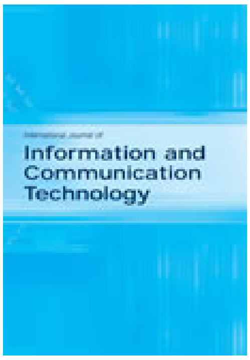


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# Intelligent traffic assignment method of urban traffic network based on deep reinforcement learning

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**Abstract:** In order to overcome the problems of high relative error and long response time of traditional methods, a new intelligent traffic flow allocation method based on deep reinforcement learning is proposed. In this method, deep reinforcement learning is introduced, and experience pool technology is used to obtain and retain samples in a certain stage to train urban traffic network. The complete track is divided into several independent state action pairs, and the sample database is established. In a certain range, the vehicle congestion density is simplified to the degree of congestion. When the starting point and the end point are known, all traffic demands between the two points are calculated, allocation and intelligent traffic network traffic assignment is then realised. Experimental results show that the average relative error of passenger travel time is 12.34%, the traffic flow prediction indexes are the lowest, and the allocation time is the highest, which is 0.878 s.

**Keywords:** deep reinforcement learning; DNQ; urban traffic; network traffic; intelligent distribution.

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## 1 Introduction

Traffic system is a nonlinear system, which has the characteristics of multiple changes, complexity and rapid change. In the face of frequent traffic problems, it is necessary to take the characteristics of the traffic system as the starting point, fully consider the relationship between pedestrians, vehicles and roads, and combine with modern technology to fully improve the operation efficiency of the traffic system (Zhang and Wang, 2017). Traffic congestion will cause great damage to the social economy. When the time is used to calculate the fuel consumption of cars, 1 kilometre can be replaced by three minutes. Assuming that the number of pedestrians on and off duty in a day is 4 million, and the social cost per capita is 20 yuan, then the economic loss caused by traffic congestion is as high as 80 million yuan per day, which is a huge data traffic jams and slow down the speed of vehicles. Relevant information shows that compared with the fast driving state, the exhaust emission of vehicles in the slow driving state will be as much as five times higher, which also increases the degree of environmental pollution, resulting in a sharp increase in the number of pollutants (Kherad et al., 2018; Rong et al., 2018). Therefore, how to apply modern technology to solve traffic congestion and alleviate environmental pollution has become an urgent problem to be solved (Liping et al., 2018).

In Cheng et al. (2019), a traffic flow assignment method based on improved ant colony algorithm is proposed. Firstly, the influencing factors of road network capacity are evaluated and the road quality evaluation system is established. The heuristic factors in the ant colony algorithm are improved by using the road section quality. Then, random nodes are added to expand the ant colony search range and the pheromone update mechanism is improved. Finally, the improved algorithm is applied to allocate the total traffic volume in batches and the flow distribution diagram is obtained. The results show that the improved algorithm comprehensively considers the travel distance and road quality, which is more in line with the traffic flow allocation requirements than before, and has better path optimisation. It can provide suggestions and support for post disaster rescue work and post disaster road network traffic assignment decision. But the prediction error is large. In Liu and Rong (2018), a multi-path traffic assignment method based on Logit assignment model. The relationship between the parameter $\theta$ in Logit model and the result of traffic assignment is studied. From the point of view that the average impedance of road network and the variance of link impedance are the minimum, the appropriate value of $\theta$ is selected to allocate the road network traffic, and the yen algorithm is used to solve the problem of $K$ short circuit to construct the set of alternative paths. The properties of $K$ short circuit in multi-path traffic assignment are studied with an example. The case study shows that with the increase of parameter $\theta$, the average impedance of road network and the variance of section impedance first decrease and then increase. When $\theta = 1$, the impedance variance of road network is the minimum. With the decrease of K value, the average impedance of road network and the variance of section impedance continue to increase. When $k = 5$, the average impedance of road network and the variance of section impedance are within the acceptable range and the amount of calculation is the minimum. But the average absolute error of prediction is large. In He (2018), a new method of traffic flow assignment based on inverse $\lambda$ basic graph is proposed. Combined with the static traffic flow assignment model, the evolution of traffic flow is analysed. The vehicle flow of the balanced road section is obtained first. The congestion state indicates that the vehicle flow of a certain section reaches the critical state. At this time, it is necessary to solve the traffic flow of the road section again to judge whether the vehicle flow is in the critical state. In summary, the vehicle flow of different road sections is calculated to complete the traffic network flow evolution analysis, but the overall prediction takes a long time.

