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Intelligent Traffic Control System Based on Cloud Computing and Big Data Mining

Mu Shengdong , Xiong Zhengxian , Tian Yixiang

Abstract—**Aiming at such problems as complex object types, large amount of data collection, high demand for transmission and calculation, and weak real-time scheduling and control ability in the construction of modern intelligent traffic information physical fusion network, Cloud based control system theory, modern intelligent traffic control network as the research object, the physical design of the intelligent transportation information fusion cloud control system scheme. The scheme includes intelligent transportation edge control technology and intelligent transportation network virtualization technology. Based on the intelligent traffic flow data, in the center of the cloud control management server using the deep learning and overrun learning machine intelligence study methods such as the forecast of traffic flow data for training, to predict urban road short-term traffic flow and congestion. Further up in the air by using intelligent optimization scheduling algorithm for real-time traffic flow control strategy, the simulation results show the effectiveness of the proposed method.**

Index Terms—**Cloud control systems, Cyber-physical, Deep learning, Extreme learning machine, Intelligent Transportation**

I. INTRODUCTION

As a new type of intelligent complex system with high integration and interaction among multidimensional heterogeneous physical objects in the network environment[1], the cyber-physical system (CPS) integrates computing, communication and control technologies, provides a feasible solution to and advanced technology for the new generation of intelligent transportation system (ITS) which in turn is the key development direction of the CPS, and solves the problems of intelligent optimal dispatch and real-time target control of ITS. At the same time, the problem of dense operation of big data computing and optimal control scheduling algorithm in large-scale ITS can be solved by the rapid development of cloud computing technology whose basic principle is that by distributing computing tasks on a large number of cloud-distributed computers, ITS management departments can match cloud computing resources to ITS cloud-controlled applications, accessing computers and storage systems as needed[2]. The application of CPS and cloud computing technology makes it possible to acquire, transmit and compute traffic data in real time, and the application of dynamic matrix model and artificial intelligence algorithm can predict traffic data in the next moment in advance.

In this paper, based on the latest new technologies above, an intelligent transportation cyber-physical cloud control system (ITCPCCS) was designed comprehensively. Figure 1 shows the ITS cloud control system and the related CPS with the core for application lying on the unique identification of identity information for drivers, vehicles and transportation infrastructure. First of all, based on data acquisition, sensor, network transmission and other technologies, the dynamic information acquired is sent to the cloud control platform of the integrated data processing of the intelligent transportation network (ITN). Then, through the systematic and intelligent processing and operation of the acquired information by the cloud control platform, the system prediction results and the control scheme are obtained which are sent to the ITS terminal to realize the unified monitoring, management, decision-making and control services for the entire ITN. By means of WIFI, 5G mobile data and other communication modes, the vehicles are connected with the mobile edge control (MEC). At the same time, the traffic terminal can communicate with the cloud directly, so that the ITS cloud control management platform can real-time perceive the traffic conditions such as vehicle queuing, congestion, accidents and signal lights, analyze, optimize, predict, make decisions and control, and make real-time road information available to unmanned vehicles and drivers of manned vehicles, and adjust the appropriate route selection behavior.

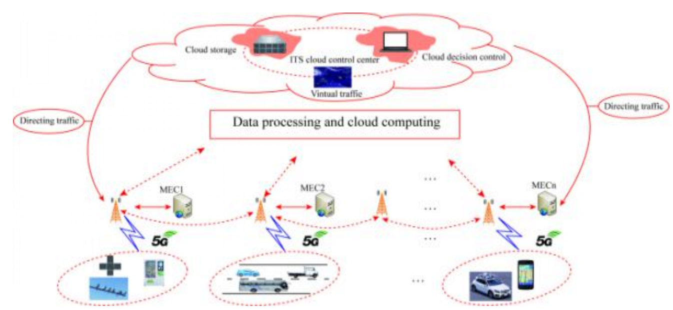

Fig. 1. Schematic diagram of intelligent transportation cloud control systems

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The ITCPCCS includes such core technologies as traffic big data cloud computing, traffic flow intelligent prediction, traffic flow cloud control and scheduling. Among them, the core idea of cloud control is to manage and dispatch a large number of computing resources connected by network, and to form a computing resource pool to provide on-demand services to traffic network equipment and end users[3-4]. As a working mode of traffic information collection, processing and application, traffic information cloud is the whole process of information consisting of cloud computing and intelligent traffic information cloud service[5]. Based on social transportation, computational experiment and parallel execution intelligent machine system, a parallel driving framework based on information physical social system is proposed in document[6] that discusses the application of parallel testing, parallel learning and parallel reinforcement learning in the key modules of intelligent networked vehicle, such as perception, decision-making, planning and control in detail. Mining the characteristics of collected data can improve the accuracy and efficiency of data acquisition, transmission, pre-processing and estimation, and provide high-quality, complete and real-time traffic data for intelligent traffic cloud control system[7]. Since the structure of urban intelligent traffic guidance and control system is complex and the calculation amount of urban traffic problem solving is huge, the application of multi-agent technology can decompose the complex system problem, reduce the computational complexity and make it easier to deal with[8-9]. Because of the demand of actual road network and traffic users, the results of short-term traffic flow forecasting can better meet the real-time needs[10-12].

In recent years, with the rapid development of artificial intelligence algorithms, traffic data processing with non-linear characteristics has entered a new stage of development[13−14]. Artificial intelligence model can acquire the essence of data by adaptive adjusting model parameters in the process of self-learning to achieve better prediction effect[15−17]. The prediction models mainly include Neural Network (NN) model [18], Support Vector Machine (SVM) model [19]. As a new machine learning method, deep learning has attracted much attention from researchers and has been successfully applied in some fields[19-20]. At present, there are some related research results about applying in-depth learning to traffic forecasting. Huang [15] and others applied traffic forecasting methods based on deep belief network model structure and multitask regression to forecast single-output and multitask output traffic. For the big data of intelligent traffic flow, deep learning can realize the distributed representation of data by combining the features at the bottom and abstracting the features at the top, which can better depict the essential characteristics of data[21−23]. Tan Juan [24] and others applied deep learning to traffic congestion prediction. Lv[25] and others proposed a self-coding deep network model prediction method for traffic flow under highway network. Huang [26] et al. proposed an extreme learning machine (ELM) algorithm which can randomly generate the number of hidden layer nodes in the training process. In 2012, on the basis of in-depth study of support vector machine (SVM), Huang et al. introduced the kernel function into the ELM [27], and obtained the least square optimization solution, which made the ELM have more stable generalization performance. Deep learning and ELM have their own advantages in training and prediction of different data sample sets. According to the accurate traffic flow prediction data, the road traffic and congestion can be predicted in advance, and the real-time traffic flow can be adjusted and controlled by the cloud-based optimal control scheduling algorithm.

