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Business Cycle Monitoring and Early Warning Model Based on BP Neural Network

Tingting Wang*

Business School, Dianchi College, Kunming, Yunnan, China
sarah_mail@163.com
**Corresponding author*

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Abstract: The fluctuation of business cycle is an important feature of China's market economy and one of the important contents of China's macroeconomics. At the same time, due to the complexity and sensitivity of the new power grid, the demand of power users for power quality is increasing. In the introduction, the background of business cycle monitoring was introduced. Then, economic monitoring and early warning and BP neural network (hereinafter the BPNN) were investigated and summarized. Finally, combining with the telecommunications system, power quality management was summarized. The second part has established the algorithm model, and proposed various algorithms to provide theoretical basis for the BPNN business cycle monitoring and early warning model. In the method part, the classification of BPNN, the problems in the research of economic cycle fluctuation monitoring and early warning, and the fuzzy logic analysis in the power quality management of telecommunications system were presented. Finally, the simulation experiment was carried out, and the experiment was summarized and discussed. The experimental results showed that the effectiveness of the business cycle monitoring and early warning model based on BPNN was 7.98% higher than that of the traditional early warning model. Therefore, how to correctly grasp the fuzzy logic in the power quality management of the telecommunications system and predict the trend of economic development to avoid the ups and downs of domestic economic growth, so as to promote the healthy development of the economy, is a research topic of great practical significance.

1. Introduction

Many scholars have studied the economic cycle monitoring and early warning. Casagli studied that many major mining countries were considering the use of wireless sensors to prevent major damage and economic losses through early warning to reduce accidents [1]. Diks constructed early warning signals by identifying key bending features based on time series observation, which had been developed for many times as a potential application field of financial crisis [2]. Shen, Tao discussed the high economic costs of various economic crises, such as the social losses caused by banking, financial and monetary crises. The development of early warning systems could help prevent economic and commercial crises, while systematically predicting adverse events [3]. Zheng, Liyang believed that manufacturing industry was a key sector in the economy of many countries and had contributed to sustainable economic growth [4]. Herrera used convolutional neural network and SVM technology to establish an early warning model for macroeconomic impact. The training set of macroeconomic panel data was transformed into a matrix, and then it was input into the CNN model. The extracted feature vector was input into the support vector machine through convolution and connection operations [5]. Piciullo proposed and used the economic early warning model of the mobile weighted average composite index to conduct an empirical test of early warning monitoring on China's current economic situation, so as to improve the accuracy and reliability of the early warning system [6]. Kitar's research showed that when scaling the periodic macroeconomic data of Russia, it was of experience and predictive value to combine the views of enterprises and households, especially during the peak period of the crisis [7]. The above research has achieved good results. However, with the continuous updating of technology, there are still some problems.

Many scholars have studied BP (back propagation) neural network. Guo, Nan analyzed the strong nonlinear adaptability of the BPNN network, considering using the BPNN network for precipitation forecast. Then, he used the sparrow search algorithm to optimize the initial threshold and weight data of the BPNN to improve the precipitation forecast performance [8]. Cui, Kai analyzed the geotechnical material properties, deposit distribution and geotechnical parameters based on the BPNN principle, and conducted the numerical simulation by using the technical geological database as a research platform [9]. In order to manage the financial risks of farmers and promote the healthy development of rural finance, Liu, Yutang established a farmers' financial risk early warning model by using the neural network based on the rough set theory and the in-depth research on the risk assessment, prediction and prevention theory [10]. Wang, Weina determined the number of nodes to the hidden layer of BPNN by gray association analysis to optimize the structure of BPNN and improve the accuracy of network prediction [11]. Lin, Min used neural network to carry out Internet early warning and credit risk assessment, extending the application of neural network in Internet finance and providing a new development direction for Internet early warning and credit risk assessment [12]. He, Fei analyzed building time-series models using genetic back-propagation and BPNN algorithms to identify individual waveforms of heat-to-temperature changes during shape decay [13]. Fuentes developed an artificial neural network model based on the backpropagation formula. It was a major challenge in many fields to predict future climate events by using meteorological data to predict the lowest temperature of the next day [14]. The above research shows that the application of BPNN has a positive effect, but there are still some problems.