In order to solve the problems of large relative error and long response time of traditional methods, and realise the average relative error of low passenger travel time and allocation time, an intelligent traffic assignment method based on deep reinforcement learning (DNQ) is proposed. The overall design scheme of this method is as follows:

1 The DNQ is introduced, and the experience pool technology is used to obtain the samples reserved in a certain stage to train the urban traffic network. The complete trajectory is divided into several independent state action pairs, and the sample database is established.

2 In a certain range, the vehicle congestion density is simplified to the degree of congestion. When the starting point and terminal point are known, all traffic demands between the two points are allocated. Considering the characteristics of dynamic traffic assignment and allocation constraints, intelligent traffic network traffic allocation is realised.

3 The average relative error of passenger travel time, traffic flow prediction index and allocation time of different methods are compared.

4 Summarise the full text and draw a conclusion.

## 2 Design of intelligent traffic assignment method for urban traffic network

### *2.1 Intensive learning*

DNQ fully combines the characteristics of reinforcement learning and deep learning, and has been widely used in various fields. Reinforcement learning can be formalised as Markov decision process, and the main idea of deep learning is to extract useful patterns from data (Aghamohammadi and Laval, 2020). Deep learning model is inspired by the multi-layer structure of human nervous system. This paper introduces the concept of DNQ, and applies it to the traffic flow allocation problem, in order to reduce the average relative error of passenger travel time and allocation time, improve the effect of intelligent traffic flow allocation in urban traffic network, and solve the problem of traffic congestion.

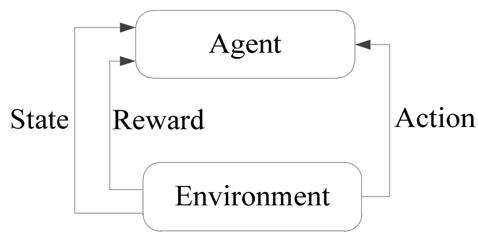
The concept of Markov property is introduced: after an action occurs, if the next state of the system is not related to the change history of the system state, but only determined by the current state and action, the formula is expressed as follows:

$$P\left[x_{t+1} \middle| x_t\right] = P\left[x_{k+1} \middle| x_k\right], k = 1, \cdots, t \tag{1}$$

where $P[x_{t+1} \mid x_t]$ is the current state of the system and $P[x_{k+1} \mid x_k]$ is the next state of the system.

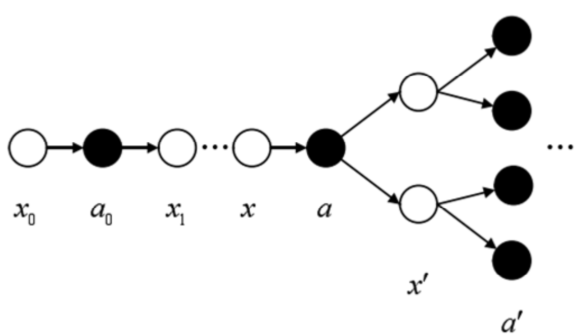
The premise of DNQ is that the next state of the system is independent of the change history of the system state, but only determined by the current state and action. The iterative process of reinforcement learning is shown in Figure 1.

**Figure 1** Iterative process of reinforcement learning




In the process of traffic flow assignment, the agent implements multi-step operation in the allocation environment to obtain the complete operation track, and obtains multiple operation trajectories under various states, which are summarised to obtain Markov chain. The specific representation is shown in Figure 2.