In the research of the ITCPCCS based on cloud control theory, in this proposed work, the international frontier artificial intelligence machine learning algorithm will be adopted to process the traffic big data of (ITS) accurately in the cloud, to realize the fast prediction of short-term traffic flow in the traffic system, providing the predictive data guarantee for the intelligent control of the traffic network system[28].

The main contributions of this paper are as follows: 1) In order to meet the technical requirements of intelligent development of traffic control network, the design scheme for ITCPCCS is proposed for the first time and the demonstrative application of could control theory in ITS is given. 2) Aiming at the implementation of ITCPCCS, ITS edge control technology, ITS network virtualization technology and cloud-based traffic flow intelligent forecasting technology are proposed on the basis of could computing and artificial intelligence. 3) Deep belief network support vector regression (DBN-SVR) and Back propagation bilateral extreme learning machine (BP-BELM) are proposed to solve the problem of cloud traffic data processing in ITS, thus realizing the accurate forecasting on short-term traffic flow of intelligent traffic cloud control system. 4) In order to solve the problem of large-scale traffic flow control of ITS network, the scheme of traffic flow distribution predicted by ITCPCCS is designed in cloud to carry out the optimal dispatch based on big data of short-term traffic flow forecasting.

II. Design of ITCPCCS

In the actual ITCPCCS, cloud control system can provide a pool of configurable resources, including intelligent computing, software, traffic data access and storage services, and end users can use it without knowing the physical location and specific configuration of service providers. With the continuous improvement of the processing capacity of cloud computing system, the processing burden of ITS network area system can be reduced. Because cloud control system combines the advantages of cloud computing, advanced theory of network control system and other recent development results[29], it can provide the latest technical support for intelligent traffic control. As shown in Figure 2, intelligent decision-making, cloud collaborative control and organic integration of human-computer interaction can be achieved by combining traffic demand scheduling with cloud computing, cloud control closed-loop feedback and edge control design methods, using intelligent traffic data analysis, coordinated control, resource scheduling and other technologies.

In the design process of ITCPCCS, edge control technology, software definition traffic virtualization technology, traffic big data analysis technology and traffic flow optimization

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scheduling technology are proposed. The interaction mechanism of cloud intelligent computing decision-making and edge closed-loop control based on edge computing is established to realize the overall establishment of ITCPCCS.

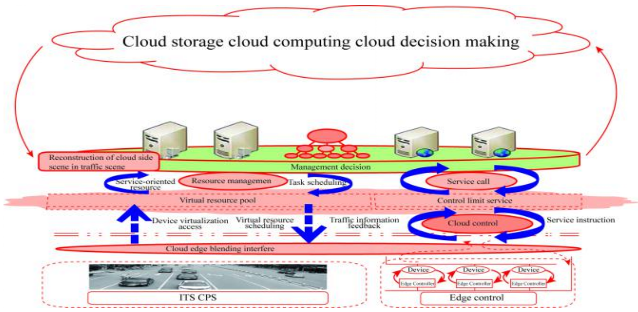

Fig. 2 Cloud coordination control for traffic demand

At present, there are three service models in cloud computing system: Infrastructure as a service (IaaS), Platform as a service (PaaS) and Software as a service (SaaS). The ITCPCCS stores large traffic data in the cloud, and realizes the optimization, decision-making, scheduling, planning, prediction and control of the system in the cloud by utilizing cloud computing capability. From the perspective of control, it is difficult to model the CPS of ITS because of its complexity. Network delay and network bandwidth saturation between cloud and terminal will make the system unable to process massive data in real time, resulting in the loss of system performance. To solve these two problems, the cloud collaborative control combining cloud control with edge control can be used to improve the real-time and availability of the control system and achieve the purpose of control as a service (CaaS).

CaaS is aimed at system administrators, developers and ordinary users of the system. Users can obtain the required virtual machines or storage resources from suppliers to load related control computing software. At the same time, CaaS provides users with control development platform including basic operating system, professional control software, network and storage configurations, which has high system integration rate and economy. In addition, any control application on a remote terminal can run through the network. As long as users connect to the network, they can adjust and modify the controller running on the cloud through the browser, so as to avoid high hardware investment. The control terminal uploads the data collected by the control system to the cloud, and the cloud controller calculates the required control system parameters and adjustment instructions. For control terminals with uncertain system models, CaaS can provide data-driven model optimization learning, model predictive control, fault diagnosis and system maintenance, and optimal scheduling decision-making services for control terminals by means of intelligent learning algorithm, relying on powerful data storage and computing capabilities. For the control terminal determined by the system model, CaaS can optimize the control algorithm resource pool and adjust the control parameters automatically in real time according to the control algorithm and the system data uploaded in real time, which saves professional debugging and maintenance personnel for the actual control system. CaaS can ensure the integrity, reliability and manageability of control system data, better dispatch and management of control system, and ensure its efficient operation. CaaS platform integrates all kinds of control services to users in the form of API. Using multi-user mechanism, it can support the huge scale of control terminals and provide customized services to meet the special needs of users.

