Short-term traffic flow prediction on campus based on modified PSOBP neural network

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Abstract. In order to ensure the efficiency of daily passage on campus and prevent the occurrence of safety accidents, an improved prediction method of optimized BP neural network based on modified particle swarm optimization algorithm (PSO) was proposed. In this modified PSO algorithm, we propose a mutation operator to avoid particles plunging into local optimization, using the modified PSO algorithm to optimize the solution of weight and threshold in BP neural network. The prediction method is applied to the time series of the observed campus traffic flow for effective verification, and the result shows that the method has better nonlinear fitting ability and higher prediction accuracy for the short-term traffic flow on campus.

1. Introduction
In the outline of national economic development in the tenth five-year plan, the Chinese government has clearly pointed out that it is necessary to accelerate the development of smart transportation on the basis of information and network. At the request of the state, smart transportation has gradually begun to flourish in various places. The traffic flow prediction is the basis and kernel of the construction of intelligent traffic system. And its significance lies in providing the important information of the transportation and offering guidance of the road traffic control. At present, traffic statistical systems have been installed on major urban roads in some metropolises. Nevertheless, in other parts of the city, especially university campuses, congestion or traffic accidents are still likely to happen since pedestrians is the majority in the traffic flow and regular surges of traffic flow happen in specific periods. So it is extremely necessary to establish a new smart campus transportation system focusing on the pedestrian volume prediction.

Compared with campus traffic flow prediction, the research on urban short-term traffic flow prediction, the vehicle flow as the mainstream, has been relatively mature. At present, domestic and foreign scholars mainly focus on three aspects: models based on statistical theory [1-2], the Kalman filter or ARIMA method has the advantages of high accuracy, and model prediction accuracy varies little with the time interval. Models based on nonlinear prediction theory [3-4], fractal theory reveals the regularity, hierarchy and scale invariance hidden in the complex natural and social phenomena, and the most prominent feature is self-similarity. Models based on intelligent algorithms [5-6], advantages of artificial neural network lie in arbitrary nonlinear mapping and adaptive self-learning. The applications of the first two mentioned models is more due to their mature theoretical basis. These algorithms are mostly based on the rigorous mathematical methods, which is to establish a subjective model of data sequence firstly, then calculate and forecast depending on it. Thus the accuracy can no longer meet the actual requirements. Moreover, these algorithms cannot guarantee the robustness of
prediction system as its lack of self-learning ability. Consequently, researchers now mainly focus on the intelligent algorithms.

Among the intelligent algorithms, BP neural network is a relatively successful prediction model. Its favorable nonlinear mapping ability, self-learning and adaptive ability can help predict short-term traffic flow on campus ideally. However the traditional BP neural network uses a gradient descent learning method. So when it comes to the complicated structure of neural network, this algorithm will emerge several questions like slow learning speed, falling into local minimum value, poor stability. In practice, researchers often use a variety of improved BP neural network model or combined model. Ziwen et al. [7] established the forecasting model based on BP and genetic algorithm (GA) which combines the stronger nonlinear approximation of BP neural network and global search capability of GA, so as to improve the convergence and forecasting precision of network. Xin Guo et al. [8] established a BP neural network sub-model and ARIMA sub-model, then taking BP neural network as the approaching machine of the most superior nonlinear combination model to establish the hybrid prediction model, and the results indicated that the hybrid prediction method is practical and feasible. Ze-guo Zhang et al. [9] proposed a SAPSO-BP neural network which utilizes the SAPSO (self-adaptive particle swarm optimization) algorithm to adjust the structure parameters of BP neural network, and this approach can achieve vessel traffic flow trend predictions with reasonable, satisfactory convergence and stability. In addition, in fields of computer application [10-11], electric power industry [12], power Engineering [13] etc., some scholars have also proved that the BP neural network model optimized by particle swarm optimization algorithm has higher accuracy and fitting degree than the traditional neural network model.