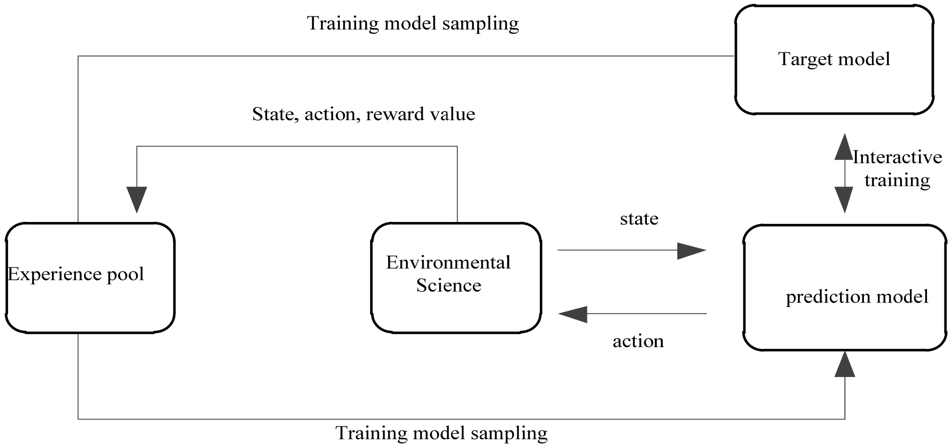
**Figure 2** Schematic diagram of Markov chain




Tuple $E = \langle X, A, P, R \rangle$ can represent the DNQ process. In the actual operation process, the target tuple needs multi action operation to achieve specific target acquisition. The allocation goal is to obtain the strategy combination with low cost of steps. In the process of calculating allocation accumulation, it is necessary to multiply it with discount factor $\gamma$ on the basis of single operation.

The main components of DNQ model include prediction network, target network, traffic environment and experience pool (Brederode et al., 2018). Due to the short-sightedness of reinforcement learning in the model, in order to avoid this defect and update the training parameters in the DNQ model in time, the samples in the training network are reserved by combining the experience pool theory, and the weight $\omega$ and offset $b$ in the prediction network are calculated through the sample data.

**Figure 3** The model of DNQ strategy




In theory, for any function, the deep neural network can be fitted. In the iterative process, based on the DNQ theory, the training set formed by samples and single-step operation is generated. The neural network is trained to fit the training set $Q(x, a)$. Based on the deep learning algorithm, the core solution results of the iteration are as follows:

$$Q^*(x, a) = E_{x'}\left(r + \gamma \max_a Q^*\left(x', a'\right)\right) \tag{2}$$

In the formula, $r$ represents the discount cumulative reward, and the parameter $\theta$ exists in the deep neural network. Based on this, the network is fitted and the result $Q(x, a, \theta) \approx Q^*(x, a)$ is obtained. According to the gradient descent method, the network is trained in the iterative process, and the sample mean square error is calculated according to the loss function $L_i(\theta_i)$ as follows:

$$L_i\left(\theta_i\right) = E_{x,p}\left[\left(y_i + Q\left(x, a, \theta_i\right)\right)^2\right] \tag{3}$$

In the formula, $y_i$ is the gradient descent coefficient and $E_{x,p}$ is the depth neural network fitting function.

DNQ algorithm guarantees the convergence and efficiency of training results through experience playback and target network mechanism.

In the iterative process of DNQ, each operation step will generate state action trajectory, which is complete, and the correlation between each state action is strong, and there are certain differences between trajectories (Xie and Wang, 2019). Therefore, the network state will be unstable and the convergence performance is poor. The intensive learning has Markov nature. The individual states in the trajectory can form individual training samples. The DNQ algorithm divides the complete action trajectory into independent action states, collects the independent states to form the sample library, and the update of the sample library is carried out through the new samples generated by each iteration. When the number of sample banks reaches saturation state, random samples are taken Used to assign policy assessments.

## 2.2 Intelligent traffic assignment in urban traffic network

In urban traffic network, the degree of lane congestion can be calculated by the length of lane and the number of vehicles (Zhao and Li, 2018; Yildirimoglu et al., 2018). The DNQ theory is introduced to control the traffic flow, which can simplify the vehicle congestion density to the degree of congestion. The calculation method of traffic network flow is as follows:

$$d = q/(l \times n) \tag{4}$$

where $q$ is the number of vehicles beside the lane in a certain time state, $l$ is the length of the lane, and $n$ is the number of lanes.