A. *ITS Edge Control Technology*

As a new computing mode, edge computing is an important computing method to realize information technology. Compared with cloud computing, it can realize the real-time processing of big data of industrial edge equipment, reducing the network bandwidth problem and real-time demand brought by data transmission to cloud computing center. Moreover, edge computing can take into account the privacy problem of edge data and power loss of edge equipment when data is uploaded. Edge calculated by integrating industrial network computing, storage, network and so on to form on the edge of the unity of the platform to provide services for industrial users, make the data source in the side can get effective and timely treatment, or will edge data processing will be spread to cloud computing data center after processing, reduce the pressure of the point cloud computing center edge calculation is mainly carried out on the edge equipment to produce huge amounts of data storage and processing, the edge of the calculation of the downstream data represents the cloud services, uplink data table represents the network edge device both content and service request from the cloud computing service center, also for data storage, processing, cache and privacy protection tasks.

The edge control technology is proposed in the integrated framework of ITCPCCS. Making full use of the advantages of terminal edge computing, edge control can control the specific system in local or small area without data transmission to the cloud for cloud decision-making and improve the real-time performance of terminal control. As shown in Figure 3, edge control and intelligent cloud are integrated in the intelligent traffic cloud control system, and the edge control includes many aspects. In the face of different system objects, the control forms are different. In modern ITN, the actual control objects mainly include: traffic vehicle user terminal, unmanned vehicle (such as Google Waymo unmanned vehicle, BY ZEUS unmanned vehicle), traffic lights, road camera terminal, road sensor terminal and other equipment.

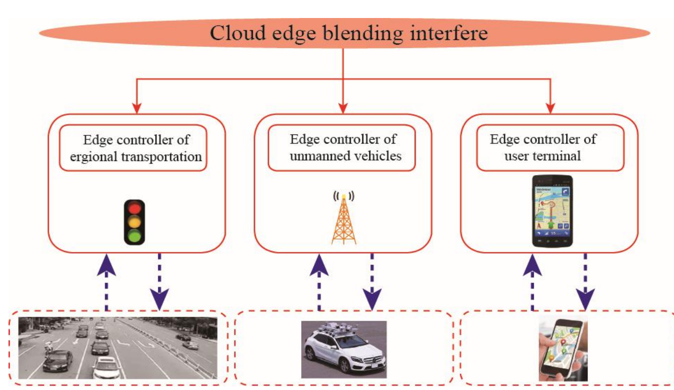

Fig. 3 Intelligent transportation bottom edge control

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The core of edge control system for ITS bottom equipment terminal is based on the running data of traffic equipment and real-time perception of traffic environment. The specific control strategy of traffic equipment is designed by using edge calculation method to realize local edge control of bottom equipment, such as traffic light control, unmanned vehicle control, traffic camera control and local user navigation equipment control. Edge control provides local information for cloud control in ITS cloud control system, which is the key to real-time operation of ITS terminal equipment. Cloud control system provides global control strategy for multiple edge control devices and coordinates the whole ITN. Only when the two systems cooperate with each other can the intelligent transportation cloud control system run well.

B. ITN Virtualization Technology

Based on the operation data of real industrial equipment, the virtual industrial system corresponding to the real industrial system is established through learning and optimization. With the aid of software and hardware interface, the two systems in operation in the process of information interaction, coordination development, based on the accumulation of knowledge in the learning process, and gradually improve the virtual system combined with the actual operation data, to evaluate industrial entity state, and evolutionary computation experiment design scenario forecast future trend, help to realize the management of the complex real industrial system control, and on the real industrial system after the implementation of controls virtual industrial system of real-time information feedback to do follow-up evaluation, this two similar interaction feedback system continuously over time.

ITN virtualization technology can virtualize physical transportation network into a virtual transportation network composed of multiple virtual transportation sub-networks, with core idea of using virtualization software to control and manage the traffic network, and simplifying the calculation and operation of the traffic cloud through the automatic deployment function. As shown in Figure 4, the overall coupling architecture of traffic cloud control network can be divided into three layers: cloud control platform, virtualization platform and physical application platform.

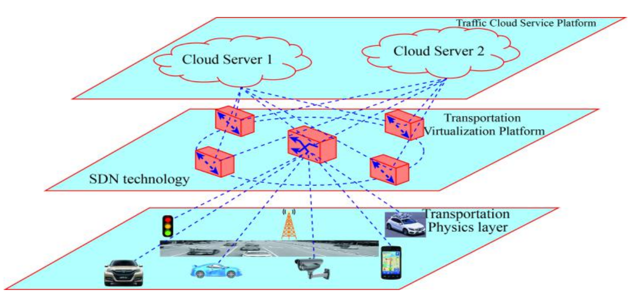

Fig. 4 Intelligent transportation cloud control Network virtualization architecture

Data computing and decision control functions in intelligent transportation architecture are deployed on cloud servers. By virtualization platform of traffic network, the bottom traffic application facilities are abstracted into multiple logical entities in cloud based on actual physical traffic law. In this way, cloud services can be decoupled from physical transport network, which facilitates the flexible deployment of cloud resources and rapid service supply. With the development of CPS, software defined technology begins to extend to the physical world. In the ITS cloud control system, the software defined transportation (SDT) technology is proposed which uses the intelligent software to define and map the intelligent transportation network topology, and virtualizes all kinds of information equipment and physical infrastructure in the ITS, so as to achieve the goal of open sharing and interconnection, and realize the fine management of the intelligent transportation cloud. The essence of SDT technology is the virtualization of traffic hardware resources, the programmable realization of management objects and functions. Traditional transport physical facilities are abstracted as virtual resources, and cloud deployment software is used to calculate and schedule virtual traffic. This technology can realize the reasonable separation of traffic physical layer and cloud computing layer. Using program software, the integrity and accuracy of virtual mapping can be guaranteed, and the diversity of traffic tasks can be satisfied.

III. Cloud-based Traffic Flow Intelligent Forecasting Technology

Traffic flow forecasting is the key technology of intelligent cloud control system, and cloud-based traffic flow forecasting and dispatch system is the center of ITCOCCS. Could control service platform can comprehensively control and deal with the traffic congestion, road condition and real-time speed of vehicles through the forecasting and analysis on the data on ITS cloud control data center.in this proposed work, for large-scale traffic flow data of large-scale road network, the cloud-based forecasting method for short-term traffic flow in road network based on DBN-SVR is studied and compared with the cloud-based forecasting method based on BP-BELM.

