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

Mu Shengdong, Xiong Zhengxian, and Tian Yixiang

***Abstract*—This article aims at discussing problems such 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, and 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 intelligent traffic flow data, in the center of the cloud control management server using 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 (ELM), 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.

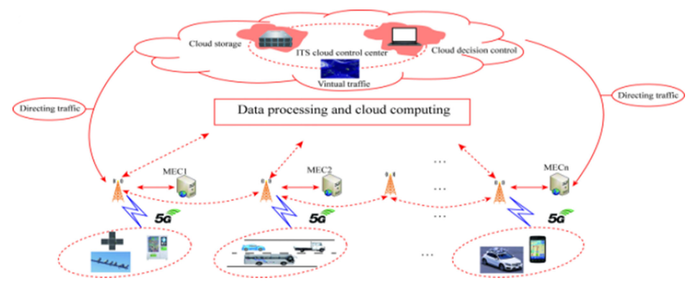

Fig. 1. Schematic diagram of intelligent transportation cloud control systems.

In this article, based on the latest new technologies mentioned above, an intelligent transportation cyber-physical cloud control system (ITCPCCS) was designed comprehensively. Fig. 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. 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

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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.

The ITCPCCS includes core technologies, such 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 [6], which 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, preprocessing, 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 multiagent technology can decompose the complex system problem, reduce the computational complexity, and make it easier to deal with [8] and [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 nonlinear characteristics has entered a new stage of development [13], [14]. An 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] and support vector machine (SVM) model [19]. As a new machine learning method, deep learning has attracted considerable 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 the 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 *et al.* [26] proposed an extreme learning machine (ELM) algorithm that can randomly generate the number of hidden layer nodes in the training process. In 2012, on the basis of in-depth study of SVM, Huang *et al*. introduced the kernel function into the ELM [27] and obtained the least-squares 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 the cloud control theory, in this article, 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 article 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 ELM (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, a 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 the 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 Fig. 2, intelligent decision making, cloud collaborative control, and organic integration of human–computer interaction can be achieved by combining traffic demand scheduling

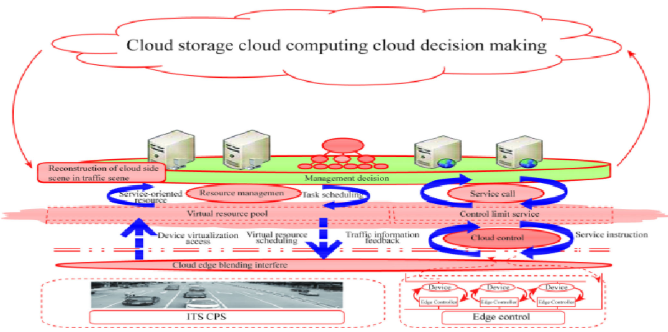

Fig. 2. Cloud coordination control for traffic demand.

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 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.

At present, there are three service models in cloud computing system: infrastructure as a service, platform as a service, and software as a service. 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 multiuser 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 are uploaded. Edge computing done by integrating industrial network computing, storage, network, etc., is based on the edge of the entire platform to provide services to industrial users, to make the data source more effective to enable timely response, to spread edge data processing to the cloud computing data center, and to reduce the pressure on the point cloud computing center edge calculation, which is mainly carried out on the edge equipment to produce huge amounts of data for storage and processing. The edge of the calculation of the downstream data is used for cloud services, and the uplink data table represents the network edge device's content and service requests from the cloud computing service center regarding 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 Fig. 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.

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

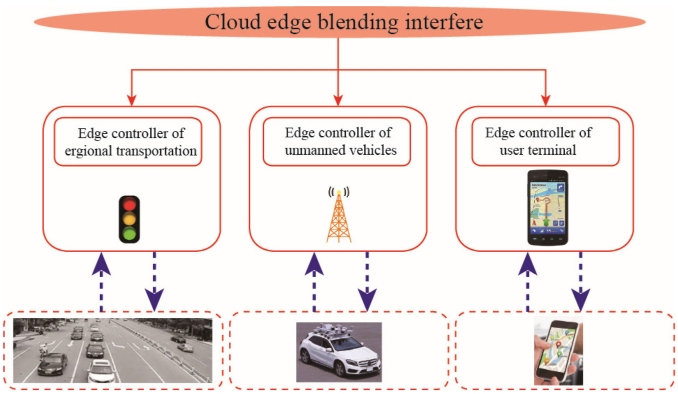

Fig. 3. Intelligent transportation bottom edge control.

