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Research on Instrumentation Health Status Evaluation MethodBased on Neural Network

Research on Instrumentation Health Status Evaluation MethodBased on Neural Network

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ABSTRACT: Metrology support includes the management of measurement equipment and measurement process, which is an indispensable part of engineering construction. Aiming at the health status of instrumentation in use in enterprises metrological verification, BP and SOFM neural networks are introduced, the characteristics of the two neural networks are introduced, the sample data system and network algorithm are designed, and a set of scientific and complete evaluation methods are produced through algorithm practice and data analysis, which provides direction for the research on the health status of instrumentation in use.

1. introduction

Metrology support is to minimize the possible incorrect measurement results through the management of measurement equipment and measurement process[1]. The number of instrumentation in our enterprise is huge, and the corresponding metrology support work is very important. However, at present, we can only judge whether the equipment is available through periodic verification, and we can't find out its health status in use. Based on this, risk prevention and control can't be carried out. The construction of our project is faced with the problem of possible damage of instrumentation at any time. In recent years, neural network theory has developed rapidly, especially BP neural network has a wide range of applications in solving complex interrelated fields such as pattern recognition and expert system[2], while SOFM neural network is applied to a wide range of fields such as process system analysis, statistical pattern recognition, communication and image coding[3]. In China, Horizon Robotics Technology Co., Ltd. has applied artificial neural network algorithm to vehicle assisted driving system; In other countries, the TruthNorth neuron chip developed by IBM has opened up the precedent of "brain-like" computing[4]. To sum up, this paper introduces BP and SOFM neural networks, selects the pressure gauge as the sample and designs its data system, determines the health status baseline through the optimization algorithm, studies the threshold division based on the clustering characteristics, and finally provides a complete analysis method for the health status evaluation of instrumentation of enterprises.

2. introduction to two kinds of neural networks

2.1 BP neural network

BP neural network, the full name of error back-propagation neural network, belongs to a kind of forward network. The network is widely used in classification and recognition, approximation, regression, compression and other fields[5]. In practical application, about 80% of neural network models adopt BP network or its variation forms[6]. Its basic structure is shown in the figure below.

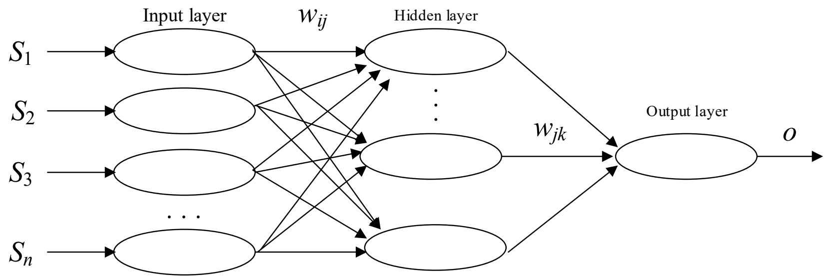

Figure 1. Basic structure of BP neural network

The basic algorithm is:

For sample set

$$S = \{(X_1, Y_1), (X_2, Y_2), \ldots, (X_n, Y_n)\} \quad (1)$$

The network calculates the actual output O_n and error measure E_n according to(X_n,Y_n), and makes the nth adjustment for $W^{(1)}$, $W^{(2)}$,…, $W^{(M)}$ respectively. This process is equivalent to a cycle of processing each sample in the sample set. This cycle needs to be repeated until the sum of error measures meets the requirements of the system for the whole sample set.

2.2 SOFM neural network

SOFM neural network is called self-organizing feature mapping network, which adopts the idea of competitive learning. The biological basis of this neural network is the phenomenon of lateral inhibition between neurons[7]. Its initial structure is as follows:

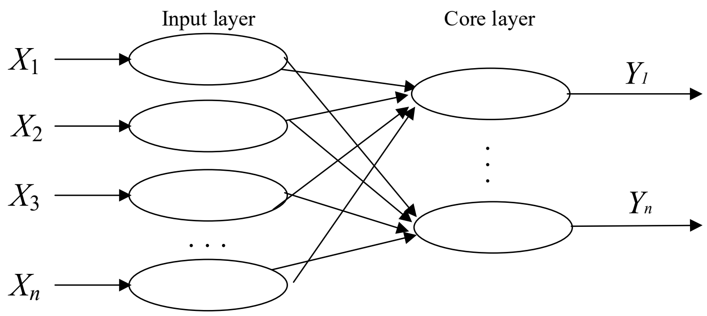

Figure 2. Initial structure of competitive neural network

The basic algorithm is summarized as follows: in a calculation, only one output neuron wins, the winning neuron is marked as 1, and the other neurons are marked as 0. The weights from the input layer to the core layer are given randomly, and finally there will be a neuron with the strongest excitation[8]. The neurons with the strongest excitation are further strengthened in the weight modulation. Through this competition, the distribution information of training samples, i.e. sample categories, can be obtained. When new samples are input, pattern classification can be carried out according to the excited neurons.