A. Short-term traffic flow forecasting algorithm based on DBN-SVR

In this proposed work, for the large-scale traffic flow data, the forecasting model based on deep learning and support vector regression is put forward. As shown in Figure 5, DBN model is a network model structure containing three hidden layers, where, the bottom node represents training data and the top node represents predictive output data.

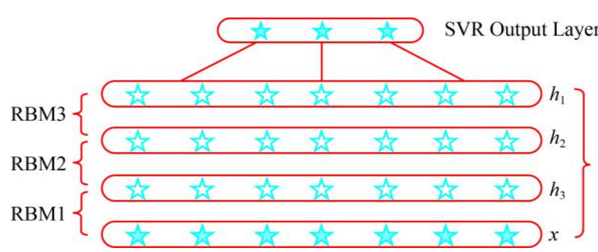

Fig. 5 Network structure of DBN-SVR model

Due to the temporal and spatial correlations between traffic flows in each section, let the input data set of forecasting model

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be X_t, then there are:

$$X_t = \{x_1, x_2, \cdots, x_p\} \tag{1}$$

$$x_i = \{x_{i,t}, x_{i,t-\Delta t}, \cdots, x_{i,t-M\Delta t}\} \tag{2}$$

Where,
i= 1,2..... p means the number of columns of data;
M=Number of data acquisition intervals;
$x_{i,t}$=Traffic flow of the i-th section at t time;
Δt =Time interval of data.

The traffic flow of any section at the next moment is forecasted by using the traffic flow data of several adjacent sections at current and preceding M moments. Suppose the output vector of the input data set is H after learning the features of DBN model, then there is:

$$H = \Phi(X_d) \tag{3}$$

Where,
Φ =Deep Learning of DBN Network Model;
X_d =Traffic data set processed according to the formula of $X_{i,t}^d = x_{i,t} - x_{i,t-d}$.

SVR as the nonlinear feed forward network with hidden elements can realize the forecasting and processing of time series. All the non-linear regression functions are as follows:

$$f(x) = \sum_{i=1}^{l} a_i^* y_i K(x_i, x) + b^*$$

Where, $K(x_i, x) = (\Phi(x_i), \Phi(x))$ =Kernel function;
a_i^* =Positive component value;
b^* =Threshold;
y_i =Output value of training set.

Thus the obtained traffic flow forecasting value of any section j at t+ Δt time is

$$y_d(j, t+\Delta t) = f(H) \tag{4}$$

Where,f=SVR forecasting model;
$y_d(j, t+\Delta t)$ =Traffic flow of section j at t+Δt time,
and j= 1, 2,... , p.

The specific processes of traffic flow forecasting algorithm are as follows:

a. According to the characteristics of traffic flow data,the input data set X_t is constructed by formula (1)and (2)

b. The traffic data set is preprocessed according to the formula of $x_{i,t}^d = x_{i,t} - x_{i,t-d}$ to obtain the residual quantity Xd;

c. X_d is used as the input of DBN network model for feature learning, and the traffic flow characteristic H is obtained by formula (3);

d. With H as input, SVR forecasting model is used to forecast traffic flow data according to the formula (4);

e. The restoration of original traffic flow data is calculated by the formula $\hat{x}_{i,t+1} = \hat{x}_{i,t+1}^d + \hat{x}_{i,t-d+1}$ to obtain the traffic flow forecasting value

B. Short-term Traffic Flow Forecasting Algorithm Based on BP-BELM

The BP-BELM algorithm proposed in this paper is used to accurately forecast the intelligent traffic flow data in real time, which uses the back propagation of network residual to calculate the optimal parameters of partial hidden layer nodes to enhance the stability of ELM algorithm.

As shown in Figure 6, the BP-BELM algorithm is used to conduct parity partition on the number of hidden layer Nodes, whose parameters can be calculated and obtained by the back propagation of network residual

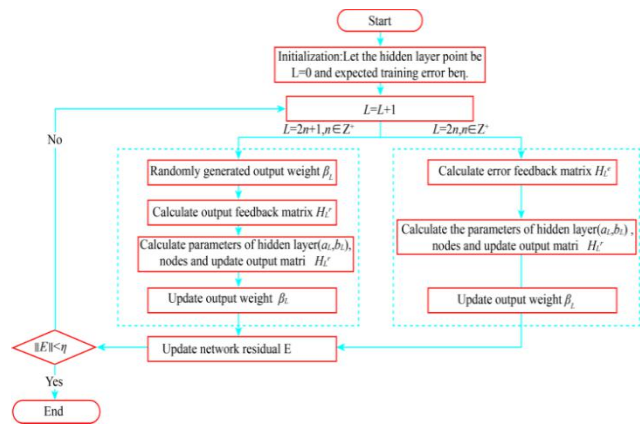

Fig. 6 Algorithm flow chart of back propagation bilateral extreme learning machine

The given training sample of NN is $\varphi = (x_i, y_i)_{i=1}^N \in R^m \times R^n$, the activation function h of hidden layer nodes is $R \to R$, the maximum number of hidden layer nodes is L-max, the expected accuracy is ε , network training error with L-1 hidden layer nodes is e_{L-1} , xi is the input and yi is the output, thus the training steps of the BP-BELM algorithm are as follows:

The first step is the initialization phase of NN: Let L=0 and the initial network error be E=Y, where $Y = [y_1, y_2, \cdots y_N]^T$.

The second step is the training phase of NN: When L $\prec$ L-max and $\|E\| \succ \varepsilon$, add a hidden layer node L, where L=L+1;

if L=2n+1, then n$\in$Z+.