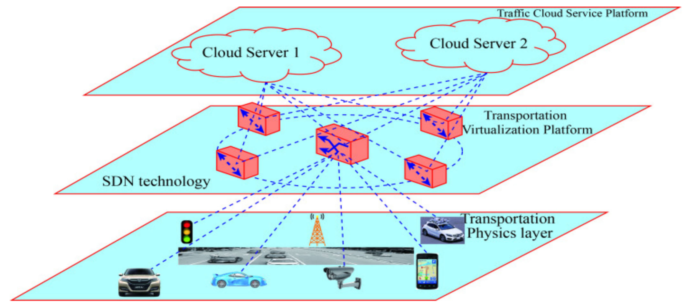

Fig. 4. Intelligent transportation cloud control network virtualization architecture.

control strategy of traffic equipment is designed by using the 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, the intelligent transportation cloud control system can 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 interfaces, the two systems can concurrently operate in the process of information interaction and coordination development based on the knowledge accumulated through the learning process, and gradually improves the virtual system combined with the actual operation data, to evaluate the industrial entity state and evolutionary computation experiment design scenario forecast future trend to help 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 subnetworks, 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 Fig. 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.

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 ITN 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 and 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 article, 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 article, for the large-scale traffic flow data, the forecasting model based on deep learning and support vector regression is put forward. As shown in Fig. 5, the DBN model

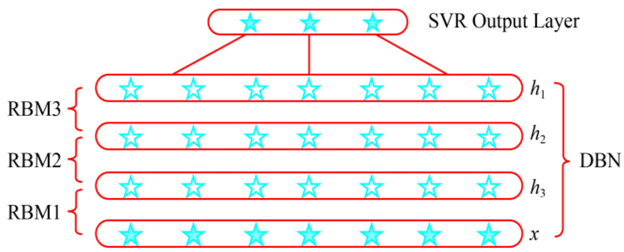

Fig. 5. Network structure of the DBN-SVR model.

is a network model structure containing three hidden layers, where the bottom node represents training data and the top node represents predictive output data.

Due to the temporal and spatial correlations between traffic flows in each section, let the input dataset of forecasting model be X_t, then

$$X_i = \{x_1, x_2, \ldots, x_p\} \tag{1}$$

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

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 ith 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 dataset is H after learning the features of the DBN model, then there is

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

where

Φ deep learning of DBN network model;
X_d traffic dataset processed according to the formula $X^d_{i,t} = x_{i,t} - x_{i,t-d}$.

SVR as the nonlinear feed forward network with hidden elements can realize the forecasting and processing of time series. All the nonlinear 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 $t + \Delta t$ time is

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

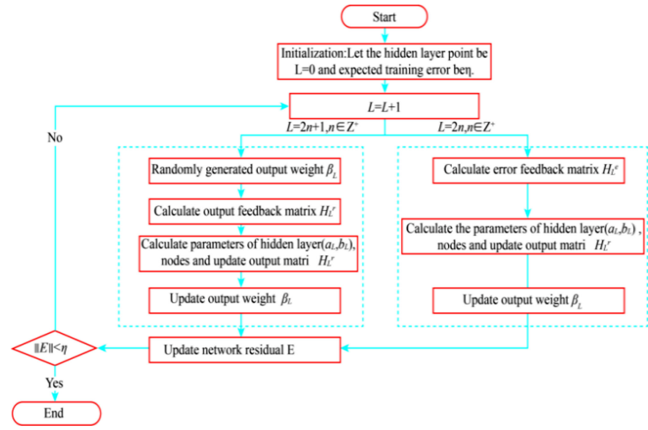

Fig. 6. Algorithm flowchart of BP-BELM.

where

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

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

1) According to the characteristics of traffic flow data, the input dataset X_t is constructed by (1) and (2)
2) The traffic dataset is preprocessed according to the formula of $x^d_{i,t} = x_{i,t} - x_{i,t-d}$ to obtain the residual quantity X_{d};
3) 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);
4) With H as input, the SVR forecasting model is used to forecast traffic flow data according to formula (4);
5) The restoration of original traffic flow data is calculated by the formula $\hat{x}_{i,t+1} = \hat{x}^d_{i,t+1} + \hat{x}_{i,t-d+1}$ 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 article 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 Fig. 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

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}, x_{i} is the input, and y_{i} 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 $L = \mathrm{L} + 1$;

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

1) Randomly generate the output weight β_L of the newly added hidden layer node.
2) Calculate output feedback matrix: $H_L^r = e_{L-1}(\beta_L)^{-1}$.
3) Calculate the parameters of hidden nodes

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

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

4) Update output feedback matrix: $\hat{H}_L^r = u^{-1}(h(a_L \cdot x + b_L))$.
5) Calculate the output weight of the updated newly added hidden layer node according to least square method

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

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

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

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

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

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 Lth hidden layer node: $E = E - \hat{\beta}_L \cdot \hat{H}_L^r$.