The problem of traffic flow allocation can be regarded as the route selection problem of travel vehicles. Knowing the starting point and end point of vehicles, solving the vehicle demand between traffic assignment, adding allocation iteration process on the basis of all existing and none, completing incremental allocation, meeting the OD demand in a certain period of time, ensuring that the flow of other paths is 0 on $N$ paths (Chen et al., 2018). The flow distribution process summary has the following limitations:

According to the length of the road section, the vehicle capacity of the road is calculated. Assuming that the maximum limited capacity of vehicles is expressed by $w_i$ on Section 1, the vehicle flow on a certain section needs to meet the following constraints:

$$\sum_{j=1}^{m} \sum_{i=1}^{n} S_{ij} x_{ij} \le w_i \tag{5}$$

The length of the road and the density of the traffic flow will affect the vehicle capacity of the road. The length of section a can be expressed by $l_a$, and the maximum density of the traffic flow can be expressed by $e_{am}$. The specific expression of the vehicle capacity $Q$ of the road is as follows:

$$Q = l_a * e_{am} \tag{6}$$

In the process of road section driving, the length of distance and the speed of traffic flow will affect the travel time of vehicles. The velocity of vehicles can be expressed as $v_f$, and the driving time $t_0$ can be expressed as follows:

$$t_0 = \frac{l_a}{v_f} \tag{7}$$

The allocation objective is set as the total travel time of traffic vehicles, and the optimal control model is obtained by using the objective function, combining with the characteristics of traffic assignment and the constraints in the allocation process :

$$\min_{u,x} J = \sum_{a} \int_{0}^{T} u_a(t) c_a(t) dt \tag{8}$$

In the formula, the section flow $x_a^s(t)$ is the state variable, the section inflow rate $u_a^s(t)$ is the control variable, and the section outflow rate $v_a^s(t)$ is calculated by the following formula:

$$v_a^s(t) = \frac{x_a^s(t)}{c_a(t)} \tag{9}$$

In order to distribute dynamic traffic flow evenly, the optimal control model can be discretised. Since the objective function of the model is in a nonlinear state, it meets the nonlinear law. In this paper, the OD demand in the process of traffic network flow allocation can be obtained through the planning function, and the constraint conditions are as follows:

$$X = f\text{mincon}\left(fun, x_0, A, b, A_{eq}, b_{eq}\right) \tag{10}$$

In the formula, the parameter *fun* is the objective function to be solved, $x_0$ is the first target point generated by the initial iteration process, $A$ and $B$ are the constraint inequality requirements, and $A_{eq}$ and $b_{eq}$ are the constraint equality requirements.

Through the allocation iteration process, the number of vehicles on the road section and the path impedance are initialised. After the iteration process starts, the OD demand is defined. The traffic flow of the traffic network is allocated according to the demand. All the allocation paths are obtained between the initial point and the end point. The impedance function is calculated according to the path information between two points, and the constraint conditions are brought into the objective function, allocate OD demand and allocate vehicle flow on the road section (Bai, 2018; Jing, 2018).

The process of characterising road network traffic state is basically the same as that of road section. Combined with relevant traffic index calculation methods, the road network index value is mainly obtained by weighting the road section value according to the vehicle kilometres of the road section. The specific calculation formula is as follows:

$$ATD = \frac{\sum_{i=1}^{l}\left(VKT_i \times ATD_i\right)}{\sum_{i=1}^{l} VKT_i} \tag{11}$$

After the road network traffic state representation is completed, the short-term traffic flow is allocated. Assuming that in a certain state, the traffic volume of a specific road section to be allocated is $\overline{Y}(K+1)$, when the time is $t_0$, the traffic volume is $V(K)$, and the traffic flow of the previous two time periods is $V(K-1)$ and $V(K-2)$ respectively. Compared with the previous several time periods, the traffic volume of time $t_0$ has a greater correlation, and the relationship is as follows As shown below:

$$\overline{Y}(K+1) = H_0V(k) + H_1V(k-1) + H_2V(k-2) + \omega(k) \tag{12}$$

In the above formula, $\omega(k)$ represents the noise interference in the allocation process, and the covariance matrix can be expressed as $R(k)$. The distribution control process is integrated and changed by Kalman filter, and the transformation results are as follows:

$$C(k) = \left(V(k), V(k-1), V(k-2)\right) \tag{13}$$

$$X(k) = \left(H_0, H_1, H_2\right)^T \tag{14}$$

Traffic network flow is a dynamic process. In the process of dynamic allocation, not only the traffic volume of this time period, but also the traffic load of this period are needed. Traffic load refers to the number of vehicles on the road in this period. In the dynamic allocation process, the dynamic traffic characteristics can not only be reflected by the traffic volume, but also need to be fully combined with the traffic load to observe the dynamic distribution process in the time period.