A) Randomly generate the output weight β_L of the newly added hidden layer node

B) Calculate output feedback matrix: $H_L^r = e_{L-1}(\beta_L)^{-1}$;

C) Calculate the parameters of hidden nodes:

$$a_L = x^T(I + xx^T)^{-1} \cdot h^{-1}(u(H_L^r))$$

$$b_L = sum(aL \cdot x - h - 1(u(H_L^r)))/N$$

D) Update output feedback matrix: $\hat{H}_L^r = u^{-1}(h(a_L \cdot x + b_L))$

E) Calculate the output weight of the updated newly added hidden layer node according to least square method:

$$\hat{\beta}_L = E \cdot (\hat{H}_L^r)^T / (\hat{H}_L^r) \cdot (\hat{H}_L^r)^T$$

F) Calculate the error of NN after adding the L-th hidden layer node: $E = E - \hat{\beta}_L \cdot \hat{H}_L^r$

The end

If L=2n and n$\in Z+$

Calculate output feedback matrix: $H_L^e = e_{L-1}(\hat{\beta}_{L-1})^{-1}$

Calculate the parameters of hidden layer nodes:

$a_L = x^T(I + xx^T)^{-1} \cdot h^{-1}(u(H_L^e))$

$b_L = sum(a_L \cdot x - h^{-1}(u(H_L^e)))/N$

Update output feedback matrix: $\hat{H}_L^r = u^{-1}(h(a_L \cdot x + b_L))$

Calculate the output weight of the updated newly added hidden layer node according to least square method:

$\hat{\beta}_L = E \cdot (\hat{H}_L^r)^T / (\hat{H}_L^r) \cdot (\hat{H}_L^r)^T$

Calculate the error of NN after adding the L-th hidden layer node: $E = E - \hat{\beta}_L \cdot \hat{H}_L^r$

The end

IV. ITCOCCS DISPATCH

Based on the idea of predictive control in the theory of cloud control system, aiming at the weight matrix of transportation network, according to the short-term forecasting data of cloud-based artificial intelligence, the real-time control of cloud-based rolling forecasting on traffic flow can be realized by using the obtained shortest route to guide and plan the travel route for users and combing the traffic flow distribution method to design the forecasting and dispatch scheme of intelligent cloud control system.

As shown in Figure 7, the shortest route is the poly line route from O to D. Due to the real variable characteristics of road traffic, the traffic flow distribution control program is conducted with cyclic update and computation at the interval of 5mins, so as to ensure the real-time of shortest route and traffic flow distribution. As an important indicator in traffic flow distribution, traffic impedance directly affects the route selection of road travelers and the flow distribution in transportation network. The road impedance function which can be used to accurately describe the traffic impedance, refers to the relationships between road travel time and road flow, intersection delay and intersection flow. In the specific process of flow distribution, traffic impedance is composed of road travel time and intersection delay. Assuming that a vehicle passes through a road, the required travel time, that is, the road impedance is t, thus the road impedance function $t_a$is:

$$2t_0(1+\sqrt{1-\frac{z_a}{c_a}})^{-1} + T_a, (when Z_a \le C_a) \tag{5}$$

$$2t_0(1-\sqrt{1-\frac{z_a}{c_a}})^{-1} + T_a, (when Z_a \succ C_a) \tag{6}$$

Where,

t_0=Zero flow impedance, namely, time required for a vehicle to travel when the traffic flow is zero;

z_a=Distribution of traffic volume in road a;

c_a=Achievable maximum distribution of traffic volume in road a, namely, traffic capacity of road;

T_a=Value of time delay in intersection;

Z_a=Required traffic volume in road a.

When Za<c_a, this road is in unblocked state, with z_a= Z_a. When c_a<Z_a2c_a, this road is in congestion state, with the distribution of traffic volume z_a<Za, resulting in overload operation and the decline in vehicle speed. When the actual traffic flow Z_a>2c_a, the actual distribution of traffic volume in road is z_a= 0, with the impedance function of t_a= .

When the road is congested, the users are induced to follow the shortest route which is optimized in real time by intelligent traffic cloud control system, and here the driver is assumed to choose the route with the least traffic impedance according to the distribution of traffic volume in road network. The OD traffic volume of a specific congested road section is reasonably distributed to the shortest path connecting this OD dot pair, and the traffic flow distribution value x_a is obtained for each section.

In this paper, the main idea of capacity-limited incremental distribution method used for traffic flow distribution is to divide OD traffic volume into several parts, distribute one OD traffic volume to the prescribed shortest path in each cycle, update the impedance time of each section, and recalculate the shortest path between each OD point pair, and then distribute the next OD traffic volume.

The steps of capacity-limited incremental distribution algorithm are as follows:

1: Initialization, that is, the matrix of OD traffic volume is partitioned appropriately for N times, and for any road section a, make k = 1 and $Z_a^o = 0$;

2: Calculate the impedance of each road section: $t_a^k = t_a(z_a^{k-1})$

3: The all-or-nothing distribution method is use to distribute the k – th OD traffic flow segmentation to the shortest route between OD dot pair which is obtained by using Floyd algorithm, and then the traffic volume distributed by the above step in each section is accumulated and recorded as w_a^k ;

4: Calculate the traffic flow in each section: $z_a^k = z_a^{k-1} + w_a^k$;

5:Judgment, that is, if k= N, then the calculation ends; on the contrary, make k = k + 1 and return to the second step

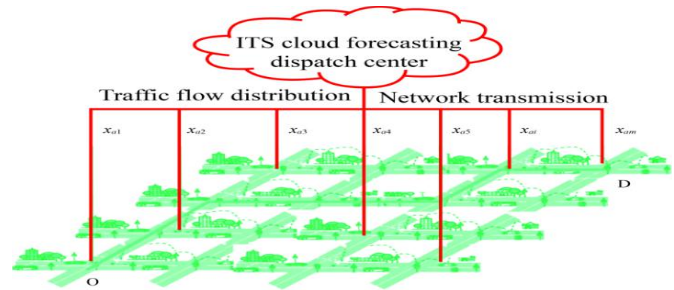

Fig. 7 Schematic diagram of prediction scheduling for intelligent transportation cloud control systems

V. SIMULATION EXPERIMENT

In the simulation experiment on key technology of ITCPCCS, the computer with 4-core CPU, highest frequency of 2.9 GHz, and 8G memory is selected as local computer. The mature commercial cloud server is rent as the cloud server: Beijing Three District, computational C2, 4-core CPU and 8G memory

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server, whose configuration is consistent with local computer for simulation experiment, with bandwidth upper limit of 100Mpbs, and the 64-bit Chinese edition of Windows server 2012R2 standard edition as the system. At the same time, multiple servers can be selected to provide multitask and multi-type operation. The more cloud servers selected, the higher the cost. The top configuration of the purchased operation server computer can choose the computing server with computational C2, 32-core CPU and 120G memory. Computational C2 is the best choice for high computing performance and high concurrent read-write applications, and when the requirement of low delay and transmission volume for information transmission is high, the high I/O type I2 server as the best choice of high-disk I/O can be selected, which can provide tens of thousands of low-latency random I/O operations per second (IOPS), and has a packet forwarding capacity of up to 30W, thus it can be used for low-latency I/O intensive applications.