IV. ITCOCCS Dispatch

Predictive control based on cloud control system theory, aimed 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 Fig. 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 5min, 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

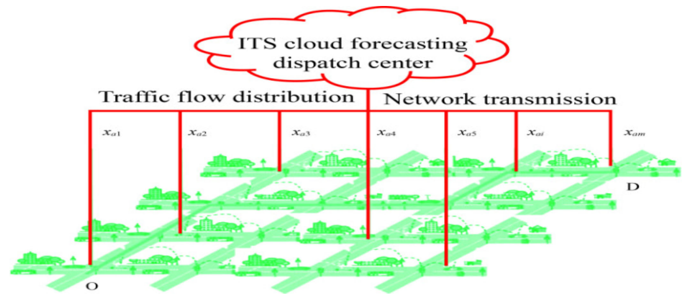

Fig. 7. Schematic diagram of prediction scheduling for intelligent transportation cloud control systems.

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, and thus the road impedance function t_a is

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

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

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 $c_a < Z_a 2c_a$, 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 article, 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 kth OD traffic flow segmentation to the shortest route between OD dot pair, which is obtained by using the Floyd algorithm, and then the traffic volume distributed by the abovementioned step in each section is accumulated and recorded asw_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.

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 a local computer. The mature commercial cloud server is rent as the cloud server: Beijing Three District, computational C2, 4-core CPU, and 8G memory server, whose configuration is consistent with the local computer for simulation experiment, with bandwidth upper limit of 100 Mpbs, 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 multitype 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 30 W; 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) are used to conduct experimental verification. Due to the strong time-dependent regularity of traffic flow data and the difference between nonweekend 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 article. 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 1152, and the total number of samples in the entire dataset is 11 520. As the input and output dataset of intelligent forecasting model, the dataset with the sampling interval of 5 min 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 2, 8 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 2880 data on July 12.

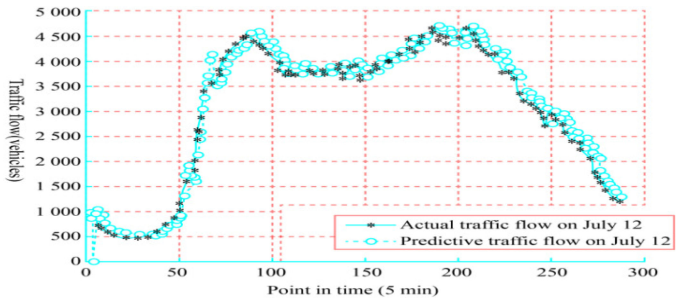

Fig. 8. Comparison of DBN-SVR prediction traffic flow and actual traffic flow.

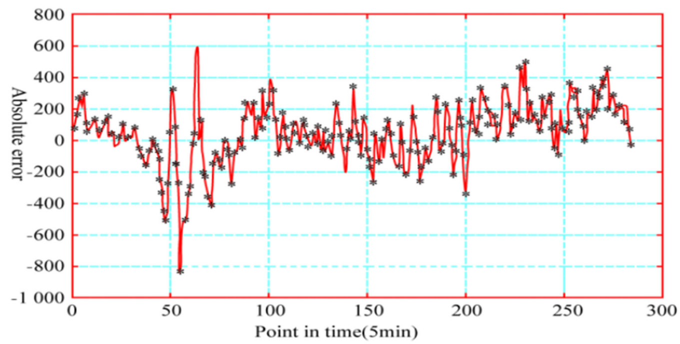

Fig. 9. Predicted error with DBN-SVR.

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

In cloud server and local computer MATLAB2014a environments, the parameters of DBN-SVR network model are set as follows: RBM network in DBN model has three layers, the number of nodes in each layer is four, four, and two, respectively, and the training iterations of corresponding weights are all taken as ten 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 dataset are conducted with comparative analysis. The simulation results of cloud server are shown in Figs. 8 and 9. The average running time is 8.5262 s in local computer and 5.2758 s in cloud server.

