factor, which is a random number from 0 to 1. *pbest* and *gbest* are the positions with the best fitness values for particles and particle swarm, respectively, and are updated in each cycle;

Step 5: Select operation, using roulette wheel to select one of the particles and reassign parameters;

Step 6: Cross operation, select the real number cross method, which refers to the linear combination of timing parameters of two chromosomes to generate two new individuals. For example, the cross operation method for the m-th particle am and n-th particle an at position j is:

$$\begin{aligned} am_j &= (1-R)am_j + Ran_j \\ an_j &= (1-R)an_j + Ram_j \end{aligned} \tag{13}$$

In the formula, R is a random number between intervals [0,1]. Cross the two chromosomes that are ranked last in the parent population;

Step 7: Mutation operation, traversing the population, randomly reassigning values to chromosomes based on probability Pm;

Step 8: Repeat steps 2-7 and check whether the constraints are met in each iteration. When the convergence conditions are met, the solution ends. The combination of the highest ranked parameter values corresponds to the optimal parameter combination.

5. Empirical Analysis

This study uses the road detection data from the Hong Kong Special Administrative Region government's open dataset (https://data.gov.hk/sc/, DATA.GOV.HK, 2023.06) as experimental data. The dataset is collected and stored in real-time 24 hours a day by a roadside video detector, which stores information such as traffic flow, speed, and occupancy rate of each lane section every 30 seconds. The detector has high density and good completeness.

The study takes Ting Kok Road in Tai Po District, Hong Kong as the experimental road network. Ting Kok Road is located in the eastern part of Tai Po District, with 4 lanes in both directions and a total length of 10.61km in both directions, near the intersection of Ting Kok Village and Ting Kok Road. Connecting multiple major roads such as Dapu Road, Tingjiao Road, and Baoxiang Bridge Road, it is an important component of the local transportation network. A total of 18 detectors were used to divide the road section into intersections and ramps in both directions. The length of the road section was measured from the road centerline of the Hong Kong road network geographic information data, and the flow and density of each section were calculated based on the flow rate and average speed collected by the detectors.

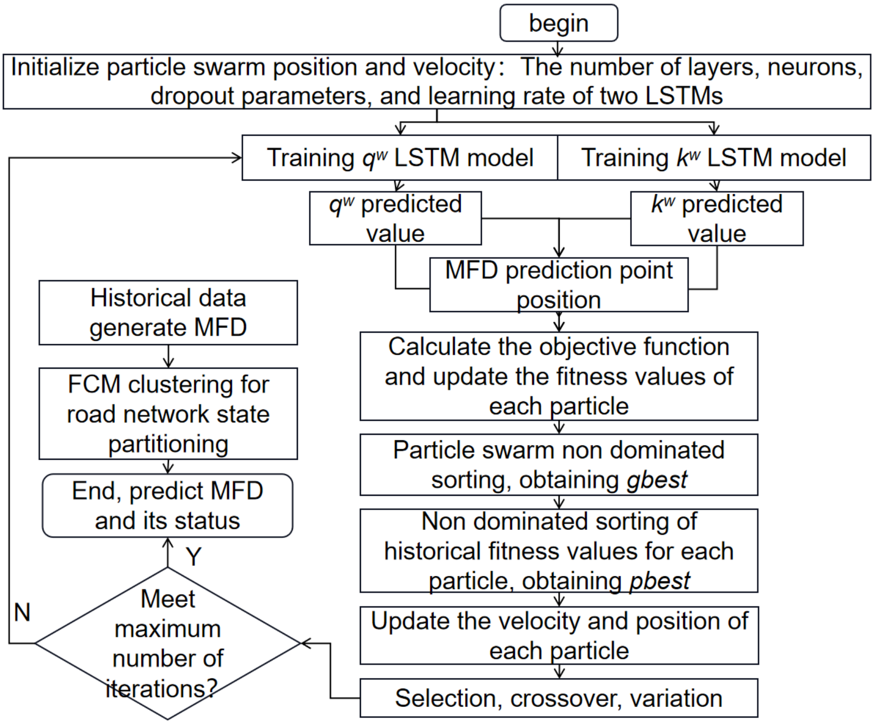


Fig 4. GA-MOPSO Optimization Process

Fig. 5. Ting Kok Road and its detectors in Hong Kong. Source: https://www.hkemobility.gov.hk/, HKeMobility, 2024.03

The training set consists of 3645 pieces of data from March 1st to April 21st, 2023, after removing abnormal data. The testing set consists of 2226 pieces of data from April 22nd to May 18th (removed on May 13th due to missing data), covering the period from 7:00 to 22:00. Firstly, the historical data was plotted and clustered using MFD. A total of 3360 data points from March 1st to April 15th, 2023 were used to plot the MFD morphology of the road network and perform FCM clustering to obtain the original MFD state of the road network, resulting in the point set shown in Figure 6.