In short-term traffic flow forecasting simulation experiment, the data of performance test system in Transportation Department of California in America (that is, Caltrans PeMS database) is used to conduct experimental verification. Due to the strong time-dependent regularity of traffic flow data and the difference between non-weekend and weekend data, ten different road traffic flow detection points including Buena, Bur-bank, Commerce, Downey Glendale, La Mirada, Los Angeles, Norwalk, Santa Clarita and Santa Fe Springs are selected to fully and effectively verify the method proposed in this paper. Four sets of traffic flow data are collected at each detection point by using the data on every Wednesday from June 21, 2017 to July 12, 2017. The number of data samples per detection point is 288 per day, the number of total data per detection point is 1,152, and the total number of samples in the entire data set is 11,520. As the input and output data set of intelligent forecasting model, the data set with the sampling interval of 5 minutes is formed by processing the raw traffic flow data acquired on a specific date to verify the effectiveness of forecasting algorithm. The first three sets of traffic flow data on June 21, June 28 and July 5 are used to train the intelligent learning model. Finally, the trained intelligent learning model is used to forecast and validate the fourth set of 2,880 data on July 12.

A. *Short-term Traffic Flow Forecasting Simulation Based on DBN-SVR*

In cloud server and local computer Matlaab2014a environments, the parameters of DBN-SVR network model are set as follows: RBM network in DBN model has 3 layers, the number of nodes in each layer is 4, 4 and 2 respectively, and the training iterations of corresponding weights are all taken as 10 times. The kernel function of the top-level forecasting model SVR is RBF radial basis function, with its parameter g of 16 and the penalty factor c of 11.3137. Then the results of traffic flow test data set are conducted with comparative analysis. The simulation results of cloud server are shown in Figure 8 and Figure 9. The average running time is 8.5262s in local computer and 5.2758s in cloud server.

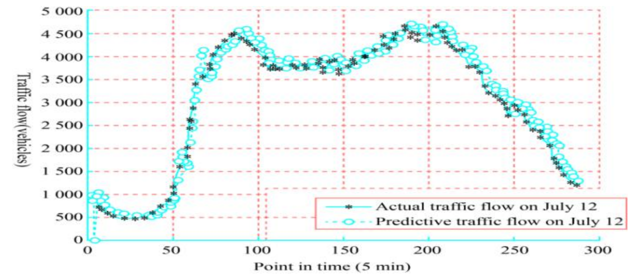

Fig. 8 Comparison of DBN-SVR prediction traffic flow and actual traffic flow

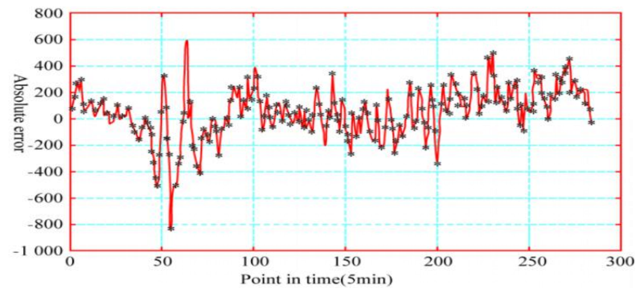

Fig. 9 Predicted error with DBN-SVR

B. *Short-term Traffic Flow Forecasting Simulation Based on BP-BELM*

The traffic data set is conducted with training and forecasting in this section to verify the performance of BP-BELM algorithm. All the test results use sigmoid function to conduct [0,1] normalization on the input and output data of traffic flow extreme learning training data set, and the simulation results of cloud server are shown in Figure 10 and Figure 11.

The average running time of BP-BELM short-term traffic flow forecasting simulation experiment is 0.6268 s in local computer and 0.3467 s in cloud server, thus the running time of simulation experiment in cloud server obviously is obviously reduced, while the data computing ability is obviously stronger than that of local computer.

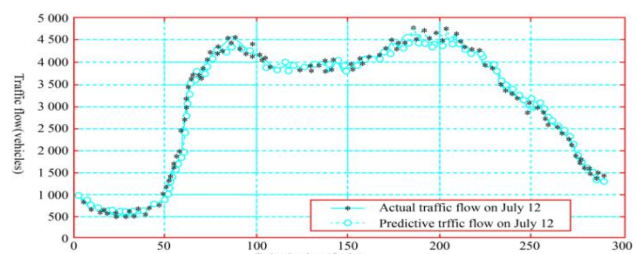

Fig. 10 Comparison of BP-BELM prediction traffic flow and actual traffic flow

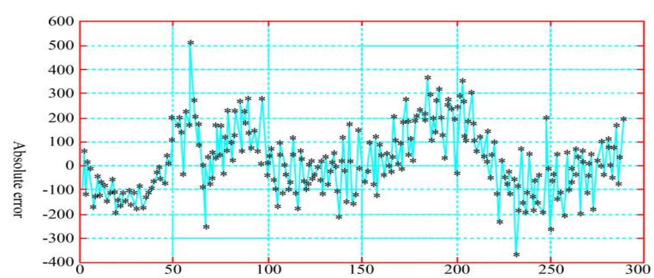

Fig. 11 Predicted error with BP-BELM

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C. Forecasting Error Analysis And Comparative Analysis

Based on the short-term traffic flow forecasting results of DBN-SVR model and BP-BELM model, the mean square error and the average absolute percentage error of the two models are calculated respectively,

$$MSE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{7}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| * 100\% \tag{8}$$

Where,

y_i =The actual traffic flow value at a certain time;

$\hat{y}_i$ =The predicted value of corresponding time.

