Research on the Key Intelligent Optimization Technology of 5G Millimeter Wave Relay

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Abstract

5G applications put forward higher and higher requirements for wireless communication technology. 5G Multi-User Multiple-Input Multiple-Output (MU-MIMO) millimeter wave communication can carry a larger number of data, which has become the key technology of 5G network millimeter wave communication. In this paper, by studying intelligent network state prediction of AI intelligent network management, we optimize the communication of millimeter-wave relay, and propose an intelligent prediction method of multi-modal fuzzy fusion network state. By using network data provided by a company in Xiamen, the simulation results show that the average prediction accuracy of the proposed method can reach 88.45%, which is 7 to 8 percent higher than the commonly used neural network and fuzzy neural network algorithms, and achieves the purpose of improving the transmission stability and efficiency of millimeter-wave relay.

Keywords: 5G network, Millimeter-Wave relay station, Intelligent optimization, Intelligent network operation and maintenance

1 Introduction

With technological innovations and progressions, 5G communication technology has entered the commercial stage, the number of network termination equipment has increased sharply, and the amount of data created by streaming media on the Internet has also continued to expand. High-efficiency and intelligent network services have become an important demand for contemporary Internet users. In order to transfer a large number of data and reduce the transmission delay [1-2], the shortage of spectrum resources needs to be solved. Millimeter wave has richer spectrum resources and higher transmission rates, so it's an inevitable trend for 5G communication to develop high-frequency millimeter wave.

Self-Organizing Networks (SON) which is a key technology of 5G network is also important for the research of large-scale MIMO millimeter wave communication. Since the stability of millimeter wave communication is weak, AI intelligent operation and maintenance technology in SON is considered to assist millimeter wave communication. Through intelligent analysis and prediction of changes in the communication environment, relevant state of equipment is adjusted in time to cope with changes in the environment to enhance the stability of millimeter wave communication.

Network AI intelligent operation and maintenance is to use automated analysis of the machine to replace the traditional manual supervision, detection and repair process. The basic idea is to use different algorithms to analyze and process the useful information obtained from the test of the analyzed network, determine whether the state of the analyzed network is abnormal or a certain state, and match the corresponding solution to achieve the analysis and processing process from network performance data to network status.

Although 5G MU-MIMO millimeter-wave communication can meet 5G requirements to carry a large number of data, the stability of millimeter-wave communication has become one of the key technical problems of 5G network millimeter-wave communication due to problems including strong attenuation and poor penetration of millimeter wave. Aiming at the problem that millimeter wave communication quality is susceptible to the communication environment, this paper uses AI intelligent operation and maintenance technology, and propose an intelligent prediction method of multi-modal fuzzy fusion network state. The gateway can monitor and analyze relevant KPIs in real time to realize intelligent prediction of the network status in a certain unit time in the future, so as to adjust the corresponding communication configuration of the millimeter-wave base station in time to deal with the sensitivity of millimeter wave to the communication environment.

The rest of the paper is organized as follows: The

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second section introduces related research in this field. The third section proposes a method of intelligent prediction of 5G millimeter-wave network status. The fourth section evaluates the performance of the proposed method through experiments. The fifth section gives the conclusion.

2 Related Work

For the study of robustness of transmission process of large-scale MIMO millimeter wave communication, Masoud Zarifneshat, Li Xiao and others proposed a prediction algorithm to realize the classification and recognition of different link barrier scenarios in terms of link barrier scenario identification for large-scale MIMO millimeter wave communication, which can effectively improve the robustness of large-scale MIMO millimeter wave communication and reduce the probability of communication interruption [3]. Rui Zhu, Yuanxun Ethan Wang and others proposed an application method based on the cooperation of relay and millimeter wave in terms of disadvantages of large-scale MIMO millimeter wave that have poor ability to penetrate obstacles and difficulties in indoor and outdoor communication, which not only ensures the effect of data transmission of millimeter wave but also can effectively improve the transmission stability of millimeter wave [4]. We found that most of optimization methods mainly use mathematical algorithms to improve the technical process of communication, but few studies have been conducted to optimize the sensitivity of large-scale MIMO millimeter wave to environmental factors from the perspective of the external environment. At the same time, the application of AI technology in recent years has brought more efficient and intelligent technologies to many fields, which has solved and improved many technical problems. Therefore, it is worth exploring whether AI technology can be used to optimize large-scale MIMO millimeter wave communication from various perspectives.

Although the purpose and effect of AI intelligent operation and maintenance technology are almost the same, with the development and application of AI technology in recent years, there have been diversification in the research on implementation methods of the technology. Zilong Tan and Peisheng Pan proposed a CNN-LSTM hybrid prediction algorithm based on network logs. The algorithm combined the advantages of two algorithms applied separately, effectively improved the accuracy of fault prediction without increasing too much computing complexity, and achieved the effect of combinatorial optimization [5]. Kaijing Chen, Wendi Wang and others proposed two deep neural network algorithms with different complexity for the operation and maintenance of millimeter-wave communication system, which can release work of man-made fault location to a certain extent and realize automatic fault location [6] Yueping Wang, Kun Zhu and others proposed a fault diagnosis system based on ensemble learning for SON self-organizing network, which automatically extracted the characteristics of fault sample data and identified the network through iterative learning, and finally use network to analyze related KPI to realize fault classification and recognition with a certain accuracy [7]. Shih-Fan Chou and Hsiu-Wen Yen and others proposed a REM-enabled diagnostic framework in cellular-based IoT networks. By a series of pre-processing of KPI data according to the framework, intelligent identification of the state was realized by sending it into intelligent analysis of the neural network. The simulation experiment proves that this method can realize the identification and judgment of the status level of indoor signal coverage through intelligent analysis of several KPIs at a certain accuracy, and can reduce the computational complexity and improve the working efficiency to a certain extent compared with the direct use of neural network [8]. Hualin Wang, Zhile Wang and others proposed a short-range wireless sensor network node diagnosis algorithm based on clustering algorithm, and an innovative diagnosis algorithm based on clustering principle was adopted for several KPIs to achieve fault classification and recognition with certain accuracy under the premise of low power consumption and low computational complexity [9]. DAVID MULVEY, CHUAN HENG FOH and others researched and summarized several methods to realize intelligent operation and maintenance through machine learning in recent years. They compared and analyzed the commonalities and differences of different methods, and proposed an idea of future improvement trends. In recent years, the effect of intelligent identification on network operation and maintenance has reached a high recognition level. In the future, we should focus on how to reduce the computational complexity and improve the working efficiency of intelligent analysis and intelligent identification [10].