For the number of clusters and classification of traffic states, this paper adopts the idealized traffic state classification method proposed in the literature (Fujian Wang et al. 2012). This method fits a quadratic polynomial and divides traffic states into five types based on weighted density: free flow, stable flow, unstable flow, restricted flow, and forced flow. The restricted flow and forced flow states require the MFD form to have a descending segment to achieve, The MFD morphology formed by the experimental data in this study only consists of an ascending segment and a partially stationary segment. Therefore, in this paper, the number of clusters is set to 3: free flow, stable flow, and unstable flow.

Using FCM clustering with a clustering number of 3, three traffic states and their boundaries can be obtained in Fig 7. The edge points between each two states are extracted for binary linear equation fitting, and the two sets of boundary lines in the figure can be obtained, providing a basis for subsequent evaluation of road network traffic status.

The prediction experiment is conducted using Python as the programming language and TensorFlow as the development framework. The statistical time interval is 10 minutes, and the proportion T of the previous 3 time intervals and the time period is used as the input. The number of particles is 10, and the maximum number of iterations is 10. Each LSTM training iteration is 50 rounds. LSTM training is conducted on two important parameters of MFD: the weighted traffic flow q^w and the weighted traffic density k^w . The LSTM structure is as presented in Table. 1.

Due to the large number of test sets, Figure 7 only shows the actual and predicted value curves of qw and kw for the first 10 days, where every 90 data points are from 1 day and each scale interval is from 7:00 to 22:00 in a day. The MRE error of the validation results of the visible model is within 7.8%. The model has made relatively accurate predictions of the temporal fluctuation curve of the parameters, which is basically consistent with the actual trend of the curve. It has good predictions for temporal changes in different time periods. The Euclidean distance between the predicted MFD point and the actual point is calculated based on $g_3(x)$ in Eqs. (10). It can be seen that the average Euclidean distance under normalization is 0.066, with a small error.

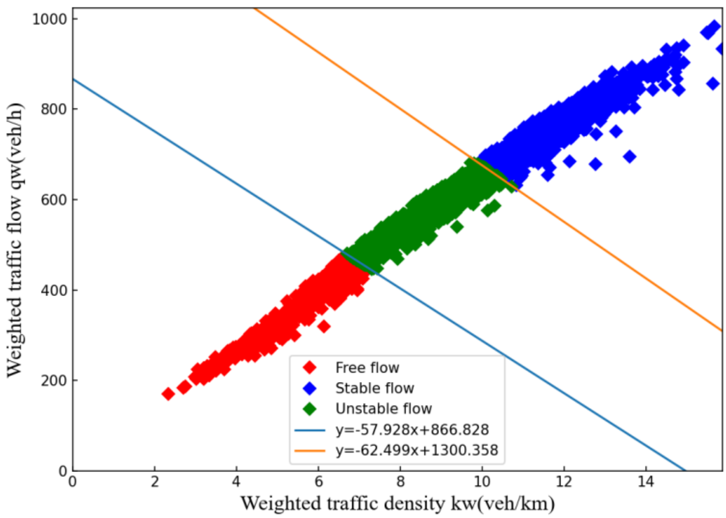
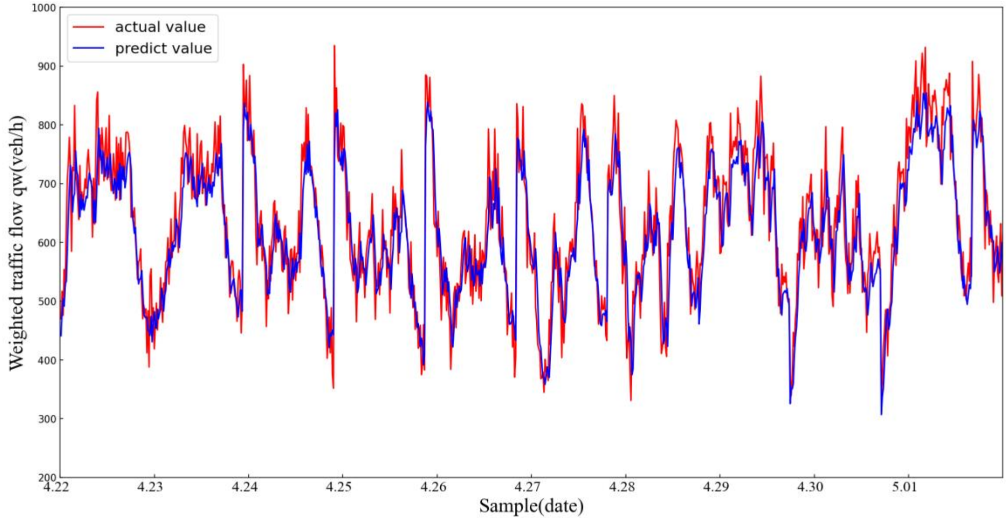