Stable development and suppression of fluctuations are important indicators in economic development. However, expanding the reproduction cycle involves all aspects of the entire economic activity. Any abnormal change in any link causes the overall fluctuation of the entire economy. According to the essential characteristics of power quality interference, a fuzzy discrimination method based on transient power quality interference is adopted. Moreover, there are so many factors causing and triggering change in different regions and contexts that it is difficult to separate this phenomenon from its roots.

2. BP Neural Network Related Utilization Algorithm Model

(1) Traditional pattern classification algorithm based on BPNN

BP network is a neural network used to train the reverse transmission of errors, which includes two processes: forward information transmission and backward errors [15]. The network usually contains three or more layers of neurons, including input layer, hidden layer and output layer. The hidden layer neurons of BPNN are nonlinear, while the output layer is linear. For a certain number of hidden layer nodes, it can approximate a continuous function in any closed interval. Among multi-layer feed forward networks using BP algorithm, the single hidden neural network shown in Figure 1 is the most widely used.

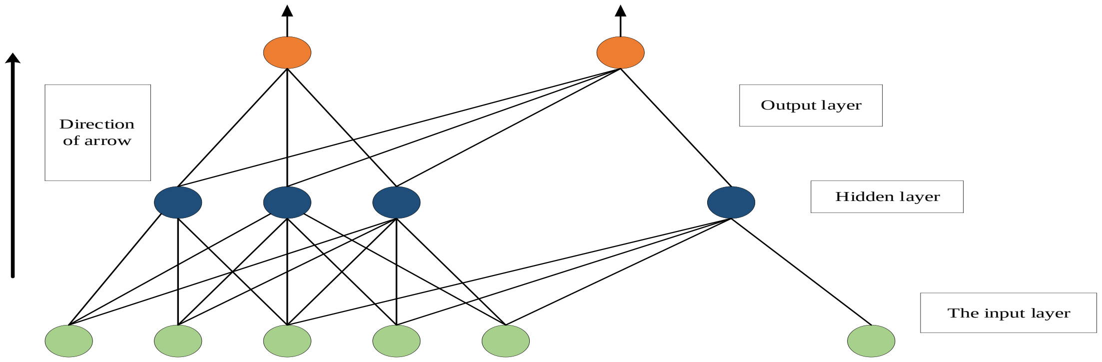

Figure 1: Single-hidden-layer neural network

The model structure serves as a classifier, and its workflow can be divided into: BPNN learns from different training samples, and adjusts the connection weight and threshold of each neuron according to the difference between the network output value and the expected value, so as to ensure that the network output reaches the required state [16].

It is supposed that the BP network can be divided into n template classes, and $W_y (y = 1,2,..., x)$ is the class space of x template classes. The network structure is usually determined. If the number of nodes in the network output layer is equal to the number of classification lines, then:

$$W = \{\{w_{11}, w_{12},..., w_{1x}\}, \{w_{21}, w_{22},..., w_{2x}\},..., \{w_{x1}, w_{x2},..., w_{xy}\}\} \tag{1}$$

W is the expected output of the network to the samples of x known pattern categories and the typical output of the ith known pattern category. The selection is:

$$w_{xy} = \begin{cases} 1, j = i \\ 0, j \neq i \end{cases} i = 1,2,..., x; j = 1,2,..., x \tag{2}$$

If the input sample is calculated by the network, the network output sequence is: $Y = \{y_1, y_2,..., y_x\}$. The decision method of traditional BPNN classification algorithm is:

$$y_j = \max_{1 \le i \le x} \{y_i\} \tag{3}$$

$$Y \in W_j; j \in [1, x] \tag{4}$$

This method is simple, practical and easy to distinguish. However, the information of other networks cannot be fully considered

$$\{y_i : j \in [1, n]; j \neq j^*\} \tag{5}$$

(2) BP algorithm

For supervised learning, supposing Y_{ok} is real measurement data, the objective function of BP algorithm can be expressed as:

$$z = \min \sum_{k=1}^{m} (Y_k - Y_{ok})^2 \tag{6}$$

1) Determination of the number of hidden nodes

When optimizing the control variables, it is assumed that the state variables are determined, and the control variables are usually difficult to solve because they are discrete. To determine the structure of the neural network, a penalty is added to the objective function, so Formula (6) can be expressed as:

$$z = \min \sum_{k=1}^{m} (Y_k - Y_{ok})^2 + \gamma \sum_{j=1}^{N} u_j (1 - u_j) \tag{7}$$