Since the concepts of smart campus and smart traffic have only been put forward in recent years and campus traffic flow has unique characteristics that pedestrian as the majority, which is different from urban traffic flow, few cases have applied the above prediction algorithm to campus. The prediction of short-term traffic flow on campus is still in the exploration stage. Considering that PSOBP algorithm’s significant performance in other fields and vessels traffic flow prediction, we applied an modified PSOBP algorithm to the measured traffic flow data of Wuhan University of Technology for testing and compared the prediction results with other model algorithms. It turns out that the modified PSOBP algorithm is of high precision, and more suitable for the pedestrian prediction.

2. Short-time traffic flow prediction model for school based on mPSOBP neural network

2.1. Data processing

To eliminate the effect of extreme data and outliers, firstly use normalization to change the range of human traffic flow data to [0,1]:

$$x'_t = \frac{x_t - \frac{1}{n} \sum_{i=1}^{n} x_i}{x_{\text{max}} - x_{\text{min}}}$$

where $x_t$ is the value of human traffic flow at time $t$, $n$ is the number of samples, $x_{\text{min}}$ and $x_{\text{max}}$ are the minimum and the maximum value among the data set of human traffic flow.

In short-term forecasts of human traffic flow, to predict the flow data at time $t+1$, we need to determine applying the historical observation flow data of how long time before the time $t+1$ as samples, which is called the selection of sliding window length $N$. After selecting the sliding window length, the human traffic flow data can be divided into many samples at the same interval, and then the sample set can be divided into training sets and test sets at a certain scale. The human traffic flow forecast is actually using the sliding window sequence \( \{x_t \mid t = 1, 2, \ldots, N\} \) to predict the human traffic flow value $x_{N+1}$ at the moment $N+1$. 

We choose 76 as $N$, since the number of original data collected each day is 108, and after changing the training percent to find out the best predicting result, we consider 70 percent of the data to be the training set, that is 76.

2.2. mPSOBP neural network

Because the particles in PSO gather to the best position in their history and the best position in the history of neighbors or groups, the rapid convergence effect of particle population is formed, and it is easy to fall into local extremes, precocious convergence or stagnation. In this paper, we draw on the idea of variation in genetic algorithm. We propose a mutation operator to avoid particles plunging into local optimization, that is, some variables are reinitialized with a certain probability. The variation operation expands the population search space which is shrinking in iteration, enabling particles to jump into the optimal position previously searched, to search in a larger space, while maintaining the diversity of the population and improving the likelihood that the algorithm will find better values.

The step of mPSOBP neural network is as follow:

Step 1: Determine the structure of the BP neural network; The base function of BP neural network is used as the transfer function of the hidden layer node, and the signal propagates forward when the error propagates in reverse. The topology has three parts, including the input layer, the hidden layer and the output layer. $x_1, x_2, \cdots, x_n$ is the input of BP neural network, $y_i$ is the output, $w_{ij}$ is the connection weight between the input layer and the hidden layer, $w_{jk}$ is the connection weight between the hidden layer and the output layer, $h(j)$ is the output of the $j$ node in the hidden layer.

Step 2: Determine the number $N$ of subpopulations of the particle swarm; the dimension $D = m \times l + l \times m$ of rate vector, which $m$ is the number of input samples, $l$ is the number of the hidden layer; the maximum iteration time $T_{\text{max}}$; the inertia weight $W$; the maximum rate $V_{\text{max}}$; the acceleration constant $c_1, c_2$. Meanwhile, we should determine the initial position and rate vector of particle swarm.

Step 3: Determine the adaptive function

$$J = \frac{1}{n} \sum_{j=1}^{m} \sum_{i=1}^{m} (y_i - l_i)^2 \tag{2}$$

where the parameter is the parameter contained in the BP neural network.

The minimum fitness function is determined as the extreme value of the particle, and the particle with the smallest individual extreme value is determined as the global extreme value. The corresponding position of the particle with the least adaptability when the algorithm stops is the optimal solution.