The essence of AI intelligent operation and maintenance technology is to use KPIs or log data in a certain way to realize intelligent judgment and prediction of network state or intelligent identification and prediction of network failure. We can find that future AI intelligent operation and maintenance will not only pay more attention to how to improve the algorithm to improve the recognition effect while reducing computational complexity and improve work efficiency, but also focus on how to apply AI intelligent operation and maintenance technology to other fields. The stability of large-scale MIMO millimeter wave communication is susceptible to changes in the network environment, so it’s worth exploring how to integrate AI intelligent operation and maintenance technology, that is, to construct appropriate algorithms or methods to realize the intelligent prediction of the network status to assist in improving the transmission stability of millimeter-wave relay communication, and finally improve the transmission efficiency of 5G communication network.

3 The Design of Intelligent Prediction Architecture of 5G Millimeter Wave Network State

3.1 Research on Intelligent Prediction Method of 5G Millimeter Wave Network State

This section proposes the intelligent prediction architecture of 5G millimeter wave network state. The gateway monitors KPIs in real time and uses intelligent prediction algorithms to achieve intelligent prediction of the network state at a certain time in the future, and transmits the predicted information to the millimeter-wave base station or relay so as to improve the operation and maintenance efficiency of 5G ultra-dense heterogeneous networks.

The intelligent prediction architecture of 5G millimeter wave network state is shown in Figure 1. The gateway can intelligently predict and analyze the changes of network state, and transmit the results to the millimeter-wave relay and base station so that the equipment can adjust adaptively [11].

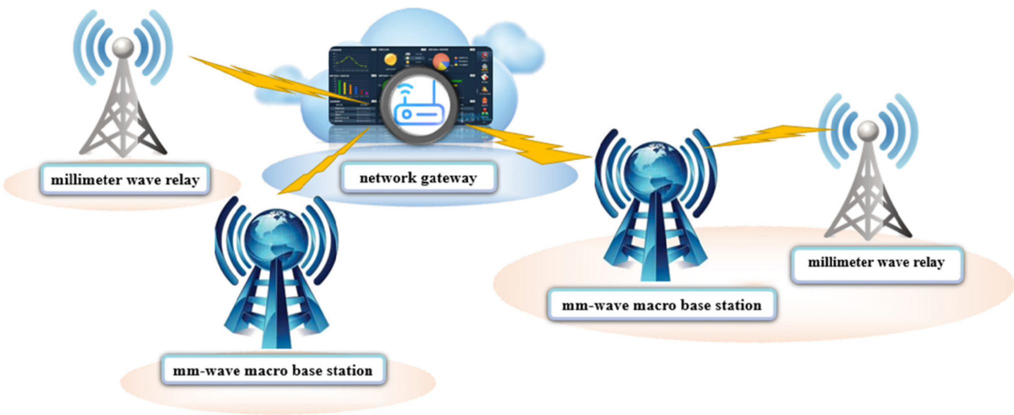

Figure 1. The intelligent prediction architecture of 5G millimeter wave network state

The flow chart of intelligent prediction method of 5G millimeter wave network state is shown in Figure 2. After inputting the required network data, it mainly includes three stages: preprocessing of network data, data training for prediction methods and experimental test of prediction method.

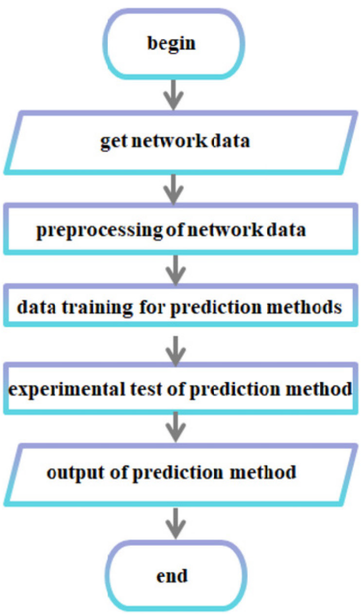

Figure 2. The flow chart of intelligent prediction method of 5G millimeter wave network state

This section studies the prediction method in Figure 2, and proposes an intelligent prediction method of multi-modal fuzzy fusion network state. As shown in Figure 3, we create the multimodality that consists of several related KPIs for predicting the target network state, and use a variety of intelligent prediction algorithms to integrate work containing certain rules so that we can improve the prediction accuracy and work efficiency.

In Figure 3, t represents the unit time for the gateway platform to perform data analysis and reporting, and T represents the time point for predictive analysis. The time point of predictive analysis is usually set according to the unit time reported by the network gateway platform, not at any time. KPI1, KPI2 and KPI3 represent related KPIs that can be used to analyze and predict the state of the target network. In the figure, it's assumed that through monitoring and analyzing KPI1, KPI2, KPI3 and time parameter T, a total of 10 parameters reported at T-t, T-2t and T-3t, the analysis and prediction of target network state at time T can be realized. If 10 parameters are directly sent to the neural network for analysis, such as Long Short-Term Memory(LSTM), the working time cost and calculation cost are relatively high, which is not suitable for a large amount of real-time data of the network state in 5G scenario. This section proposes an intelligent prediction method of multi-modal fuzzy

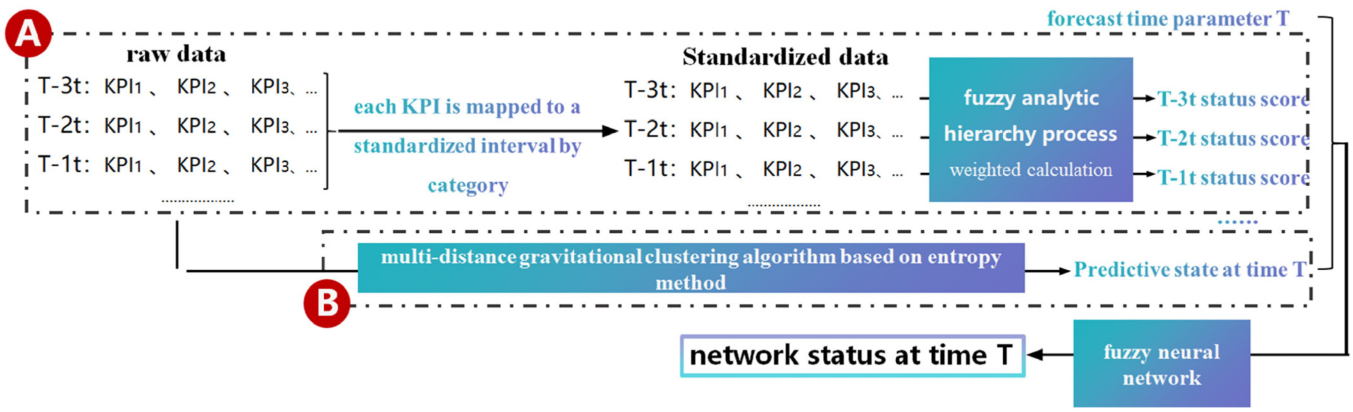

Figure 3. The block diagram of intelligent prediction method of multi-modal fuzzy fusion network state

fusion network state, which works with other algorithms to reduce parameters that are sent to fuzzy neural network for analysis to 5, and the method can reduce work complexity without negative effects on prediction.