The performances of the two forecasting models are analyzed and compared, which are then compared with the latest method of long short-term memory(LSTM) for traffic flow forecasting . The results are as follows:

TABLE I
PERFORMANCE COMPARISON OF THREE PREDICTION MODELS

Model	MSE	MAPE
DBN-SVR	0.05999	1.68051
BP-BELM	0.34084	10.7250
LSTM	0.37157	105.6117

It can be seen from the comparison between Figure 9 and Figure 11 that DBN-SVR model has high accuracy in intelligent traffic flow forecasting and small fluctuation range in the later period of variance, while the forecasting accuracy of BP-BELM model is low in the early stage, and the difference between the predicted value in the early stage and the actual value, with a large fluctuation range of forecasting error. For large-scale traffic flow data, DBN-SVR model has better forecasting effect than BP-BELM model.

The traffic data set is conducted with training and forecasting in this section to verify the performance of BP-BELM algorithm. All the test results use sigmoid function to conduct $^{[0,1]}$ normalization on the input and output data of traffic flow extreme learning training data set, and the simulation results of cloud server are shown in Figure 10 and Figure 11.

The average running time of BP-BELM short-term traffic flow forecasting simulation experiment is 0.6268 s locally and 0.3467 s in cloud server, thus the running time of simulation experiment in cloud server obviously is obviously reduced, while the data computing ability is obviously stronger than that of local computer.

The comparative LSTM forecasting method selected in this paper has poor effect on the data set in this experiment, and the average percentage variance is too large. Due to the high sampling frequency of short-term traffic data and the large number of data in the data set for experiment, LSTM is required to have 846 input nodes and 288 output nodes, with the difficulty in parameter adjustment, and the cloud computing time is 512.1125 s. In addition, in the research process, we also get the relevant results when accurately predicting and researching the small sample traffic data of single detection point in ITS: DBN-SVR model has poor forecasting effect and large forecasting error for small sample traffic flow data of single node. However, BP-BELM model has very high forecasting accuracy and little prediction error for small sample traffic flow data of single node. Therefore, considering the research on traffic flow forecasting in intelligent traffic cloud control system, DBN-SVR model can be used to accurately predict the large sample data of multiple detection nodes, and BP-BELM model can be used to accurately predict the small sample data of a single detection node, thus the two intelligent machine learning algorithms can be used in parallel and cooperate with each other to ensure the intelligent traffic cloud control system running well.

D. ITS Forecasting and Dispatch Simulation

In the traffic flow forecasting and dispatch simulation experiment of ITS cloud control system, the prediction of traffic flow distribution is simulated and verified on a rented cloud server. The analog data on urban road traffic is used here, and 83 road nodes with their locations are selected for traffic network. The capacity of urban highway is set to 35,000 vehicles per hour, the capacity of urban expressway to 25,000 vehicles per hour, the capacity of urban four-lane to 10,000 vehicles per hour, the capacity of urban two-lane to 6,500 vehicles per hour, and the capacity of urban suburban third-classed road to 1,550 vehicles per hour.

In Figure 12, the narrowest section represents less traffic flow and good traffic condition; width-increased section represents the increased traffic flow and general traffic condition; wider section represents large traffic flow and congestion; the section of reaching the upper limit of width represents the saturated traffic flow and serious congestion; the widest section represents the seriously overloaded and impassable traffic flow.

In addition, the thickness of the line connecting the sections in traffic network represents the volume of traffic flow. As shown in the figures, the section from node 13 to node 31 has serious congestion, and the section from node 52 to node 57 has the overloaded traffic flow and is impassable. The next is to consider the forecasted traffic flow of congested sections, thus with a newly established OD traffic flow distribution matrix, the traffic flow is distributed by using capacity-limited incremental distribution method. First, OD traffic is conducted with segmentation for N = 62 times, then the shortest path between any two points is obtained by using Floyd algorithm, and finally, the traffic flow is distributed point by point according to the all-or-nothing method.

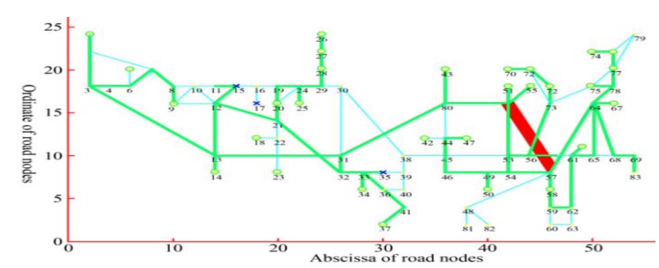

Fig. 12 Simulation result of traffic jam

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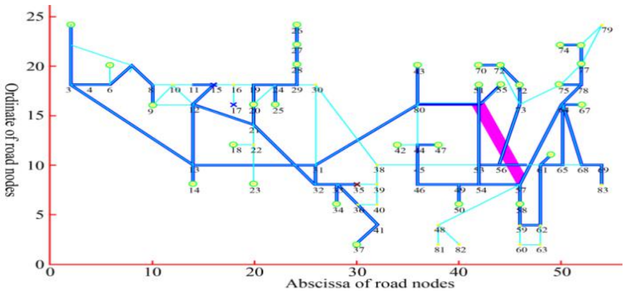

Fig. 13 Simulation result after incrementa traffic flow assignment

It can be seen from Figure12 and Figure13 that they are very close to each other, indicating that the effects of predictive simulation and scheduling simulation can cooperate with each other. This indicates that the cloud computing and big data mining methods proposed in this paper can realize traffic flow prediction and scheduling.

VI. CONCLUSIONS

In this paper, the structure and core technology of ITCPCCS are designed and analyzed, the application mode of cloud control technology in ITS is explored, and the application demonstration of cloud control technology in ITS is promoted. The forecasting algorithm based on deep learning and ELM is used to accurately predict the traffic flow in overall transportation network with a large number of traffic detection nodes and prejudge the traffic congestion, thus traffic flow distribution algorithm can be used to conduct intelligent optimal dispatch on traffic flow, so as to improve the traffic congestion. In addition, the operation of intelligent learning algorithm and traffic flow dispatching strategy in ITS cloud with resource optimization and integration can avoid the limitation of computing and storage of traditional ITS equipment, prevent equipment failure, and save the cost of construction and maintenance of ITS. In fact, the ITCPCCS proposed in this paper is a preliminary application of cloud control technology which is still in the development stage, thus how to classify and process complex traffic data efficiently in the cloud to get the best ITS.