Then constraints are added:

$$0 \le u_j \le 1 \tag{8}$$

Formula (7) is optimized under the following conditions:

$$\partial z = \sum_{k=1}^{m} 2(Y_k - Y_{ok}) \partial Y_k = 0 \tag{9}$$

The formulas can be further rewritten as follows:

$$\partial Y_k = \beta_{jk} h_j \tag{10}$$

$$\sum_{i=1}^{n} a_{ij} x_i + a_{0j} \tag{11}$$

2) Determination of network parameters

The gradient method is usually used to train the grid parameters. Although the gradient method often falls into the local optimal solution, it is still possible to obtain a better optimal value through a better initial value. Since the determination of hidden nodes determines the grid structure, the gradient algorithm can obtain ideal results. For the network parameter determination problem, the control variable u_j has been determined, and there is no corresponding inequality constraint. The gradient method is applied to modify the network parameters, and its iterative formulas are as follows.

$$\Delta \beta_{jk} = \partial \beta_{jk} = (Y_k - Y_{ok}) u_j h_j \tag{12}$$

$$\Delta \beta_{0k} = \partial_Z = Y_k - Y_{ok} \tag{13}$$

Then the correction formulas can be expressed as:

$$\beta_{jk}^{(l+1)} = \beta_{jk}^{(l)} + \eta \Delta B_{jk} \tag{14}$$

$$\beta_{0k}^{(l+1)} = \beta_{0k}^{(l)} + \eta \Delta B_{0k} \tag{15}$$

3. Correlation Factors of BP Neural Network Economic Cycle Monitoring and Early Warning Model

(1) Classification of BPNN

1) The development of neural network

In the development of artificial neural networks, there has been no effective method to adjust the connection weight of hidden layers. On this basis, a multi-layer feedforward neural network is used to weight and adjust the nonlinear continuous function [17].

BP is an error code algorithm of reverse transmission, which consists of the first and the last two parts [18]. The neurons of each input layer receive the input data from the external world and pass it to the neurons in the different intermediate layer. The middle layer is the internal information processing layer of information transformation, which can be designed into one or more layers according to the changes of information requirements. Then, the final data is transmitted to each neuron of the output layer for a transmission, and finally the data processing results are output to the external world. When the actual result is inconsistent with the expected result, an error return occurs. The error of the output layer is corrected for each weight layer by gradient error increment and propagated back to the hidden and input layers. This cycle is a kind of learning and training for the neural network until the errors on the network are reduced to an acceptable level or reach the predetermined learning times.

2) Characteristics of neural networks

Thinking generally believes that the thinking of human brain can be divided into three basic modes: abstract thinking, image thinking and inspiration thinking, as shown in Figure 2.

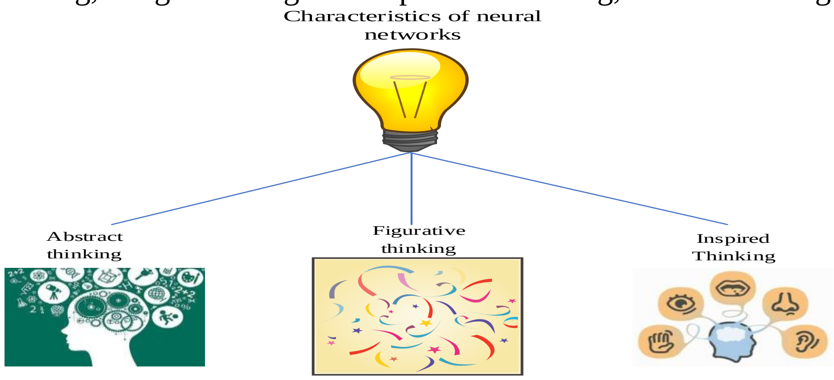

Figure 2: Characteristics of the neural network

Logical thinking is the reasoning based on logical laws. Information is first converted into concepts, and then logical reasoning with symbolic expressions in a series of symbolic operations programs can be written into a series of commands executed by a computer [19]. However, intuitive thinking is the integration of information stored in a decentralized way, so that an idea or an answer to a question suddenly emerges. There are two basic points of this thinking method. One is to store messages separately in the network. The other is through the stimulation mode among neurons. The information processing is carried out by the dynamic interaction between neurons.