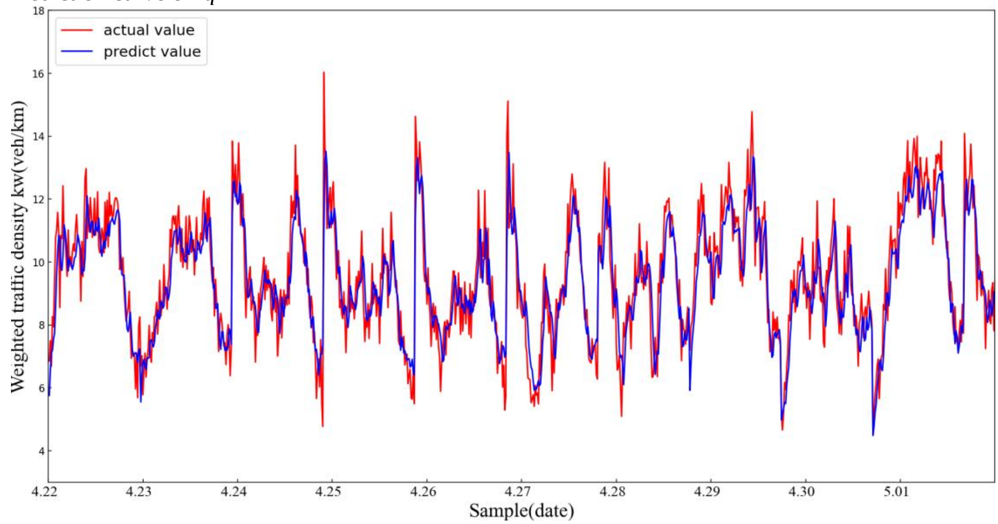
Fig. 6. Historical MFD and Cluster Results of Ting Kok Road Network

Table 1. Two sets of LSTM structures

MFD parameters	Number of hidden layers	Number of neurons in each layer			Dropout	Learning rate	Training Set MRE	Test Set MRE	Test Set MAE	MFD Euclidean distance error
		1	2	3						
q^w	1	52	0	0	0.173	0.06	7.32%	7.747%	44.99	0.066
k^w	1	25	0	0	0.141	0.016	7.91%	7.765%	0.726	



(a) Prediction curve of q^w



(b) Prediction curve of k^w

Fig. 7. Two sets of MFD parameter prediction results

The prediction of MFD morphology can be seen in the Fig. 8. Fig. 8 shows the prediction performance of MFD morphology in the test set for 16 consecutive days. The red point set represents the actual MFD points for one day, and the blue point set represents the predicted points. It can be seen that the daily MFD patterns of the road network are generally similar, and most of the predicted MFD point sets overlap with the actual values. For some discrete points such as April 26th and May 6th, they are also well captured and characterized, providing a basis for short-term MFD pattern prediction and evaluation.