REFERENCES

[1] Wang Z J, Xie L L. Review on information physics fusion system. Acta Automatica Sinica, 2011, 37(10): 1157−1166
[2] Xia Y. Cloud control systems and its challenges. IEEE/CAA Journal of Automatica Sinica, 2016, 42(1): 1−12
[3] Xia Y. From networked control systems to cloud control systems. In: Proceedings of the 31st Chinese Control Conference (CCC). HeFei, China, 2012. 5878-5883
[4] Ma Q L, Si H L, Guo J W. Cloud control strategy for urban traffic area linkage under the environment of Internet of things. Application Research of Computers, 2013, 30(9): 2711−2714
[5] Wang F Y, Zheng N N, Cao D, Martinez C M, Li L, Liu T. Parallel driving in CPSS: a unified approach for transport automation and vehicle intelligence. IEEE/CAA Journal of Automatica Sinica, 2017, 4(4): 577−587
[6] Chan K Y, Dillon T S, Singh J, Chang E. Neural-network- based models for short-term traffic flow forecasting using a hybrid exponential smoothing and Levenberg Marquardt algorithm. IEEE Transactions on Intelligent Transportation Systems, 2012, 13(2): 644−654
[7] Meng D, Jia Y. Finite-time consensus for multiagent Systems, IEEE, 2017tems via terminal feedback iterative learning. IET Control Theory & Applications, 2011, 5(8): 2098−2110
[8] Nascimento J C, Silva J G, Marques J S, Lemos J M. Manifold learning for object tracking with multiple nonlinear models. IEEE Transactions on Image Processing, 2014, 23(4): 1593−1604
[9] Xue J, Shi Z. Short-time traffic flow prediction based on chaos time series theory. Journal of Transportation Systems Engineering and Information Technology, 2014, 8(5): 68−72
[10] Polson N G, Sokolov V O, Deep learning for short-term traffic flow prediction. Transportation Research Part C Emerging Technologies, 2017, 79, 1−17
[11] Kumar S V, Traffic flow prediction using filtering technique. Procedia Engineering, 2017, 187, 582−587
[12] Luo X L, Jiao Q Q, Niu L Y, Sun Z W. Short term traffic flow prediction based on deep learning. Application Research of Computers, 2017, 34(1): 91−93
[13] Xu Y, Kong Q, Klette R, Liu Y, Accurate and interpretable bayesian MARS for traffic flow prediction. IEEE Transactions on Intelligent Transportation Systems, 2014, 15(6): 2457−2469
[14] Oh S, Kim Y, Hong J, Urban traffic flow prediction system using a multifactor pattern recognition model. IEEE Transactions on Intelligent Transportation Systems, 2015, 16(5): 2744−2755
[15] Moretti F, Pizzuti S, Panzieri S, Annunziato M, Urban traffic flow forecasting through statistical and neural network bagging ensemble hybrid modeling. Neuro computing, 2015, 167(C): 3−7
[16] Jeong Y S, Byon Y J, Castro-Neto M M, Easa S M, Supervised weighting-online learning algorithm for short-term traffic flow prediction. IEEE Transactions on Intelligent Transportation Systems, 2013, 14(4): 1700−1707
[17] Chan K Y, Dillion T S. On-road sensor configuration design for traffic flow prediction using fuzzy neural networks and taguchi method. IEEE Transactions on Instrumentation and Measurement, 2013, 62(1): 50−59
[18] Man R J, Liang X C. Traffic flow forecasting based on multiscale wavelet support vector machine. Computer Simulation, 2013, 30(11): 156−159
[19] Huang W H, Song G J, Hong H K, Xie K. Deep architecture for traffic flow prediction: deep belief networks with multitask learning. IEEE Transactions on Intelligent Transportation Systems, 2014, 15(5): 2191−2201
[20] Koesdwiady A, Soua R, Karray F. Improving traffic flow prediction with weather information in connected cars: a deep learning approach. IEEE Transactions on Vehicular Technology, 2016, 65(12): 9508−9517
[21] Hinton G, Osindero S, Teh Y. A fast learning algorithm for deep belief nets. Neuro computing, 2006, 18(7): 1527−1554
[22] Kuremoto T, Kimura S, Kobayashi K, Obayashi M. Time series forecasting using a deep belief network with restricted Boltzmann machines. Neuro computing, 2014, 137(15): 47−56
[23] Tan J, Wang S X. Traffic congestion prediction model based on deep learning. Application Research of Computers, 2015, 32(10): 2951−2954
[24] Lv Y, Duan Y, Wang W, Li Z, Wang F, Traffic flow prediction with big data: a deep learning approach. IEEE Trans- actions on Intelligent Transportation Systems, 2015, 16(2): 865−873
[25] Huang G B, Chen L, Siew C K. Universal approximation using incremental constructive feed forward networks with random hidden nodes. IEEE Transactions on Neural Net- works, 2006, 17(4): 879−892
[26] Huang G B, Zhou H, Ding X, Zhang R. Extreme learning machine for regression and multi-class classification. IEEE Transactions on Systems Man and Cybernetics, 2012, 42(2): 513−529
[27] Huang W H, Song G J, Hong H K, Xie K. Deep architecture for traffic flow prediction: deep belief networks with multitask learning. IEEE Transactions on Intelligent Transportation Systems, 2014, 15(5): 2191−2201
[28] Xia Y, Qin Y, Zhai D H, Chai S. Further results on cloud control systems. Science China Information Sciences, 2016, 59(7): 073201:1 073201:5
[29] Xia Y, Mahmoud M S, Li H F, Zhang J H. Interaction between control and computation theory: cloud control. Journal of Command and Control, 2017, 3(2): 99−118

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