The state change of dynamic road section can be reflected in the form of formula to fully express the dynamic characteristics of the network. The basic expression is as follows:

$$x_r^a - x_{r-1}^a = \left(d_r^a - u_r^a\right)\delta, \forall r, a \tag{15}$$

Thus, the traffic flow assignment model can be obtained as follows:

$$X\left(k\right) = A\left(k\right)X\left(k-1\right) + v\left(k-1\right) \tag{16}$$

$$\overline{Y}(K+1) = C(k)X(k) + \omega(k) \tag{17}$$

where $X(k)$ is the state vector, $A(k)$ is the state transition matrix, $\overline{Y}(K+1)$ is the observation vector, $C(k)$ is the observation matrix, $\omega(k)$ and $v(k-1)$ are the observation and process noise respectively.

To sum up, this method introduces DNQ, uses experience pool technology to obtain and retain samples in a certain stage to train the network, divides the complete trajectory into multiple independent state action pairs, and establishes a sample database; the vehicle congestion density is reduced to congestion degree according to a certain range, and the optimal control model is established when the starting point and end point are known. According to the road section state equation, the dynamic characteristics of traffic network are reflected, and the intelligent traffic network traffic assignment model is obtained.

## 3 Experimental study

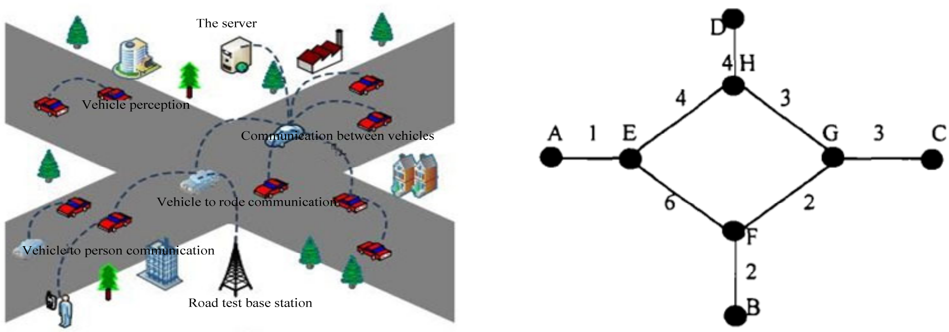
### *3.1 Experimental scheme design*

In order to fully verify the effectiveness of the intelligent traffic assignment method in this paper, an experimental study is designed. The overall experimental scheme is designed as follows:

1 Experimental environment and experimental data

Map Info is an OCX control, which is mainly used to realise cartographic work. It has powerful functions. It can edit and input the required data through external devices, such as scanners and data collectors. In the test network, the number of traffic network nodes is 8, and the road section is 8. Under the condition of time unit, the weight of road section is marked. Different routing protocols should be chosen for different application requirements. The schematic diagram of Internet of vehicles is shown in Figure 4.

**Figure 4** Test network (see online version for colours)




The data used this time are all from the network, and the data collected are de duplicated and cleaned. The processed data are divided into two parts, one is training sample, and the other is test sample. The parameters of neural network are shown in Table 1.

**Table 1** Related parameters of neural network

| | |
|---|---|
| Training samples | 958 groups |
| Test samples | 482 groups |
| Maximum number of training sessions | 100 |
| Minimum error | 1/10,000 |
| Weight learning rate | 0.01 |
| Translation factor and scaling factor learning rate | 0.001 |
| Momentum factor | 0.3 |

## 2 Experimental methods

The traffic flow assignment method based on improved ant colony algorithm in reference Cheng et al. (2019), the traffic flow assignment method based on Logit model in reference Liu and Rong (2018), the traffic flow assignment method based on inverse $\lambda$ basic graph of traffic flow in reference He (2018) and the traffic flow assignment method based on DNQ designed in this paper are selected as the experimental comparison methods.

## 3 Experimental evaluation index

Because the individual behaviour of passengers varies greatly, and there are some random factors in the process of route selection, it is difficult to analyse the simulation results accurately. In this paper, the simulation results are verified from the perspective of single passenger travel time. The relative error between simulated travel time of individual passengers and travel time recorded by AFC data is analysed. The calculation formula is as follows:

$$RE_T = \sum_{i=1}^{p} \frac{\left|t_i - t_i^*\right|}{t_i^*} / \, p \times 100\% \tag{18}$$

where $t$ is the travel time calculated by passenger $i$ after system simulation, $t_i^*$ is the actual travel time calculated by AFC records, and $p$ is the total number of simulated passenger trips in the analysis phase.