3. data system design

As an important part of instrumentation of our enterprise, general pressure gauges are prone to unqualified conditions in use. Therefore, taking the general pressure gauge (hereinafter referred to as pressure gauge) as an example, this paper introduces the process of data reconstruction, which brings universal design method to the data system of various instrumentation.

The verification items of the pressure gauge mainly include the indication error, hysterisis error and friction error under the two strokes of pressure rise and pressure drop. The indication data of pressure’s rise and drop directly characterize the performance of the pressure gauge in operation. The record format is as follows:

2. Error of indication/hysterisis/friction: Unit: MPa

Nominal Pressure	VOIEAT Boost	VOIEAT Depress	PCBAT Boost	PCBAT Depress	Result	Project	Below 90% max range	At&above 90% max range
0	0.000	0.000	0.000	0.000	Indication Error	Permission	± 0.0096	± 0.0150
0.1	0.102	0.106	0.000	0.000		Max	0.006	0.002
0.2	0.202	0.206	0.000	0.000	Friction Error	Permission	0.0048	0.0075
0.3	0.302	0.306	0.000	0.000		Max	0.000	0.000
0.4	0.402	0.406	0.000	0.000	Hysterisis Error	Permission	0.0096	0.0150
0.5	0.502	0.506	0.000	0.000		Max	0.004	0.000
0.6	0.602	0.602	0.000	0.000	Result		√ Qualified\	□ Unqualified

Figure 3. Original record format of the pressure gauge

Considering the generalization ability of the research method, this paper needs to reconstruct the collected sample data. Pressure gauges in use have different ranges and accuracy levels, and their error levels cannot be directly compared. Therefore, a method for determining the error level is designed:

$$r = \frac{|e|}{|MPE|} \times 100\% \tag{2}$$

Where r represents the relative error based on the maximum allowable error limit, e represents the error value of a single data, and MPE represents the maximum allowable error. The algorithm of maximum allowable error is:

$$MPE = \pm(FS \times \mathrm{LOA}\%) \tag{3}$$

Where FS refers to the value of full scale, which refers to the range of the pressure gauge; LOA indicates the accuracy level[9].

The relative error r can fully represent the error degree of the current pressure gauge, but if you expect to have a clearer performance in network training and result display, the training data samples need to be sorted in two-dimensional or three-dimensional form. Several data of each pressure gauge are summarized into two typical characteristic values, and the calculation method is as follows:

$$r_{11} = Max(r^{(2)}, r^{(3)}, \dots, r^{(m)}) \tag{4}$$

$$r_{12} = \frac{r^{(2)}+r^{(3)}+\dots+r^{(m)}}{m} \tag{5}$$

Where m represents the number of verification points. The zero point is removed from the value because the pressure gauge is often set with a stop pin, which makes the zero position error unable to accurately express the error level. r_{11} and r_{12} constitute an array to meet the basic description of the health status of the pressure gauge. r_{11} can reflect the linear error of a single pressure gauge or the nonlinear data jump caused by structural damage, and r_{12} can systematically describe the indication error level of the pressure gauge; The composition of r_{11} and r_{12} is not deeply processed to provide offset free information input for the neural network as much as possible. All data groups also performed preliminary normalization in the above reconstruction process, and the form is simplified as follows:

$$\mathrm{R} = \{(r_{11}, r_{12}), (r_{21}, r_{22}), \dots, (r_{n1}, r_{n2})\} \tag{6}$$

4. design and implementation of algorithms

4.1 Design and implementation of BP network algorithm

4.1.1 Algorithm design and implementation

A total of 100 samples are used in this round of algorithm, including 50 newly purchased pressure gauges (referred to as new gauges) and 50 old gauges in use. By default, the data of new gauges represent good health, while the other ones represent its health under actual working conditions. 25 groups are selected from the samples as the training data of BP neural network, and the remaining samples will be brought into the network for testing its classification performance.