Taking specific prediction results as an example, the experiment randomly sampled the prediction results of the test set, selected 10 consecutive time intervals (i.e. 10 * 10 minutes) MFD points from each day, and plotted their point trend. Fig. 9 to Fig.12 shows the comparison between the predicted and measured MFD results for each date in the test set. The label numbers in the figure represent the order in which the points appear. Taking the MFD change trajectory of 10 time intervals on the day of amplification as an example.

It can be seen that over time, the morning peak gradually fades and the MFD point gradually shifts from the upper right corner to the lower left corner. The predicted MFD point also changes according to this trend, indicating that the sparse distribution and trajectory prediction of MFD points are basically consistent with reality. In the afternoon forecast, as the evening rush hour approaches, the MFD point gradually shifts to the upper right corner, transitioning towards an unstable flow state, which is in line with reality. The prediction of MFD points by the model is generally not precise enough. To achieve accurate prediction of specific points, it is necessary to improve and optimize the model while improving the quality of data collection in the future, or directly predict the running trajectory of points.

For the prediction of traffic status, it is necessary to determine the point location based on the predicted coordinates of q^w and k^w, and determine its status based on the clustering results mentioned earlier. In this paper, the accuracy is calculated based on whether the predicted state matches the actual state. Using data from April 22nd to May 18th as the test set, the results are shown in Table 2. It can be seen that the overall prediction accuracy can reach over 80%, but there is a significant difference in prediction accuracy in specific traffic conditions. Some prediction results are not good, while some dates can achieve a prediction accuracy of over 90%.

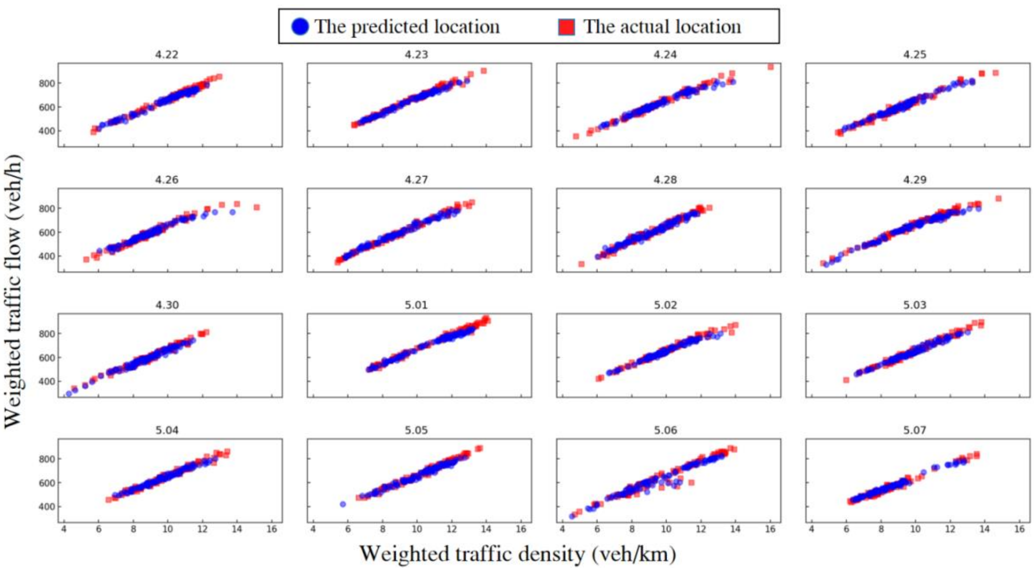
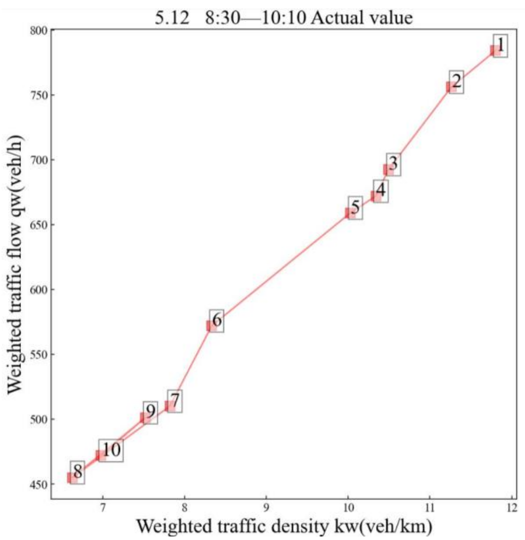
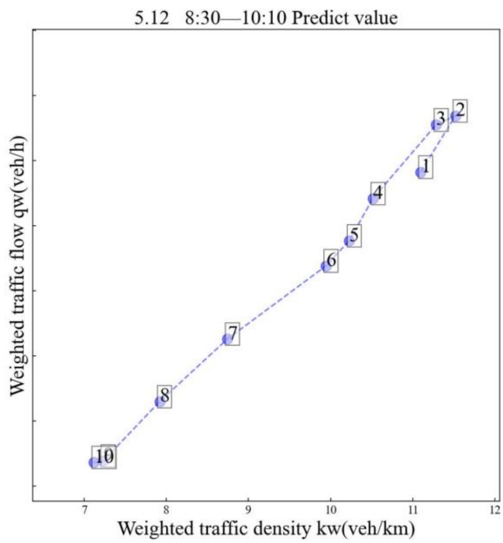