The results of flow prediction are as follows:

$$MSPE = \frac{1}{N}\sqrt{\sum_{t=1}^{N}\left(\frac{X_{real} - X_{pre}}{X_{real}}\right)} \times 100\% \tag{19}$$

Among them, *MAE* represents the absolute average value of the error between the predicted value and the actual value, indicating the smaller the deviation between the two; *RMSE* represents the distribution of the error; the smaller the value of *RMSE*, the more concentrated the error distribution is, the better the prediction effect will be; the smaller the value of *MSPE*, the better the prediction effect will be.

The long response time represents the time consumed by the distribution system services, and represents the time interval between the input of allocation information and the completion of the allocation information. The calculation method is as follows:

$$T = t1 + t2 + t3 \tag{20}$$

In the formual, $T$ is the corresponding delay; $t1$ is the response time of the server; $t2$ is the network response time; $t3$ is the response time of the client.

### 3.2 Analysis of experimental results

Taking the actual AFC data of a certain day in 2018 as the passenger flow input data, the travel process of 80,250 passengers in a certain period of time is simulated. The relative error of travel time of each passenger is shown in the figure below, and the average relative error of travel time is 12.34%. The results show that the simulation system has good simulation accuracy from the perspective of individual passenger travel.

The comparison results of different prediction methods are shown in Figure 6.

Comprehensive analysis of the experimental data in Figure 6 shows that compared with the four evaluation indicators of the four prediction methods, it can be seen that the indicators of the proposed method are the lowest among the four short-term traffic flow prediction methods, which fully indicates that the proposed method can achieve very satisfactory prediction results. The main reason is that this method introduces DNQ, uses the experience pool technology to obtain and retain the samples of a certain stage to train the network, divides the complete trajectory into several independent state action pairs, and establishes the sample database; the vehicle congestion density is simplified into congestion degree according to a certain range, and when the starting point and end point are known, the two road points are selected in order to improve the efficiency of traffic operation, the traffic flow is allocated according to the demand.

**Figure 5** Distribution of relative error of passenger travel time (see online version for colours)

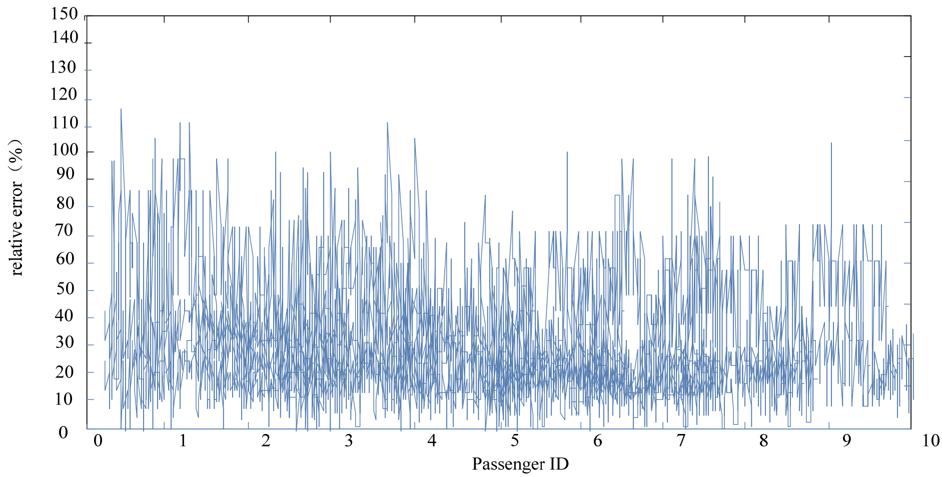
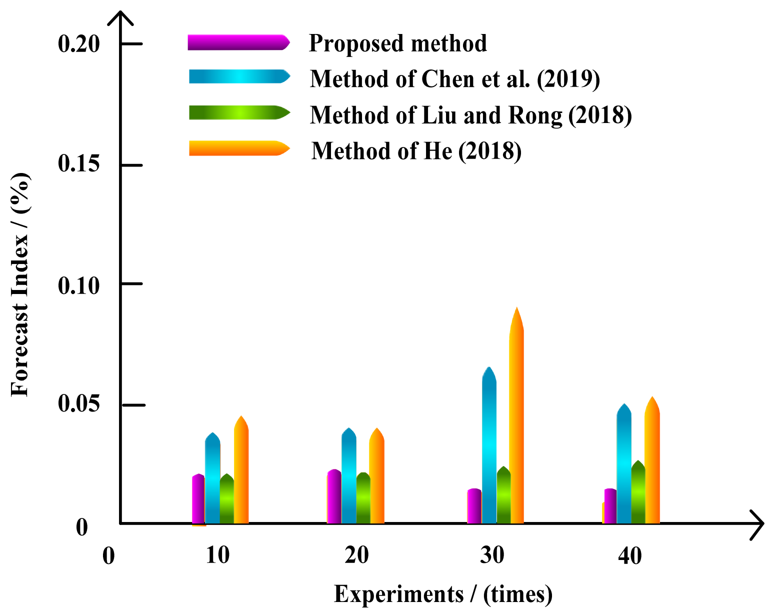