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

The traffic dataset is conducted with training and forecasting in this section to verify the performance of the BP-BELM algorithm. All the test results use sigmoid function to conduct

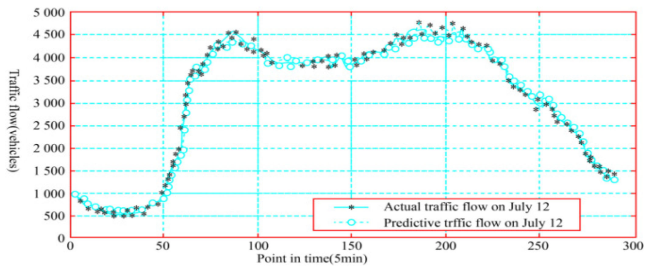

Fig. 10. Comparison of BP-BELM prediction traffic flow and actual traffic flow.

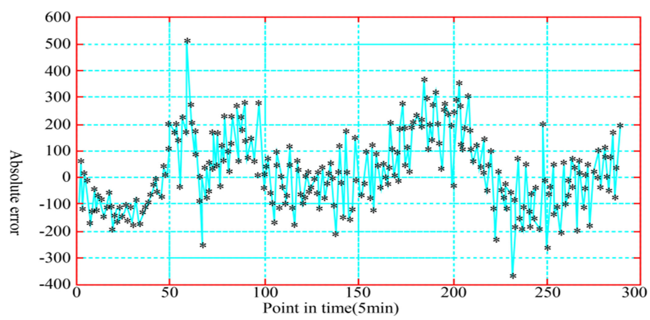

Fig. 11. Predicted error with BP-BELM.

[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 Figs. 10 and 11.

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

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,

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

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

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 presented in Table I.

According to the comparison of Figs. 9 and 11 that the DBN-SVR model has high accuracy in intelligent traffic flow

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

forecasting and small fluctuation range in the later period of variance, whereas the forecasting accuracy of the 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, the DBN-SVR model has better forecasting effect than the BP-BELM model.

The traffic dataset 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 Figs. 10 and 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, and thus the running time of simulation experiment in cloud server obviously is obviously reduced, whereas the data computing ability is obviously stronger than that of local computer.

The comparative LSTM forecasting method selected in this article has poor effect on the dataset 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, the 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, the DBN-SVR model can be used to accurately predict the large sample data of multiple detection nodes, and the 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

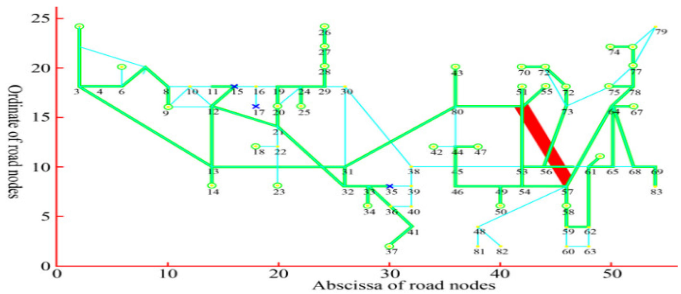

Fig. 12. Simulation result of traffic jam.

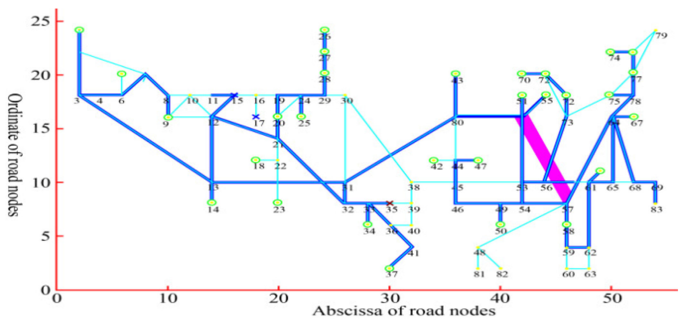

Fig. 13. Simulation result after incrementa traffic flow assignment.

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 lanes to 6500 vehicles per hour, and the capacity of urban suburban third-classed road to 1550 vehicles per hour.

In Fig. 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 the Floyd algorithm, and finally, the traffic flow is distributed point by point according to the all-or-nothing method.

It can be seen from Figs. 12 and 13 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 article can realize traffic flow prediction and scheduling.

VI. Conclusion

In this article, the structure and core technology of ITCPCCS were designed and analyzed, the application mode of cloud control technology in ITS was explored, and the application demonstration of cloud control technology in ITS was promoted. The forecasting algorithm based on deep learning and ELM was 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 article is a preliminary application of cloud control technology, which is still in the development stage, how to efficiently classify complex traffic data in the cloud and get the optimal real-time cloud control scheme of intelligent traffic is still the technical difficulty to be solved in the research of intelligent traffic information physical fusion cloud control system.

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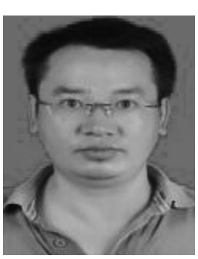

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