Fig. 8. Test set all day MFD morphology. The red dot represents the actual location, and the blue dot represents the predicted location

Fig. 13 shows the visualization results of the state prediction from April 22nd to May 18th, with the vertical axis representing the date from top to bottom, 1 representing the day, and the horizontal axis representing the daily time transition from left to right, with a scale of 1 hour. Each small square in the figure represents a traffic state at a statistical interval of 10 minutes, with white, light green, and dark green representing free flow, stable flow, and unstable flow, respectively. From the actual data graph a and the predicted graph b, it can be seen that most of the traffic in this road network is concentrated during the evening rush hour, with a continuous unstable state from 17:00 to 20:00, and a continuous stable state for most of the time. On some dates such as May 1st and May 6th, there may be prolonged periods of unstable flow, which may result in temporary traffic control on the surrounding road network. It can be seen that the color block distribution patterns of the two are generally consistent. In actual data, there are significant fluctuations in the state, such as the sudden appearance of free flow and unstable flow states in a continuous stable flow state, or frequent transitions between the three states over a period of time. However, the model is relatively conservative in prediction, with smooth state transitions and a lack of control over sudden state transitions. Most prediction errors are concentrated in this area. To further consider the possibility of data type classification, segmented prediction, and improved accuracy, this paper also divided the dataset into three parts: morning, afternoon, and evening. The GA-MOPSO fusion LSTM method was used to find two sets of model parameter settings, and training and testing were conducted in different time periods; And based on working days and non working days, the classification and prediction were carried out, and the results is shown in the Table. 3. It can be seen that the fluctuations during the afternoon and evening peak hours are still difficult to predict. On the other hand, the model has high prediction accuracy on some dates and time periods, and the overall prediction accuracy on weekdays is relatively high. It can be seen that, with sufficient dataset, applying pattern recognition technology for date pre classification, time period pre classification, and then separately training the model may improve the accuracy of model prediction.