**Figure 6** Comparison of prediction results of different prediction methods (see online version for colours)




The following simulation tests will compare the time consumption of four different traffic flow assignment methods. The lower the time consumption, the higher the operation efficiency of the methods. The specific experimental results are shown in the table below:

The analysis of the experimental data in Table 2 shows that the maximum allocation time of this method is 0.878 s, which is significantly lower than the four prediction methods. The main reason is that the proposed method builds a prediction model through wavelet neural network on the basis of the traditional method, and forecasts the traffic flow through the model, which can effectively improve the operation efficiency. The main reason is that the method in this paper cites the Internet of vehicles technology, which mainly refers to the extension of the Internet of things in the field of intelligent transportation system research, which integrates the technologies of Internet of things, smart gateway and mobile Internet. The application and development of Internet of vehicles technology can greatly improve the current traffic status.

**Table 2** Time consumption of different methods

| *Data sample/(piece)* | *Time consuming/min* | | | |
|---|---|---|---|---|
| | *The proposed method* | *Cheng et al. (2019) method* | *Liu and Rong (2018) method* | *He (2018) method* |
| 600 | 0.752 | 0.985 | 0.899 | 1.101 |
| 1,200 | 0.763 | 1.021 | 0.965 | 1.203 |
| 1,800 | 0.778 | 1.114 | 1.012 | 1.304 |
| 2,400 | 0.785 | 1.251 | 1.184 | 1.410 |
| 3,000 | 0.791 | 1.325 | 1.201 | 1.512 |
| 3,600 | 0.802 | 1.454 | 1.289 | 1.632 |
| 4,200 | 0.813 | 1.526 | 1.305 | 1.741 |
| 4,800 | 0.821 | 1.687 | 1.368 | 1.895 |
| 5,400 | 0.835 | 1.758 | 1.412 | 1.956 |
| 6,000 | 0.847 | 1.856 | 1.478 | 2.012 |
| 6,600 | 0.856 | 1.963 | 1.522 | 2.110 |
| 7,200 | 0.867 | 2.012 | 1.597 | 2.223 |
| 7,800 | 0.878 | 2.212 | 1.684 | 2.356 |

## 4 Conclusions

This paper proposes an intelligent traffic assignment based on DNQ. In this method, DNQ is introduced, and experience pool technology is used to obtain and retain samples in a certain stage to train the network. The complete track is divided into several independent state action pairs, and the sample database is established. The vehicle congestion density is simplified into congestion degree according to a certain range. When the starting point and the end point are known, the traffic congestion density between the initial point and the end point, and within the road section, is divided into several independent state action pairs according to the characteristics and constraints in the process of distribution, the optimal control model is established. Combined with the dynamic characteristics of traffic network, the network traffic is allocated intelligently. The experimental results show that the average relative error of travel time is 12.34%, the traffic flow prediction indexes are the lowest, and the allocation time is the highest of 0.878 s. However, there are many factors that affect traffic flow, such as the delay time of signal lights, the interaction between motor vehicles and non-motor vehicles, which will affect the traffic flow distribution. Therefore, the next research direction should fully combine different factors and conduct integrated analysis to further improve the traffic network flow distribution results.

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