Firstly, batch training is adopted to input all samples at the same time to calculate the overall error. The network flow is shown in Figure 4.

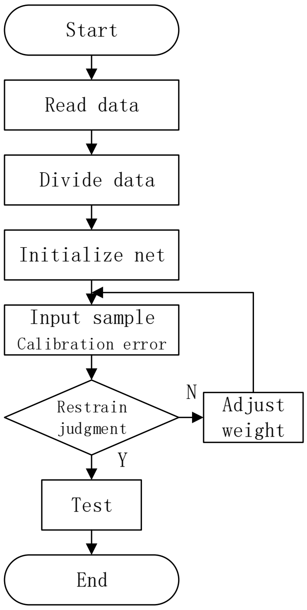

Figure 4. BP network process

1	Num	Attribute	Rn1	Rn2
2	21120254	New	0.375	0.1655
3	210100019	New	0.56	0.248
4	21120152	New	0.48	0.24
5	202202429	New	0.2	0.1175
6	202202449	New	0.5	0.1625
7	202111217	New	0.4	0.08
8	202111293	New	0.5	0.18
9	202202431	New	0.5	0.2125
10	202111288	New	0.5	0.13
11	202111213	New	0.2	0.07
12	202202441	New	0.3	0.06
13	202202444	New	0.5	0.17125
14	02220242З	New	0.2	0.05
15	202111285	New	0.5	0.23
16	202202456	New	0.4	0.1575
17	202202442	New	0.3	0.13
18	202202432	New	0.5	0.1575
19	202111212	New	0.4	0.175
20	202202448	New	0.1	0.0225
21	202202428	New	0.2	0.085
22	202202463	New	0.1	0.03
23	202202437	New	0.2	0.1075
24	202202433	New	0.4	0.1725
25	202111289	New	0.3	0.1275
26	202202436	New	0.3125	0.1325
27	1237147	Old	0.32	0.168
28	1237101	Old	0.32	0.264
29	1237136	Old	0.5	0.356
30	1237107	Old	0.8	0.58
31	11124330	Old	0.8	0.492
32	11107148	Old	0.64	0.4
33	1607048	Old	0.32	0.196
34	0298016	Old	0.5	0.2625
35	1607059	Old	0.96	0.504
36	YQXF004	Old	0.25	0.18125
37	04112171	Old	0.32	0.296
38	0612415	Old	0.96	0.528

Figure 5. Training data form

(1) Data reading and division. The data information is saved in an XLS format table, listing the number, attribute, r_{n1} and r_{n2} respectively, as shown in Figure 5. Use MATLAB to read the information and save it in data; 1 represents the new and 0 represents the old. Save the attribute in label; Random positive integers are generated by Randperm function to disperse the data, then divide it into two parts for training and testing.

(2) Initialize the BP network and calculate the sample error. The neural network contains a hidden layer, and the training method adopts the steepest descent method including momentum, which is carried out in batch. Since the output value of the output layer is not 0 or 1, the transfer functions of the hidden layer and the output layer use the Log-Sigmoid function:

$$logsig(n) = \frac{1}{1+e^{-n}} \tag{7}$$

Combine the threshold into the weight, write the function to construct the network, initialize the weight to a small random number, and set the number of hidden layer neurons to 3 in order to speed up the training;

In order to offset the possible relative error rate greater than 100% in data, the samples must be normalized again. Move the data to the center of the coordinate axis by subtracting the samples average, and then divide it by the sample standard deviation to standardize the variance. After completion, input the sample into the network and calculate the error.

(3) Judge whether the error converges and adjust the weight accordingly. Define an error tolerance, which is set to 0.01. When the sum of squares of sample errors is less than this tolerance, the algorithm converges; In addition, given a maximum number of iterations, set it to 2000 times, and stop the iteration when it reaches this number.