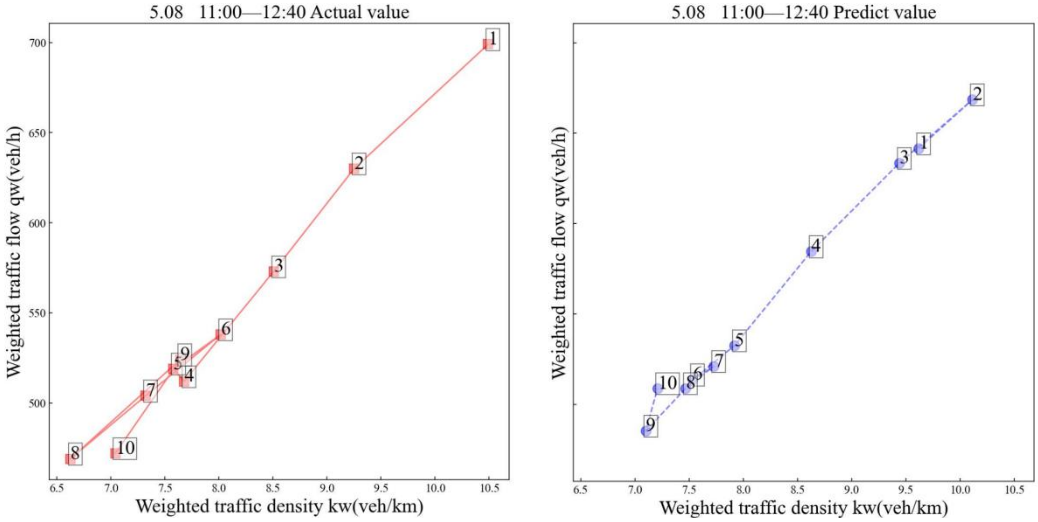
(a)Actual MFD point trajectory



(b)Predicted MFD point trajectory

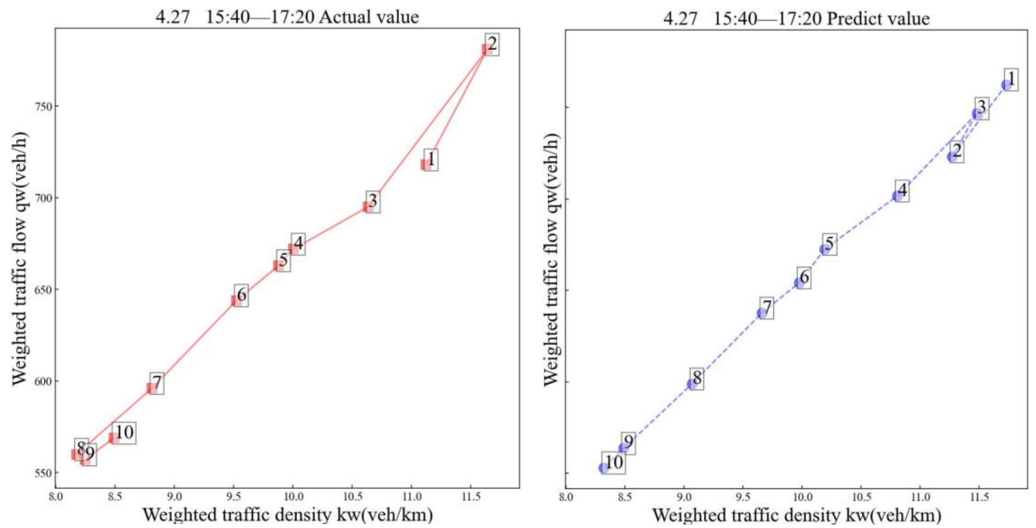
Fig. 9. Example of MFD in the morning peak hour

Finally, to test the LSTM advantage of the fusion GA-MOPSO search algorithm, traditional LSTM and RNN were used as comparisons, with their hyperparameters set to default values: Double hidden layer, 20 neurons, learning rate of 0.1, dropout of 0.1. The test dataset uses data from April 22nd to May 18th. It can be seen that the hyperparameters selected in this method have higher accuracy in MFD parameters and state prediction accuracy, proving the effectiveness of this search algorithm.



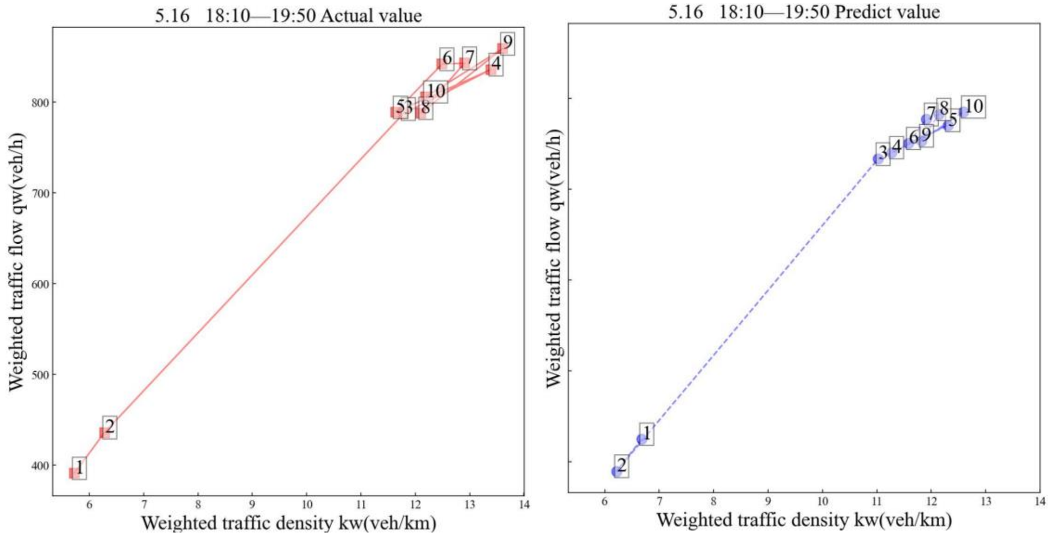
(a)Actual MFD point trajectory (b)Predicted MFD point trajectory