Artificial neural network has certain adaptability and self-organization function. In order to better meet the needs of the environment in learning and training, the same network can play different roles according to different learning methods and contents. Generally, the learning methods can be divided into two types. One is guided or guided learning. At this time, certain sampling criteria are used to classify and simulate it. The second is learning without guidance. In this case, only specific learning methods or rules are specified. The specific learning content changes with the change of the environment, so that the characteristics and laws of the surrounding environment can be found automatically to make it closer to the human brain [20].

(2) Problems in monitoring and early warning of business cycle fluctuations

The problems in three aspects are summarized here, as shown in Figure 3.

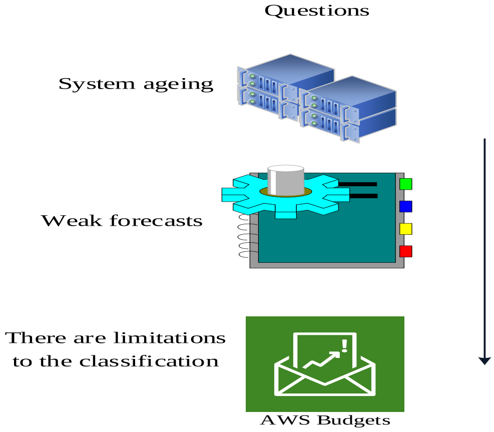

Figure 3: Problems existing in the monitoring and early warning research of economic cycle fluctuations

1) System aging

Economic cycle monitoring and early warning is guided by macroeconomic theory and starts from the history and current situation of economic development. It uses relevant prediction techniques and methods to analyze and calculate them, so as to understand the law of their development to determine whether they are in supercooling, overheating, stability, expansion or contraction. Some existing indicators have not been timely adapted to the needs of new economic development. In particular, the originally set threshold range of macroeconomic and various indicators can no longer meet the needs of new economic development, which has a certain impact on the normal operation of the monitoring and early warning system.

2) Weak prediction

Early warning technologies are mostly those used by developed countries in Europe and the United States in the late 1970s. Their development level is relatively low. Some existing indicators have not been timely adapted to the new needs of economic development. In particular, the originally set threshold range of the overall economy and various indicators can no longer meet the needs of new economic development, which has affected them to some extent.

3) Limitations of classification

At present, KL (Kullback Leibler) information is the most commonly used method for time difference classification of economic indicators. KL information is used to classify the time difference of economic indicators, that is, KL information is used to judge the phase difference between indicators. In the calculation of KL information amount, if the initial phase is not taken into account, the KL information amount obtained by the left and right movement of the corresponding data on the time axis is the same.

(3) Factors influencing economic cycle monitoring and early warning of electric energy telecommunication system

In the prediction of power system, the prediction of power economic indicators is a very important work. The scientific prediction of the economic indicators of the power grid helps the power grid to reduce the power supply cost, so as to reasonably dispatch the operation of the units and formulate the marketing strategy. Power system is a very complex system. Its operation is affected by many economic indicators, as shown in Figure 4.