3.2 Preprocessing of Network Data

The intelligent prediction method of 5G millimeter wave network state needs to first obtain relevant network data, including equipment work logs and various KPIs, and perform data preprocessing such as data cleaning.

According to the intelligent prediction method of multi-modal fuzzy fusion network state proposed in Figure 3, after data acquisition and preprocessing, a complete training sample data including corresponding network state categories should contain KPI1, KPI2, KPI3 and time parameter T, a total of 10 parameters reported at T-t, T-2t and T-3t, as shown in Table 1.

Table 1. Example of training sample data

sample number	time	reporting indicators at T-3t time pint			r reporting indicators at T-2t time pint			reporting indicators at T-t time pint			Network statue category
	T	KPI1	KPI2	KPI3	KPI1	KPI2	KPI3	KPI1	KPI2	KPI3	
1	*	*	*	*	*	*	*	*	*	*	Status category 1
2	*	*	*	*	*	*	*	*	*	*	
3	*	*	*	*	*	*	*	*	*	*	
......	*	*	*	*	*	*	*	*	*	*	
1	*	*	*	*	*	*	*	*	*	*	Status category 2
2	*	*	*	*	*	*	*	*	*	*	
3	*	*	*	*	*	*	*	*	*	*	
......	*	*	*	*	*	*	*	*	*	*	
1	*	*	*	*	*	*	*	*	*	*	Status category 3
2	*	*	*	*	*	*	*	*	*	*	
3	*	*	*	*	*	*	*	*	*	*	
......	*	*	*	*	*	*	*	*	*	*	
...... sample data of other status categorles of the network statue											

3.3 Data Training for Prediction Methods

According to Figure 3, if we make intelligent prediction, it will be necessary to train the data for 5G millimeter wave network state. After completing the network data preprocessing, the training sample data shown in Table 1 needs to be standardized, which can be explained by two factors. Firstly, because the KPI values of different types of network state are quite different, if the intelligent analysis of fuzzy neural network is directly used, the large difference of KPI values will not only affect the result of network training, but also increase the complexity of neural network operation process. Secondly, KPI values of the same Network states vary widely. Some KPI values may have a relatively concentrated distribution with a relatively small variation range, while others may have a large variation range, also, KPI values of different Network states have a large variation range. All of these will have a negative influence on the prediction and data training of fuzzy neural network.

3.4 Multi-Distance Gravitational Clustering Algorithm Prediction State Based on the Entropy Method

Weighted combination is used to calculate different KPI values at the same time point according to certain weighted values, and then the state scores of T-t, T-2t and T-3t can be obtained. The weighted value is the degree of contribution of different KPIs to the target network state prediction. We refer to the correlation degree of each KPI and the target network state as well as actual operation and maintenance experience for manual qualitative setting, and use the Fuzzy Analytic Hierarchy Process to convert qualitative judgments into quantitative weighted values. Fuzzy Analytic Hierarchy Process (FAHP) introduces fuzzy mathematics processing process, which can effectively reduce the number of iterations of calculations, increase the speed of convergence, and don't need to perform final consistency checks [12-13]. According to the data extraction and standardization of box A in Figure 3 and the Fuzzy Analytic Hierarchy Process that the qualitative judgments is converted into quantitative weighted value and the state score is obtained, we carry out the T time state prediction in box B of Figure 3 and figure out the multi-distance gravitational clustering algorithm based on entropy methods as shown in Figure 4.

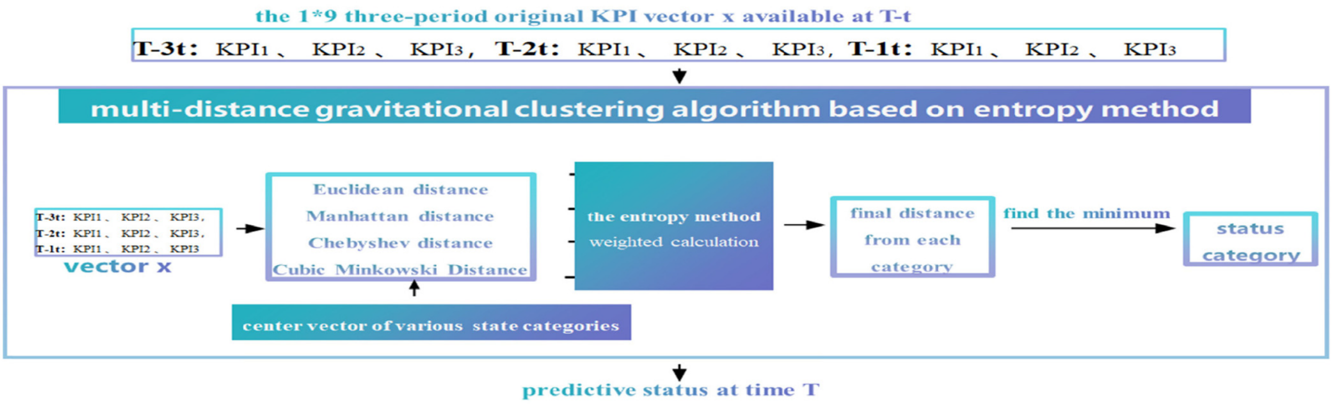

Figure 4. Block diagram of multi-distance gravitational clustering algorithm based on entropy methods

(a) Create input vector X

We use KPI1, KPI2, and KPI3 reported at three time points of T-t, T-2t, and T-3t to get the input vector X through formula (1).

$$X = [KPI1_{T-3t}, KPI2_{T-3t}, KPI3_{T-3t}, KPI1_{T-2t}, KPI2_{T-2t}, KPI3_{T-2t}, KPI1_{T-t}, KPI2_{T-t}, KPI3_{T-t}] \quad \textbf{(1)}$$

(b) Calculate the center vector C_j of each network state

In the training stage, the input training sample vector X is used to calculate the center vector C_j of each network state

$$C_j = \frac{\sum_{i=1}^{m} X_{ji}}{m} \quad \textbf{(2)}$$

In formula (2), C_j represents the center vector of the j-th network state, m represents the number of samples of the j-th network state in the training sample data, and $X_{ji} = (i = 1, 2, \ldots, m)$ represents the vector converted by sample data of the j-th network state in the sample database by using formula(1)

(c) Calculate the correlation with the network state-distance dist(X, C_j)

In the experimental verification and application prediction stage, the input vector X is used to calculate the correlation with the center vector C of different network states obtained in the training stage. By introducing four commonly used distance formulas, including Euclidean distance, Manhattan distance, Chebyshev distance, and cubic Minkowski distance, the vector distance between the input vector X and the center vector C of various network states is calculated.