Fig. 10. Example of MFD during lunchtime



(a)Actual MFD point trajectory (b)Predicted MFD point trajectory

Fig. 11.Example of MFD in the afternoon session

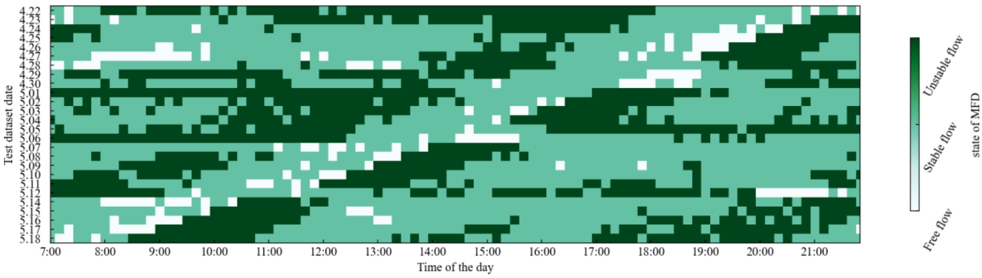


(a)Actual MFD point trajectory (b)Predicted MFD point trajectory

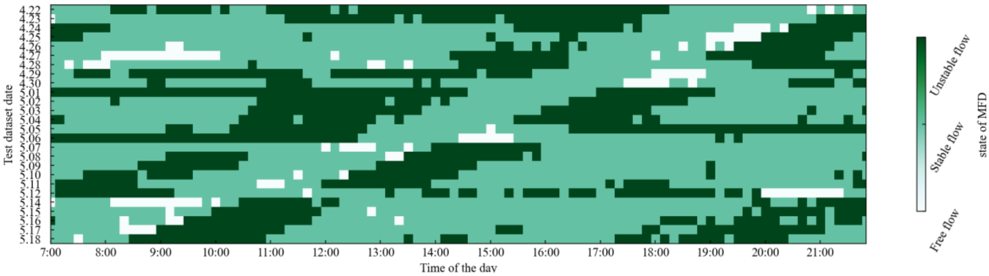
Fig. 12.Example of MFD in the evening peak hour

Table 2. MFD state prediction accuracy

Date	Accuracy
4,24	75.50%
4,25	82.22%
4,26	85.56%
4,27	85.56%
4,28	83.33%
4,29	80,00%
4,30	76.67%
5,01	81.11%
5,02	76.67%
5,03	95.56%
5,04	78.89%
5,05	77.78%
5,06	84.44%
5,07	90,00%
5,08	86.67%
5,09	84.44%
5,10	86.67%
5,11	82.22%
5,12	78.89%
5,13	78.89%
5,14	82.22%
5,15	84.44%
5,16	73.33%
5,17	80,00%
5,18	78.89%
Overall accuracy:	81.45%