Step 4: Initialize the position and rate.

Step 5: Iterate with the best position of previously generated particles as the iteration point.

Step 6: Update the rate and position of particles based on steps from 2 to 5.

The formula is as follow:

$$V_{id}^{k+1} = W V_{id}^{k} + c_1 r_1 (P_{id}^{k} - X_{id}^{k}) + c_2 r_2 (P_{gd}^{k} - X_{gd}^{k}) \tag{3}$$

$$X_{id}^{k+1} = X_{id}^{k} + V_{id}^{k+1} \quad d = 1, 2, \ldots, D, i = 1, 2, \ldots, m \tag{4}$$

where the rate and the individual extremum of the $i$ particle is $V_i$ and $P_i$, and the extremum of the particle swarm is $P_g$.

During the update process, the particle should be constrained to ensure that the maximum rate of the particle per dimension does not exceed the set maximum rate $V_{\text{max}}$, that is, if $V_{id}(t+1) > V_{\text{max}}$, then $V_{id}(t+1) = V_{\text{max}}$; if $V_{id}(t+1) < -V_{\text{max}}$, then $V_{id}(t+1) = -V_{\text{max}}$. If the global search capability of particle swarm is required to be strong, then set a bigger $V_{\text{max}}$; if the local search capability of particle
population is required to be stronger, then set a smaller $V_{\text{max}}$. After updating, we can have the new particle swarm.

Meanwhile, the mutational probability of mutation operator is set to be between 0.01 and 0.05. After updating particles, the particle is likely to be reinitialized, then we should get the fitness of new particles and update the individual and global extreme value.

Step 7: When the number of iterations reaches the maximum preset value $T_{\text{max}}$, or the error accuracy meets the preset value, the iteration stops and we can get the global optimal solution $P_{\text{gd}}$, that is, the weight and threshold of the BP neural network. Finally, the optimal solution is replaced into the BP neural network for training and learning.

3. Empirical analysis of the time series of measured traffic flow

3.1. Data acquisition methods
This study uses the observation method of combining device image entry and manual counting, to ensure the credibility of the study and the adequacy and validity of the data, representative campus road intersections should be selected as observation points. We selected the intersection of Wenhui Street and Liuyuan Road with obvious characteristics and large traffic as the research object, and took its four corners as observation points.

3.2. Changing characteristics of traffic flow
In order to obtain the changing characteristics of traffic flow, it is necessary to analyze the change distribution process of traffic flow data first. Figure 1 shows traffic flow data from observation nodes in the northwest corner in a day, where the horizontal axis represents the time. The first five days are working days and the second two days are weekend. The vertical axis represents the number of people passing through the observation node every five minutes, that is, the size of traffic flow. If the traffic flow makes analysis of the entire week, it's not hard to see the differences between traffic flow change workdays and weekends. Weekdays adding and dropping classes daily activities of students, can lead to early peak, noon and evening peak spike. By contrast, the weekend two days of traffic flow is relatively gentle change process, only one peak appeared in the noon time. If only the traffic flow variation of a day is analyzed, it can be seen that for weekdays, the morning peak, evening peak and the interval between them, the traffic flow presents a relatively sharp change trend in most of the time, while the traffic flow changes relatively gently in the rest of the time. On weekends, even in the middle of the day when traffic is heavy, the trend is not dramatic.

![Figure 1. Changes of traffic flow from the observation node within a day.](image-url)
3.3. Simulation experiments and results analysis

The simulation experiment selected traffic data from the observation node in the northwest corner, including this point every 5 minutes from September 9 to 22, 2019, 8:00-17:00 traffic data. In conjunction with some literature [14], changes in traffic flow on research days are of greater significance to daily economic production activities. Therefore, this empirical analysis removes the data of weekends and holidays. Therefore, in this empirical analysis, the data of weekends and holidays were removed, and there were 9 remaining working days and 972 remaining data. This paper divides the remaining data set into training set, validation set and test set three parts, of which the training set selected the first 648 traffic flow data, that is, about 70% of the total data. The validation set contains the next 108 traffic data, which is about 10% of the total data, and the last 216 data as test sets, about 20%. The parameter of BP neural network is set as follows: The training time is 5000, the training goal is 1e-8, the learning rate is 0.035. The parameter of particle swarm algorithm is set as follows: The population size is 100, the maximum generation is 200, the acceleration factor is c1=c2=1.49445, the mutation operator is 0.01-0.05, the position and rate of particles are [-5,5] and [-0.5,0.5].