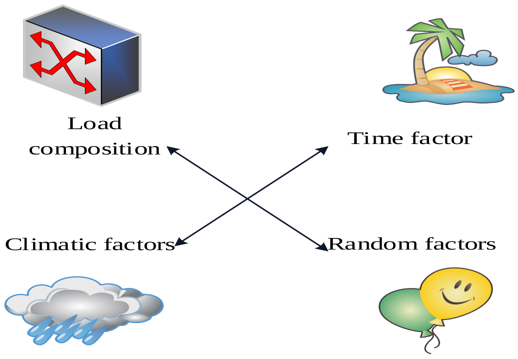

Figure 4: Impact on the operation and operation of the power system

1) Load composition

According to the nature of load, it can be divided into industrial load, commercial load, residential load, agricultural load and other load types. With the continuous development of electrification, the annual growth rate and seasonal fluctuation of residents increase, especially the rapid development of air conditioning equipment, which has greatly affected the peak load of the power grid. The commercial load varies with seasons, which has the greatest impact on the night peak. Industrial load is usually regarded as basic load and is not affected by other factors. The agricultural load has obvious seasonal characteristics, and has a great correlation with precipitation. The variation rules of various loads are different. Therefore, different load compositions have different impacts on the system load.

2) Time factor

Seasonal changes, cycles, statutory holidays, traditional festivals and other ways have an impact on the load. When seasons change, temperature, day and night length, lifestyle, etc., all lead to changes in load. Because production and living habits change periodically in different periods, the change of power load usually takes a week or a day as a cycle.

3) Climatic factors

The impact of meteorological factors on system load is affected by temperature, wind, cloudy days, rain and snow and other factors, the most important of which is the sudden change of load. From the influence degree of the above factors on the load, the temperature has the most obvious influence on the load. In addition, humidity has an important impact on the load of the power system, especially in drought years when large-scale drainage and irrigation are required.

4) Random factors

In addition to the above three factors, other factors that affect the system load are collectively referred to as random factors. For example, the startup and shutdown of large industrial equipment produces impact power loads, which causes large load fluctuations. In addition, although some specific events, such as political events and celebrations, can predict the occurrence of events, their impact on the load is unknown.

4. Simulation Experiment of Economic Cycle Monitoring and Early Warning in Electric Power Enterprises

The experiment shows that under the condition of using BPNN, this experiment collects 4 foreign telecommunications companies as data samples to give early warning to the economic cycle monitoring in the system power quality management. The traditional business cycle monitoring and early warning model (hereinafter referred to as the traditional early warning model) is compared with the business cycle monitoring and early warning model under BPNN (hereinafter referred to as the new early warning model).

The warning line is also called the detection value. It is the dividing line between two adjacent signal lamps of four different types (A-D). The selection of early warning scope is very critical, which directly affects the judgment of the operation of the entire national economy. Therefore, it should be chosen carefully. Generally, empirical discrimination is used to determine the early warning range, as shown in Table 1.

Table 1: Early warning limits of early warning indicators

Name of index	A	B	C	D
Value added	15.7%	13.9%	7.4%	3.7%
Total energy production	11.6%	9.7%	6.8%	2.9%
Total retail sales of social consumer goods	21.9%	18.7%	11.7%	7.4%
Deposit balances of financial institutions	22.8%	16.9%	11.4%	11.7%
Loan balance of various financial institutions	18.9%	13.1%	13.7%	5.9%
Commodity retail price index	7.8%	4.7%	0.9%	0.1%

(1) Economic cycle stage in telecommunication system

The Economic cycle, also known as the business cycle and the boom and depression cycle, generally refers to the regular expansion and contraction of economic activity that occurs in the course of economic development. It refers to changes in GNP, GNI and total employment, and alternating or periodic movements between increases and decreases in GNP and total activity.

Figure 5 shows the analysis of the traditional model and the new model in the four stages of the economic cycle.

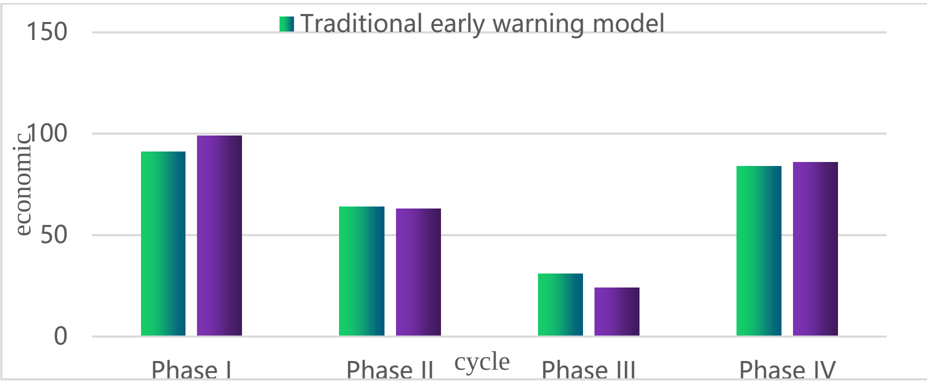

Figure 5: Analysis of traditional model and new model in four stages of economic cycle