(a) Actual MFD status results of the test set



(b) Test set prediction of MFD state results

Fig. 13. MFD state prediction results

Table 3. Accuracy of MFD state prediction under classification prediction

Test set date	Divided by time periods			Divided by weekday or not	
	7:00-12:00	12:00-17:00	17:00-22:00	Weekday	Weekend
4.22	60%	87.5%	83.33%		86.67%
4.23	86.67%	79.17%	90%		83.33%
4.24	93.33%	95.83%	60%	86.67%	
4.25	86.67%	95.83%	73.33%	88.89%	
4.26	90%	83.33%	76.67%	81.11%	
4.27	76.67%	79.17%	76.67%	81.11%	
4.28	66.67%	79.17%	80%	72.22%	
4.29	76.67%	58.33%	73.33%		66.67%
4.30	70%	91.67%	96.67%		96.67%
5.01	90%	79.17%	70%	90.00%	
5.02	90%	83.33%	83.33%	80.00%	
5.03	96.67%	75.00%	90%	82.22%	
5.04	80%	87.50%	93.33%	82.22%	
5.05	100%	91.67%	90%	78.89%	
5.06	90%	100%	63.33%		80%
5.07	90%	83.33%	83.33%		70%
5.08	90%	83.33%	73.33%	85.56%	
5.09	93.33%	79.17%	66.67%	87.78%	
5.10	86.67%	83.33%	90%	84.44%	
5.11	73.33%	66.67%	66.67%	73.33%	
5.12	73.33%	91.67%	80%	88.89%	
5.14	76.67%	83.33%	40%		44.44%
5.15	90%	75%	80%	84.44%	
5.16	93.33%	83.33%	76.67%	80.00%	
5.17	100%	87.50%	100%	71.11%	
MFD state prediction accuracy:	84.126%	82.48%	77.46%	81.72%	78.84%

Table 4. Comparison of prediction accuracy among different models

Model	MFD parameters	Test Set MRE	Test Set MAE	MFD Euclidean distance error	MFD state Prediction accuracy
GA-MOPSO LSTM	q^w	7.747%	44.99	0.0662	81.45%
	k^w	7.765%	0.726		
LSTM	q^w	7.463%	46.624	0.0673	79.66%
	k^w	7.769%	0.789		
RNN	q^w	7.246%	44.681	0.0721	79.2%

6. Conclusions

At the macro level of road networks, the importance and application of MFD and its parameters have been proven in many studies. Mastering MFD parameters and their evolution will profoundly affect regional traffic control strategies. However, there is currently limited research on predicting MFD parameters and their forms. In view of this, this paper proposes using two sets of LSTMs to make short-term predictions of MFD parameters, in order to capture future short-term point changes in MFD and predict macroscopic changes in road network status. Intelligent search algorithms are also used to participate in model construction. Based on experimental analysis, the following results were obtained:

(1) This paper uses massive data collection to obtain flow, speed, and other data of each road section in the experimental road network area. Further processing is carried out to obtain the MFD parameters q^w and k^w of the road network. The FCM method is used to cluster and divide the MFD states, obtaining three types of road network states and their boundaries.

(2) To predict the short-term MFD and its state changes of the road network, the key lies in whether the MFD parameters q^w and k^w can be accurately predicted. Therefore, this paper proposes to use two sets of LSTM models to predict them separately. The input of the LSTM model is the MFD parameters of the first three time intervals and the current time point, and the output is the prediction result of the next time interval.

(3) To obtain the best two sets of LSTM structures and hyperparameters, this paper establishes a multi-objective optimization framework for GA-MOPSO. The framework aims to optimize the number of layers, neurons, learning rate, and other parameters of the two sets of LSTMs based on the MRE error of the training sets q^w and k^w, as well as the Euclidean distance difference between points. This algorithm takes into account the prediction errors of both sets of LSTMs and the point position errors under their combination during the optimization process.

(4) The paper takes the Tingjiao Road Network in Hong Kong and its actual data as the research object, and uses GA-MOPSO and LSTM models for prediction. The results show that the model has high prediction accuracy for MFD parameters q^w and k^w, with MRE errors within 7.8%. The average Euclidean distance of MFD points is 0.0662, and the predicted parameter variation curve and point trend are basically consistent with the actual situation. The overall accuracy of the model in predicting MFD state categories is 81.45%, but its prediction performance for sudden changes in traffic states is unsatisfactory and needs to be improved in subsequent research.

(5) Compared with the prediction results of typical LSTM and RNN models, the results show that the LSTM model incorporating the GA-MOPSO optimization framework has higher prediction accuracy and better prediction stability, demonstrating the effectiveness of the algorithm proposed in this study.

(6) The MFD parameter is a macro parameter that aggregates all road sections within the road network and is highly condensed. Its value and location are all influenced by the traffic flow, surrounding environment, and traffic control of the road network. The accurate evaluation and prediction of its data are still difficult in the academic community. At present, there is still limited research on the prediction of MFD parameters and MFD status in road networks. The experimental design and results of this study will provide useful references for the prediction of macro traffic conditions. In the future, research will focus on MFD pattern recognition, improving prediction accuracy, and considering more influencing factors to further improve the model.

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