Euclidean distance

$$\operatorname{dist}(X, C_j)_1 = \sqrt{\sum_{i=1}^{n} (x_i - c_{ji})^2} \quad \textbf{(3)}$$

Manhattan distance:

$$\operatorname{dist}(X, C_j)_2 = \sum_{i=1}^{n} | x_i - c_{ji} | \quad \textbf{(4)}$$

Chebyshev distance:

$$\operatorname{dist}(X, C_j)_3 = \max(| x_i - c_{ji} |) \quad \textbf{(5)}$$

Cubic Minkowski Distance:

$$\operatorname{dist}(X, C_j)_4 = (\sum_{i=1}^{n} | x_i - x_{ji} |^3)^{\frac{1}{3}} \quad \textbf{(6)}$$

In formula (6), C_j represents the center vector of the j-th network state, and n is the vector dimension. In this prediction rule, n=9, x_i is the i-th element of the vector X, and c_{ji} is the i-th element of the center vector C_j [14-15]

(d) Calculate Weighted value W_h

On the basis of calculating the four kinds of distances between vector X and each kind of state center vector C, the weighted value W_h of the four kinds of distances is calculated by entropy method, and the smallest category which is corresponding to the final distance is found as the pre-judgment category after the weighted calculation of four kinds of distances. The entropy method is a method that can objectively determine the weight of each indicator in the vector based on the amount of information of the vector data. The weighted value can be determined based on the distance obtained by each distance algorithm, and this is equivalent to using different weights by different distance algorithms in corresponding prediction rule from an objective perspective, which can better reflect the distance difference so that the algorithm can achieve better classification effect.

(e) Calculate the final distance S_j to the center vector of each network state

Suppose that weighted values of the entropy method corresponding to Euclidean distance $\text{dist}(X,C)_1$, Manhattan distance $\text{dist}(X,C)_2$, Chebyshev distance $\text{dist}(X,C)_3$ and Cubic Minkowski Distance $\text{dist}(X,C)_4$ are W_1', W_2', W_3' and W_4' respectively, and then the final distance S_j between vector X and the j-th the center vector C_j of the network state is calculated as follows

$$S_j = W_1' \times dist(X,C_j)_1 + W_2' \times dist(X,C_j)_2 + W_3' \times dist(X,C_j)_3 + W_4' \times dist(X,C_j)_4 \quad \textbf{(7)}$$

(f) Pre-judgment of time state T

According to the calculation result of formula (7), the shortest final distance min(S_j) is found, and the network state corresponding to this distance is the final predicted state output by the method.

3.5 Network State Prediction Based on T-S Fuzzy Neural Network

The neural network has a parallel structure, can carry out the parallel data processing, has the strong robustness, the memory ability, the nonlinear mapping ability and the powerful self-learning ability, and is convenient for the computer implementation. Due to the large amount of data in 5G network state and the high real-time requirement, traditional Support Vector Machines (SVMs) algorithm is difficult to implement for large-scale training samples, and it's difficult to solve Multiclass Classification problems with SVM. For data with fewer features, random forest algorithms may not produce good classification. In the case of such a large amount of data, the performance of neural network is better than that of tree models such as random forest. So we consider applying neural networks to intelligent operation and maintenance in 5G scenarios.

Fuzzy neural network is an intelligent algorithm that combines the powerful logical reasoning and knowledge expression ability of fuzzy mathematics on the basis of the existing training learning and intelligent analysis functions of neural network. In short, it's a neural network algorithm that integrates the fuzzy logic reasoning ability. This method not only retains the intelligent learning and analysis capabilities of neural network, but also integrates capabilities of fuzzy mathematics, so that the advantages of two methods can compensate for the shortcomings of the single method, and it's more suitable for network state intelligent prediction which requires the knowledge of operation and maintenance for intelligent training and analysis.

using fuzzy neural network for state prediction analysis is shown in Figure 3. The input time parameter T, the state score obtained at each time point (Tt, T-2t andT-3t) and the state prediction at time T are sent to T-S fuzzy neural network for predictive analysis. The T-S fuzzy neural network is composed of two parts: the antecedent network and the posterior network. The network flow diagram of its multiple input and single output is shown in Figure 5. The parameters input to the fuzzy neural network are state scores at three time points of T-t, T-2t, and T-3t, time parameters T, and pre-judgment state of time T, a total of 5 input parameters, and the output result which is the network status category of the judgment is a single numerical output. Suppose the input of the T-S fuzzy neural network is $x_1, x_2, \ldots, x_n$, there are m rules inside [16], and the output of the entire system is:

$$y = \sum_{j=1}^{m} y_j \overline{w}_j \quad \textbf{(8)}$$

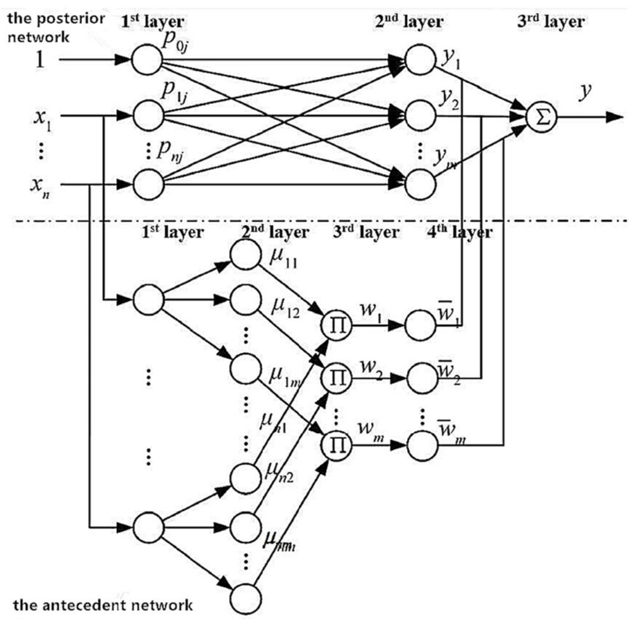

Figure 5. Structure diagram of T-S fuzzy neural network

$y_j (j=1,2,\ldots,m)$ is the output of each node in the middle layer, $\overline{w}_j$ is the method that uses Weighted Mean to achieve normalization calculation to obtain the output of each node in the defuzzification layer [17]

After setting the input and output structure of the T-S fuzzy neural network, we perform the training of the T-S fuzzy neural network. According to input $x_1, x_2, \ldots, x_n$ and output $y_j (j=1,2,\ldots,m)$, the upper limit T^0 of the training iteration times and the error accuracy requirement ε were set. Based on the error, the weight parameter p_{ij}, the width b_{ij} and the center of degree of membership function c_{ij} were continuously adjusted and trained in accordance with a certain gradient.