It can be seen from Figure 5 that in the traditional early warning model of Phase I, the economic development power is 91%, while the economic development power of the new early warning model is 99%. It can be seen that the economy in the telecommunications system in Phase I is in a prosperous stage and the results of the new early warning model are more detailed. In the second stage, the economic development power of the traditional early warning model is 64% and that of the new early warning model is 63%. It can be seen that in the second stage, the economy in the telecommunications system changed from prosperity to recession. In the third stage, the economic development power of the traditional early warning model is 31%, while the economic development power of the new early warning model is 24%. It can be seen that in the third stage of the telecommunications system, the economy changed from recession to depression. In the traditional early warning model of Phase IV, the economic development power is 84%, while the economic development power of the new early warning model is 86%. It can be seen that in the fourth stage of the telecommunications system, the economy changed from depression to recovery. According to the above description of the figure, the following results can be obtained. The four telecom enterprises have roughly experienced four stages of prosperity, recession, depression and recovery in the economic cycle stage of the system, and the results of the new early warning model in each stage are more specific than the traditional model.

(2) Efficiency

According to the economic cycle stage of the telecommunications power system in the telecommunications enterprises in the above experiment and literature review, the traditional early warning model and the new early warning model are compared for four enterprises, as shown in Figure 6.

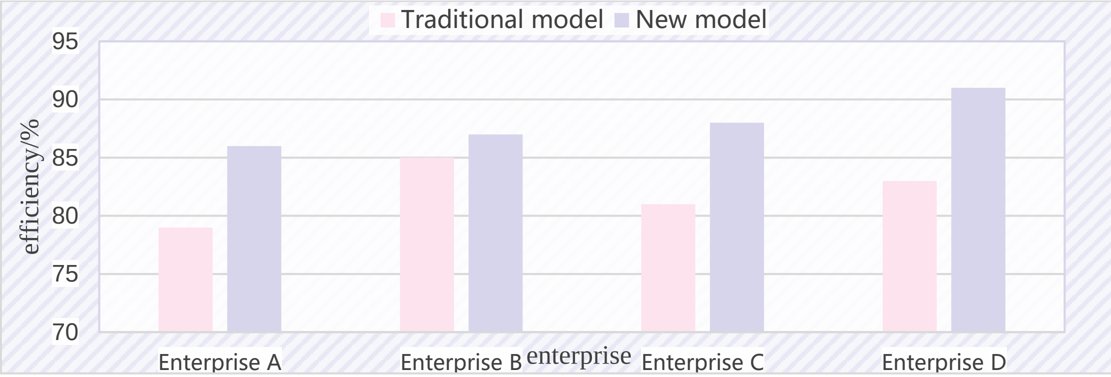

Figure 6: Efficiency situation of the two models in the four telecom enterprises

It can be seen from Figure 6 that among the four telecom enterprises, enterprise B has the highest efficiency in the traditional early warning model, and enterprise D has the highest efficiency in the new early warning model. Among them, the efficiency ratio of enterprise A's traditional model to the new model is 79%: 86%. The efficiency ratio of enterprise B's traditional model to the new model is 85%: 87%. The efficiency ratio between the traditional model and the new model of enterprise C is 81%: 88%. The efficiency ratio between the traditional model and the new model of enterprise D is 83%: 91%. It can be seen that no matter which enterprise uses the model under BPNN, the efficiency of the model is higher than that of the traditional model. Therefore, it can be seen that the new model is worth popularizing.

(3) Accuracy

The accuracy of the model is also one of the criteria for testing whether the model meets the requirements of the current enterprise development. In this part, the accuracy analysis of the two models in four power quality management projects is shown in Figure 7.