The weight is adjusted according to the following formula:

$$\Delta\omega_{ij}(n) = \eta\delta_j^i v_I^i(n) \tag{8}$$

Among them, δ^i_j is the local gradient, η is the learning rate. In addition, the steepest descent method with momentum factor is used here. Therefore, except for the first iteration, the weight modification of the previous iteration shall be considered in subsequent iterations:

$$\Delta\omega(n) = -\eta(1-\alpha)\nabla e(n) + \alpha\Delta\omega(n-1) \tag{9}$$

(4) Testing. The network is used for attribute recognition. The sample distribution, error classification, iteration times and accuracy are shown in the following figure:

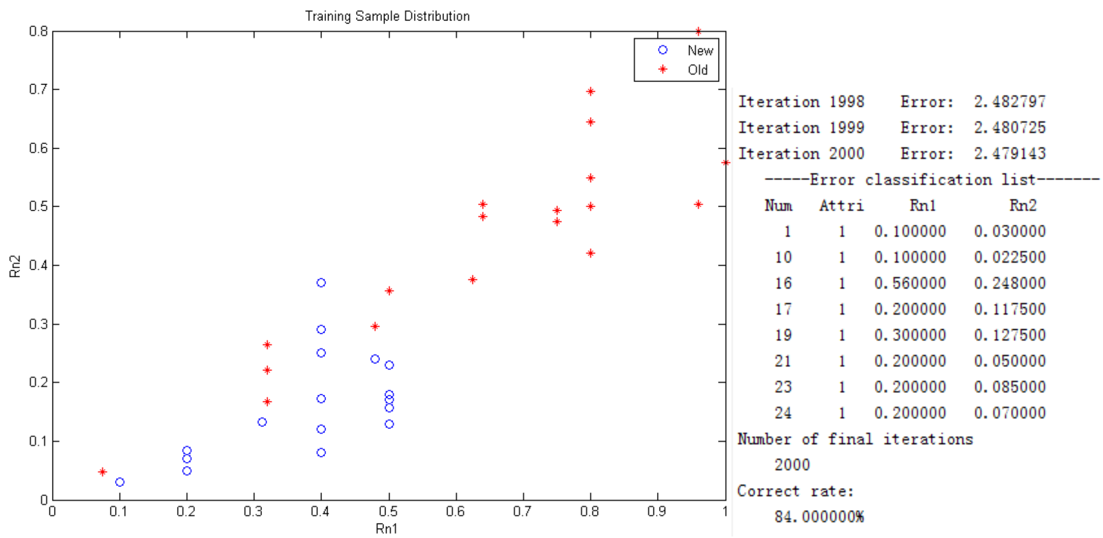

Figure 6. Batch algorithm results

Draw the error decline curve during training:

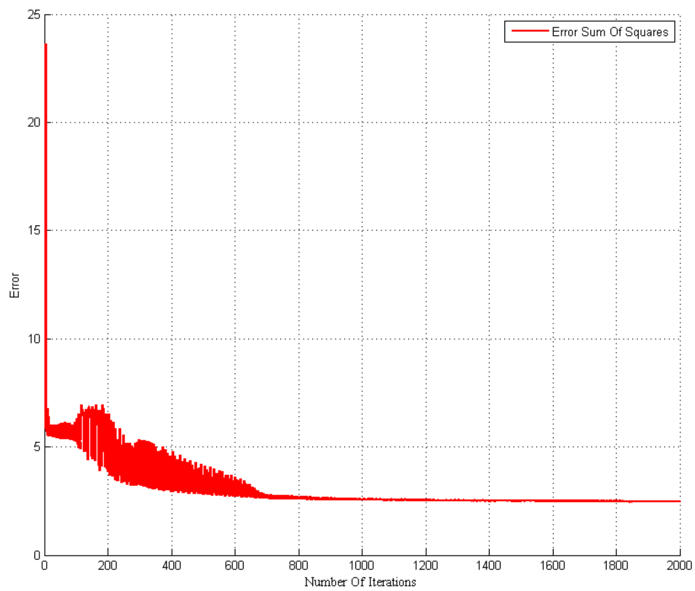

Figure 7. Iterative error decline curve

4.1.2 Algorithm optimization

The above method uses batch training method, which is prone to local optimal solution, resulting in no correction of training. The serial mode inputs the samples randomly one by one, which can avoid this problem to a certain extent, may also improve the division ability of training samples.

The design process of serial training method is similar, and the learning rate, momentum factor and iteration times need to be adjusted continuously in the test. Finally, when the learning rate is 0.1, the momentum factor is 0.2 and the number of iterations is 9000, the step-by-step advantage of the algorithm is brought into full play, and the classification accuracy is 92%.