Let E be the error between the actual output value of the training sample data and the training output value of the model:

$$E=\frac{1}{2}\sum_{k=1}^{r}(y_{dk}-y_k)^2 \quad \textbf{(9)}$$

In formula (9), y_{dk} represents the training output value of a certain sample, and y_k represents the actual output value of the sample. r represents the amount of the output variable y. For the network of multiple inputs and the single output, r is set to 1.

$$\Delta E(t)=E(t+1)-E(t) \quad \textbf{(10)}$$

In formula (10), t represents the amount of the training, the error accuracy of network training is ε, 0≤ε<1, and the stop sign of iterative training is to satisfy any one of the following two formulas:

$$\Delta E(t)\le \varepsilon \quad \textbf{(11)}$$

$$t \ge T^0 \quad \textbf{(12)}$$

The initial values of weight parameter p_{ij}, the width b_{ij} and the center of degree of membership function c_{ij} are randomly generated by the system, and the appropriate network model is obtained through constant modification and adjustment in the process of iterative training. The algorithm of iterative training is as follow.

$$c_{ij}(t+1)=c_{ij}(t)-\theta\frac{\partial E}{\partial c_{ij}} \quad \textbf{(13)}$$

$$b_{ij}(t+1)=b_{ij}(t)-\theta\frac{\partial E}{\partial b_{ij}} \quad \textbf{(14)}$$

$$p_{ij}(t+1)=p_{ij}(t)+\theta(y_{dk}-y_k)\overline{w}_j x_i \quad \textbf{(15)}$$

The width b_{ij} and the center of degree of membership function c_{ij} are firstly corrected, and then the weight parameter p_{ij} of formula (15) is iteratively corrected. t represents the number of training times, k = 1, 2, ..., r represents the number of output parameters, if it’s a multiple-input single-output network, r can be set as 1. y_d represents the training output value of a sample, y represents the output value of the actual sample, and θ is the efficiency of network learning.

After completing a T-S fuzzy neural network training, certain test sample data can be used to simulate and predict the network. If the prediction accuracy of the test process is too low and the effect is not satisfactory, we can adjust the corresponding parameters and perform network training again until the test effect is reached ideally, and the trained T-S fuzzy neural network can be used for prediction [18-19].

4 Experimental Test of Network State Intelligent Prediction Method

4.1 Experimental Site and Data Analysis of Network State Intelligent Prediction

An operator provided 35 kinds of KPI data from 0:00 to 24:00 in a site on a certain day, and the unit reporting time was 15 minutes. A total of 59,713 data records were collected. After data cleaning, 40,478 available data were obtained. We experiment with the method proposed in this paper, perform data preprocessing based on operation and maintenance experience, and select three related KPIs of “average CQI”, “SINR average”, and “CQI greater than 7 ratio” for intelligent prediction experiment of network state.

The target network status is set as the “channel quality level”, and the network status is set to include four categories, and each category is divided by the KPI standard of “average CQI level”. As shown in Figure 6, the reference standard for dividing the network state is marked on the right, and the number of model training samples and experimental samples is marked in each category after data cleaning.

The prediction rule is set as follows: 10 parameters, time T and three kinds of KPI indicators including “Average CQI”, “SINR average”, “CQI greater than 7 ratio” reported at three time points of T-t, T-2t and T-3t, are used to predict and analyze the channel quality level of time T. The intelligent prediction method of network state based on multi-mode fuzzy fusion was trained with the training sample data, and the standardized parameter indexes of various KPIs of the model are obtained

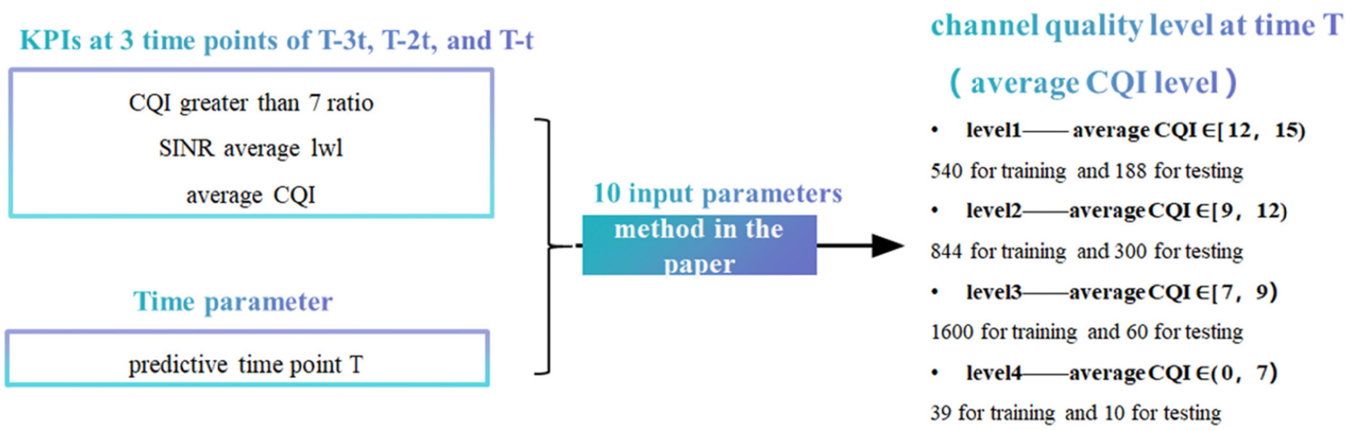

Figure 6. Experimental scheme diagram of intelligent prediction of network state

Table 2. Standardized reference table for various KPI

parameters of various KPI data standardization		
KPI	maximum value	minimum value
CQI greater than 7 ratio	0.999	0.3
SINR average lwl	19	3
average CQI	14	6

4.2 Research on the Importance and Weighted Values of Each KPI of Fuzzy Analytic hIerarchy Process

The use of fuzzy analytic hierarchy process for weight calculation requires the construction of a priority relationship matrix for pairwise comparison. Referring to the operation and maintenance experience and the correlation value of the data preprocessing stage, the constructed priority relationship matrix is as follows:

$$\begin{bmatrix} 0.5 & 0.7 & 0.2 \\ 0.3 & 0.5 & 0.6 \\ 0.8 & 0.4 & 0.5 \end{bmatrix} \quad \textbf{(16)}$$

The corresponding items in the matrix of formula (16) from left to right and top to bottom are “CQI greater than 7 ratio”, “SINR average”, and “average CQI”. In the final decision-making step of the fuzzy analytic hierarchy process, the sorting algorithm is selected, and the parameter a=1 is set, and the obtained analysis weight is shown in Table 3.