Figure 7: Accuracy analysis of the two different models

According to Figure 7, the highest accuracy of the traditional early warning model in the four projects is 88%, while the highest accuracy of the new early warning model in the four projects is

98%. The specific accuracy of the four projects is as follows: The accuracy of the traditional model in Item 1 is 85%, while the accuracy of the new model is 8% higher than that of the traditional model. The accuracy of the traditional model in Item 2 is 83%, while that of the new model is 12% higher. The accuracy of the traditional model in Item 3 is 86%, while that of the new model is 12% higher. The accuracy of the traditional model in Item 4 is 88%, while the new model is 9% higher. It can be seen that the accuracy of the new early warning model is higher than that of the traditional model.

(4) Satisfaction analysis

This part collects and analyzes 100 questionnaires about the use of the two models by relevant staff from four telecom companies. Among them, 50 copies of traditional models and 50 copies of new models are valid. Figure 8 shows the satisfaction type analysis.

It can be seen from the line chart that the trend of the two lines is: the trend of the first line is first down, then up, and then down. The second broken line is rising first and then falling. In the traditional model, there are 13 people who show "dissatisfaction", 6 people who show "average", 27 people who feel "satisfied" and 4 people of "other" types. In the new model, there are 5 people who show "dissatisfaction", 7 people who show "average", 35 people who feel "satisfied", and 3 people of "other" types. Through data calculation, the "dissatisfaction rate" and "satisfaction rate" of the traditional model are 26% and 54%. The "dissatisfaction rate" and "satisfaction rate" of the new model are 10% and 70%.

How to correctly grasp the fuzzy logic in power quality management of telecommunication system and predict the economic development trend is worth discussing. To sum up, the experimental results show that the effectiveness of the business cycle monitoring and early warning model using BPNN is 7.98% higher than that of the traditional early warning model.

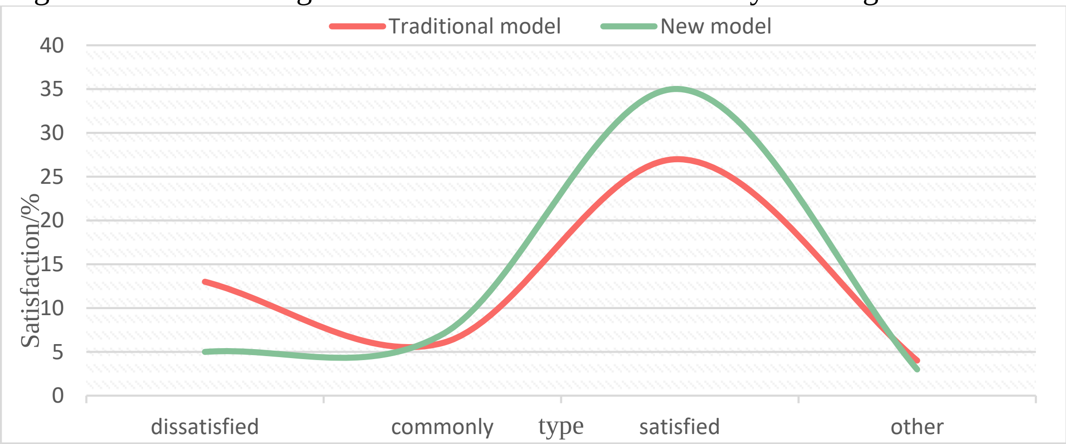

Figure 8: Satisfaction type analysis

5. Conclusion

The prediction and early warning of power quality steady-state index is the key to optimize power grid operation mode. BPNN was used to establish a complex neural network prediction system. A hierarchical early warning method of power quality based on fuzzy clustering was proposed, which could flexibly set the critical value according to the actual situation and provide corresponding power quality early warning according to the needs. Through the model construction simulation experiment, the experiment has obtained the research results of economic cycle stage analysis, efficiency analysis, accuracy analysis and satisfaction analysis in the telecommunications system. Finally, it was concluded that the business cycle monitoring and early warning model using BPNN was more effective than the traditional early warning model.

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