Through MATLAB programming, as shown in Table 1 and Figure 2 below, the training set, verification set, test set and the overall regression value are all above 0.8, indicating high correlation and good fitting degree.

Table 1. Training set, verification set, test set and overall R values.

| Regression value | Training | Validation | Test | All |
|------------------|----------|------------|------|-----|
|                  | 0.91636  | 0.92439    | 0.82965 | 0.89483 |

![Training and Validation plots](image1)

![Test and All plots](image2)

Figure 2. Training set, verification set, test set and overall R values.
In order to better demonstrate the prediction effect of modified PSO-BP neural network, we use MATLAB software to compare the prediction results of modified PSO-BP with other prediction algorithms, including PSOBP neural network [15], PNN neural network [16], GRNN neural network [17] and regression algorithm [18]. The detailed result is shown in Figure 3 and 4 below.

As shown in Figure 3 below, compared with the PSOBP neural network, mPSOBP neural network is closer to the prediction results of real values at all times and can reflect the changing trend better, indicating that the forecast result of mPSOBP neural network has great improvement.

Figure 3. Comparison of traffic flow data simulation and prediction results of modified PSOBP model and PSOBP model for the measured traffic flow data.

As shown in Figure 4 below, the prediction result of mPSOBP neural network model is more consistent with the real value and can better reflect the changing trend of traffic flow. Although GRNN and PNN can also reflect the trend and size of pedestrian traffic flow, the prediction effect of the two models is poor during the low peak period of some pedestrian traffic flow. Meanwhile, the prediction effect of the regression model is poor, and cannot reflect the change of pedestrian traffic flow in each time period.

Figure 4. Simulation and prediction results of traffic flow data for other four models of measured traffic flow data.
In order to compare the accuracy of prediction results of mPSOBP neural network and other models, the MAPE and RMSE values of each model were shown in Table 2.

**Table 2.** Prediction errors of the measured traffic flow time series.

|       | mPSOBP | PSOBP | PNN  | GRNN  | regression | BP     |
|-------|--------|-------|------|-------|------------|--------|
| **MAPE** | 0.07816 | 0.1340 | 49.8662 | 0.2111 | 0.2375 | 3.4542 |
| **RMSE**  | 3.99609 | 5.3298 | 9.9199 | 7.4896 | 8.1228 | 10.4736 |

Can be seen from Table 2, compared with PSOBP neural network and other models, the MAPE value and RMSE value of modified PSOBP neural network are the smallest, which can prove that the decision-making accuracy of modified PSOBP neural network model is higher. The RMSE value of the BP neural network is greater than 10, showing that the degree of difference between predicted values and the actual value is large.

4. Conclusions
In this paper, a campus traffic prediction model based on modified PSOBP neural network is proposed, aiming at the problems of local minimum defects and slow convergence speed in BP neural network prediction, an adaptive mutation operator is introduced into the PSO algorithm, and a time series prediction method is proposed to optimize BP neural network with improved PSO algorithm. It is applied to the micro-measured traffic flow prediction and compared with PSOBP prediction model and BP model. The results show that this method can effectively reduce the possibility of BP neural network prediction model falling into local minimum and improve the convergence rate of the model.

The main data collected in this paper is the pedestrian traffic flow data every five minutes, and since campus traffic flow is a complex mixed traffic flow system, the mixed traffic flow model for vehicle flow prediction can become the future research direction.

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