Table 3. Reference table of various KPI weighted values

Weight determined by fuzzy analytic hierarchy process			
KPI	CQI greater than 7 ratio	SINR average lwl	average CQI
weight	0.3167	0.3167	0.3666

Table 4 shows the weight of the calculated distance results of each distance formula in the multi-distance gravitational clustering algorithm based on the entropy method.

Table 4. Reference table for the weighted value of each algorithm distance

Distance weights of different algorithms determined by the entropy method				
distance	Eucidean distance	cubic Minkowski distance	Manhattan distance	Chebyshev distance
weight	0.2588	0.5477	0.1448	0.0514

In addition, the target network state of the multi-distance gravitational clustering algorithm based on entropy methods can realize the training structure of the model through the various center vectors and the final fuzzy neural network, and generate the storage for experimental inspection and the application of actual output.

5 Experimental Simulation and Comparative Analysis of Intelligent Network State Prediction

5.1 Prediction and Analysis of Channel State Level

After completing the data training work, we experiment with the test sample data. As shown in Figure 7, the test experiment was performed on 558 test sample data, and the experimental simulation results of the channel state level prediction were obtained. The abscissa is the serial number of the test data sample, and the ordinate is the channel state level; the red dot represents the result that the trained network analyzes and predicts the sample data, and the blue dotted line represents the actual channel state level corresponding to the sample data. If the red dot coincides with the top blue dot of the blue dotted line, it means that the analysis and prediction is correct; if the red dot does not coincide with the top of the blue dotted line, it means that the analysis and prediction are wrong.

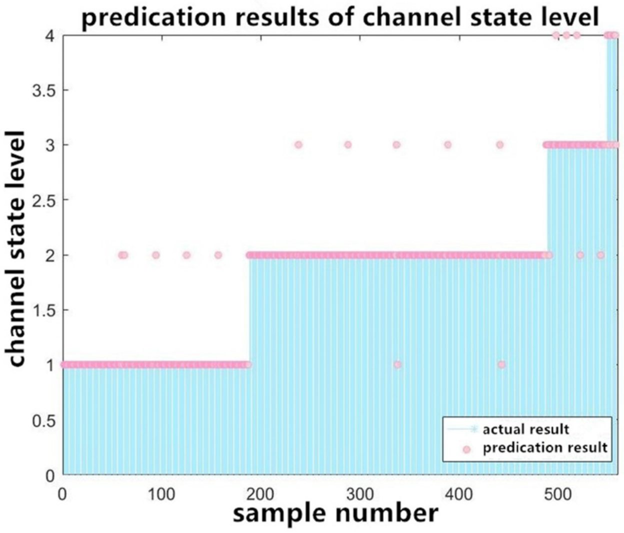

Figure 7. Test simulation of network state intelligent prediction based on multi-modal fuzzy fusion

The experimental results in Figure 7 were statistically analyzed by categories, and the results of different grade analyses are shown in Figure 8 and Table 5. In Figure 8. It can be seen that the overall average prediction accuracy rate has reached 88.45%. The prediction effect of channel state level 1, level 2, and level 3 are relatively ideal, while the prediction effect of level 4 is indeed relatively weak. The main reason is that the number of data samples for channel state level 4 is small. According to the overall prediction effect, the method proposed in this paper can realize the intelligent prediction and analysis of the network state of "channel state level" with high accuracy.

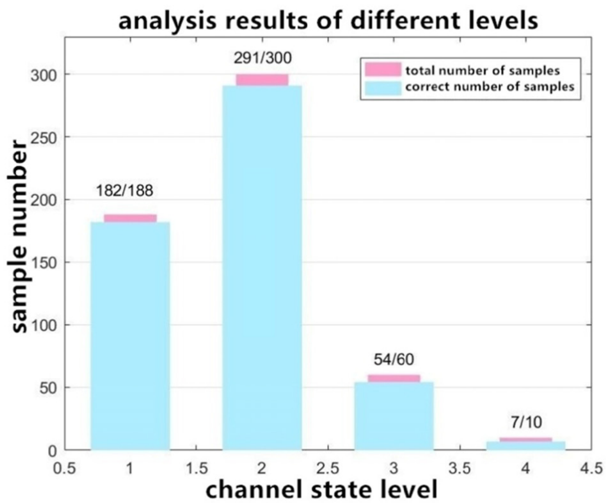

Figure 8. Test result category statistics

Table 5. Statistical table of prediction rate of test results

chanel state level	level 1	level 2	level 3	level 4	average value
Predictive accuracy rate (%)	96.8	97	90	70	88.45

5.2 Comparative Experiment of Different Methods for Predicting Channel State level

Through experiments on four different algorithms based on the same experimental plan, prediction rules, and experimental data, four comparison algorithms are: comparison method 1:replace the last fuzzy neural network module of the method proposed in Figure 3 of this paper with the traditional neural network, and the others remain unchanged; Comparison method 2: directly use fuzzy neural network; Comparison method 3: directly use traditional neural network [20]; Comparison method 4: use the centroid clustering algorithm which is commonly used in clustering algorithms [16]. The simulation results are shown in Figure 9 to Figure 12:

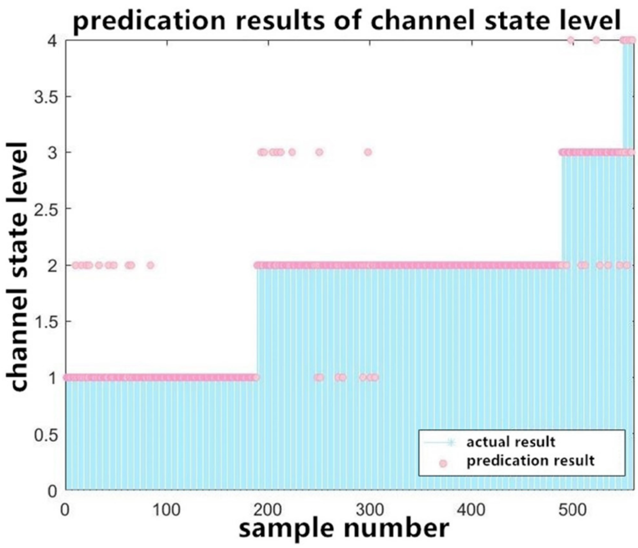

Figure 9. experimental simulation results of comparison method 1

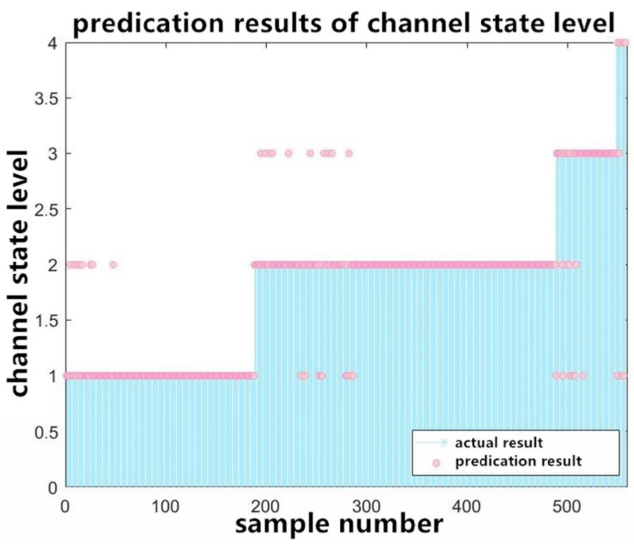

Figure 10. Experimental simulation results of comparison method2

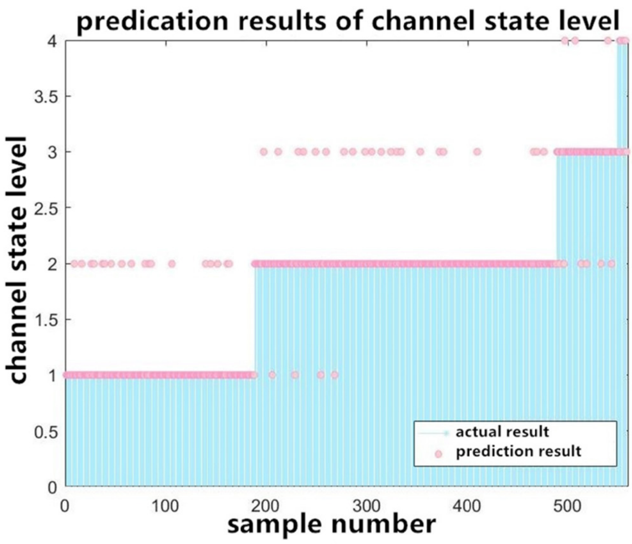

Figure 11. Experimental simulation results of comparison method3

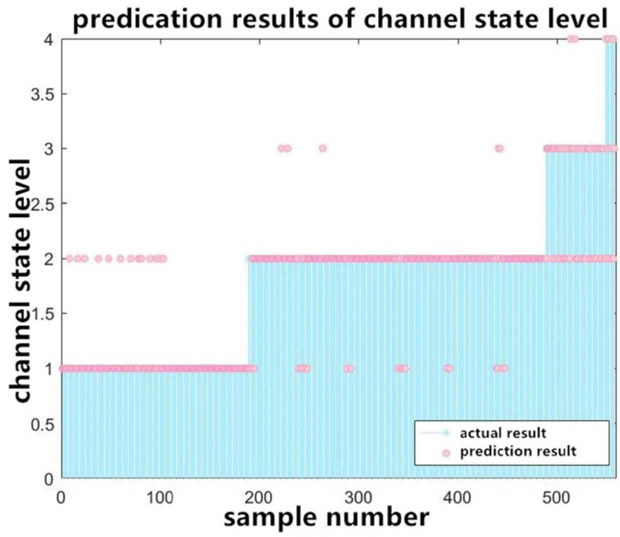

Figure 12. Experimental simulation results of comparison method4

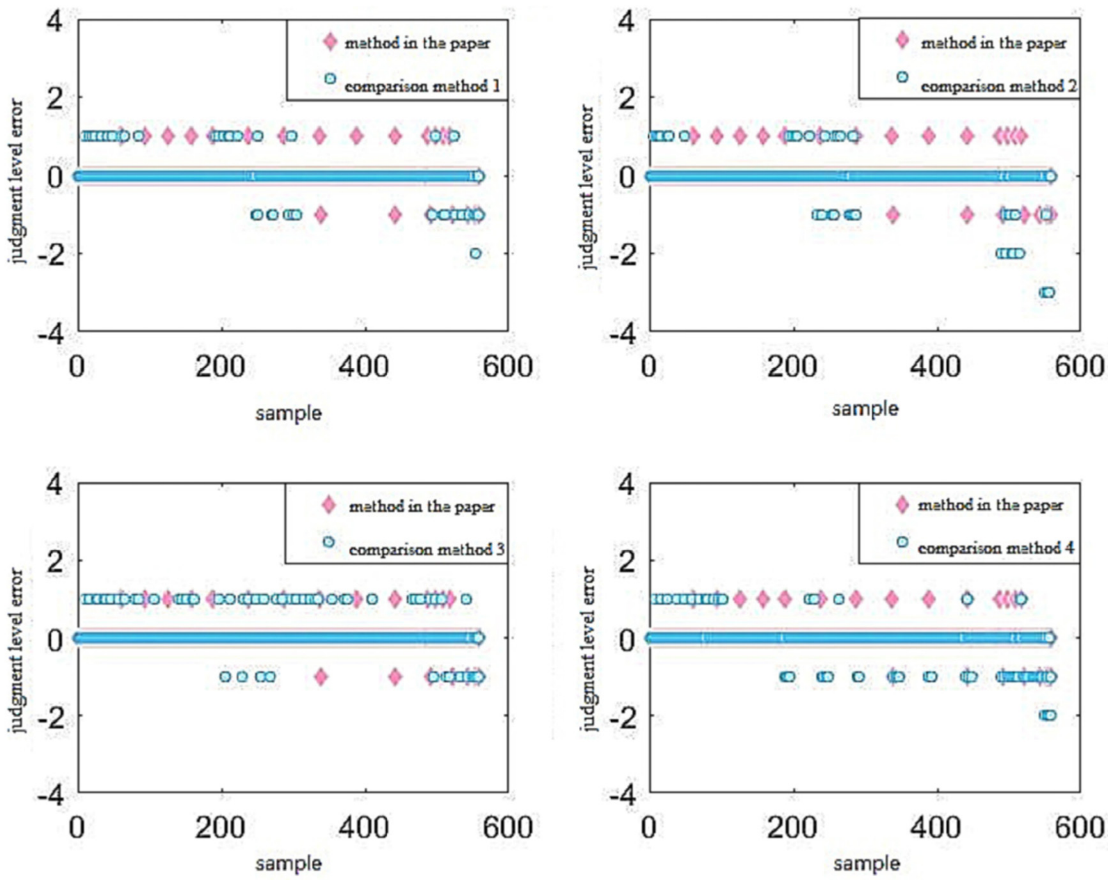

Figure 13. Comparison of experimental error scatter points of different prediction algorithms

In Figure 9 to Figure 13, the abscissa of each subgraph is the sequence number of each sample of test data, and the ordinate is the error of judgment grade. The red diamond points represent the prediction error of the method in this paper, and the blue circle points respectively represent the prediction error of each comparison algorithm. If the scattered points are on the 0 axis, the prediction is correct. If the scattered points are not on the 0 axis, it means that there is a prediction error. If a certain method has more points on the 0 axis and fewer points outside the 0 axis, it means the method has high prediction accuracy and good prediction effect. As can be seen from Table 6, compared with the commonly used neural network and fuzzy neural network algorithm, the prediction accuracy of the method proposed in this paper is improved by 7 to 8 percentage points by using the experimental samples in this paper, which can achieve better prediction effect.

Table 6. Numerical table of prediction accuracy of different methods (the recall)

chanel state level prediction	level 1	level 2	level 3	level 4	Average prediction accuracy (%)
the method in this paper	96.81	97	90	70	88.45
comparison method 1	94.68	95	86.67	50	81.59
comparison method 2	95.74	93.33	83.33	50	80.60
comparison method 3	90.43	91.67	85	40	76.78
comparison method 4	9255	90.67	53.33	30	66.64

We also use F1 score for the final evaluation of the above data. The F1 score is the harmonic mean of the recall and precision. The recall equates to data showed in the Table 6, and the precision is shown in the Table 7.

According to the equation 17, we can get F1 score of each method, which is shown in the Table 8

$$F_1 = 2 \times \frac{precision \cdot recall}{precision + recall} \tag{17}$$

Table 7. Numerical table of the precision of different methods

precision	level 1	level 2	level 3	level 4	mean value
the method in this paper	0.9945	0.9603	0.8308	1	0.9464
comparison method 1	0.9889	0.9406	0.7429	1	0.9181
comparison method 2	0.9836	0.9396	0.6944	1	0.9044
comparison method 3	0.977	0.9106	0.6538	1	0.88535
comparison method 4	0.9721	0.8662	0.5161	1	0.8386

As shown in the Table 8, the F1 score of the method proposed in this paper is higher than that of other four comparison methods, It can also prove that the method proposed in this paper has better performance than the commonly used neural network and fuzzy neural network algorithms.

Table 8. Numerical table of F1 score of different methods

F1-score	level 1	level 2	level 3	level 4	mean value
the method in this paper	0.9811	0.9651	0.864	0.8235	0.908425
comparison method 1	0.9674	0.9453	0.8	0.6667	0.84485
comparison method 2	0.9703	0.9364	0.7575	0.6667	0.832725
comparison method 3	0.9392	0.9136	0.7391	0.5714	0.790825
comparison method 4	0.9482	0.886	0.5246	0.4615	0.705075

5.3 Comparison Experiment of State Prediction of Multi-distance Gravitational Clustering Algorithm Based on Entropy Method

The multi-distance gravitational clustering algorithm based on the entropy method is improved on the basis of the traditional simple clustering algorithm. A comparative analysis of the prediction effect of the algorithm on the network state is shown in Figure 14 to Figure 15. The more points fall outside the horizontal axis, the greater the prediction error of the experiment is. It can be seen that the red dotted line in the figure is more distributed outside the horizontal axis than the blue dotted line. Compared with the multi-distance gravitational clustering algorithm based on the entropy method, the algorithm in this paper has a better prediction effect. It's necessary to input the fuzzy neural network for overall training and prediction after completing the sub-module prediction for the T time network state, which can bring better prediction effect.

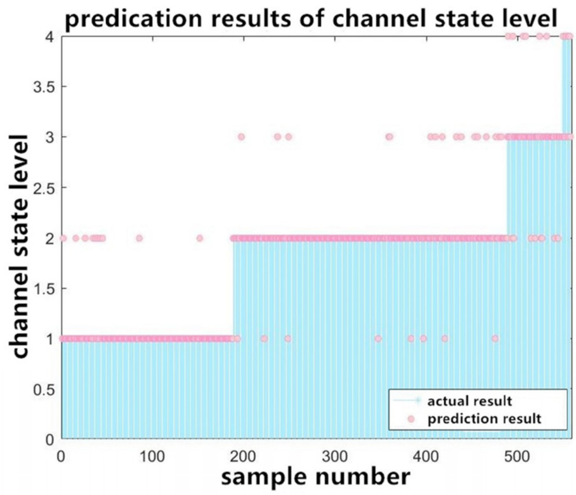

Figure 14. Experimental simulation results of multi-distance gravitational clustering algorithm based on entropy method

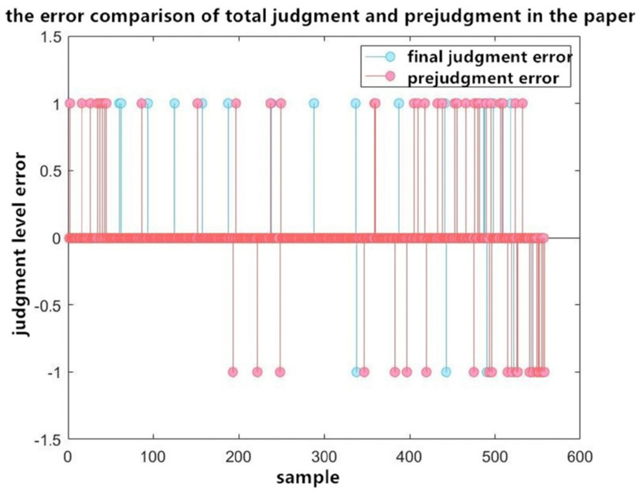

Figure 15. error comparison chart of total judgment and prediction in this paper

6 Conclusion

Millimeter wave communication is an important support for 5G networks in terms of transmission rate and transmission capacity in the future. This paper proposes the intelligent prediction method of network state based on multi-modal fuzzy fusion, and realizes intelligent prediction of network state in a certain unit time in the future through real-time monitoring and analysis of related KPIs. The millimeter wave relay or terminal device that receives the prediction information of the network gateway can make corresponding adjustments in time according to the change of the communication environment in order to solve the sensitivity problem that millimeter wave communication is susceptible to environmental changes and increase the stability of millimeter wave communication. Through the real network data obtained, the MATLAB platform is used for simulation experiment and comparative analysis. The average prediction accuracy of the proposed method in the experiment can reach 88.45% and improves 7% to 8% compared with the commonly used neural network and fuzzy neural network algorithm, which can better improve the stability of millimeter wave communication.

In the future, on the basis of this article, we can optimize the accuracy and complexity of the prediction algorithm for network state intelligent prediction, apply reinforcement learning and improved neural network to network state intelligent prediction, and explore the combination of machine learning and intelligent operation and maintenance in 5G scenarios, So that the intelligent prediction of network status can be realized efficiently to better support the implementation of 5G network millimeter wave communication.

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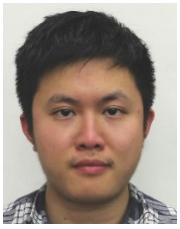
Biographies



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