At this time, the variation curve of training error is:

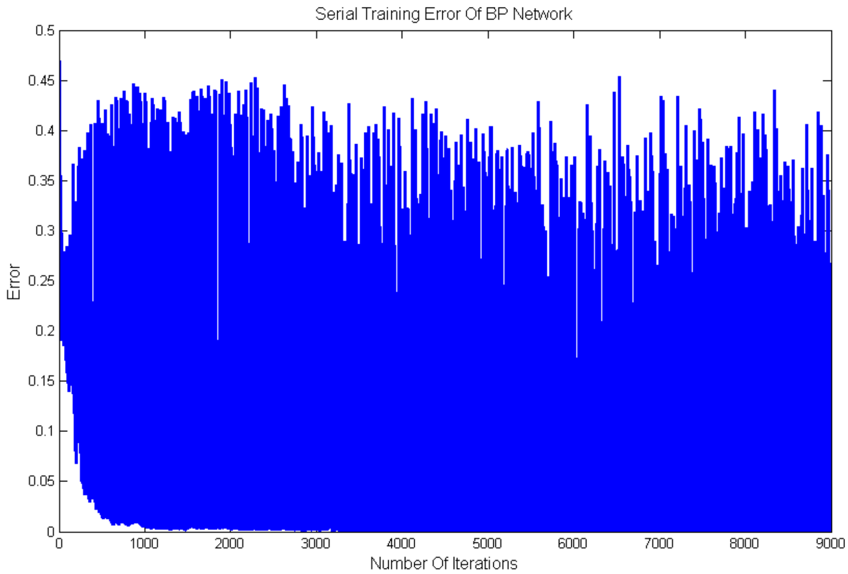

Figure 8. Variation curve of serial training error

So far, the algorithm has achieved 92% classification accuracy and reached a relatively excellent classification level.

4.1.3 Algorithm practice

A batch of pressure gauges submitted for inspection were selected as measured data, with a total of 183. The reconstructed data is brought into the serial algorithm training, and the partition accuracy is 37.7%; When the data is returned to the algorithm in the form of training for reiteration, it is found that the result fluctuates greatly, and the accuracy is directly related to the sampling data of the current old gauges.

4.2 SOFM neural network algorithm implementation

The custom SOFM algorithm still adopts the process of input network construction iterative update training classification, introduces the learning radius, and clusters by using the similarity and topology of the data itself. The specific design process will not be repeated.

Drawing the above 183 groups of data, it is found that the scale of the measured arrays r_{n1} and r_{n2} extends from 0 to nearly 15000 (if it is greater than 1, it refers to an unqualified pressure gauge), so that the image cannot be displayed correctly. Therefore, 15 groups of disqualified are eliminated. Draw the remaining data and cluster it with 8×8 topology network:

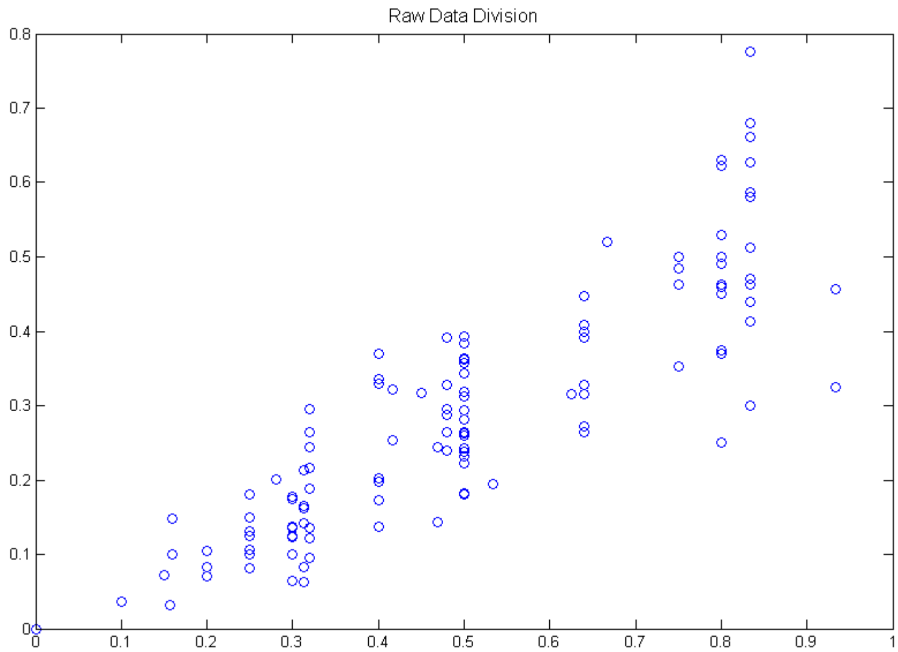

Figure 9-A. Preliminary drawing

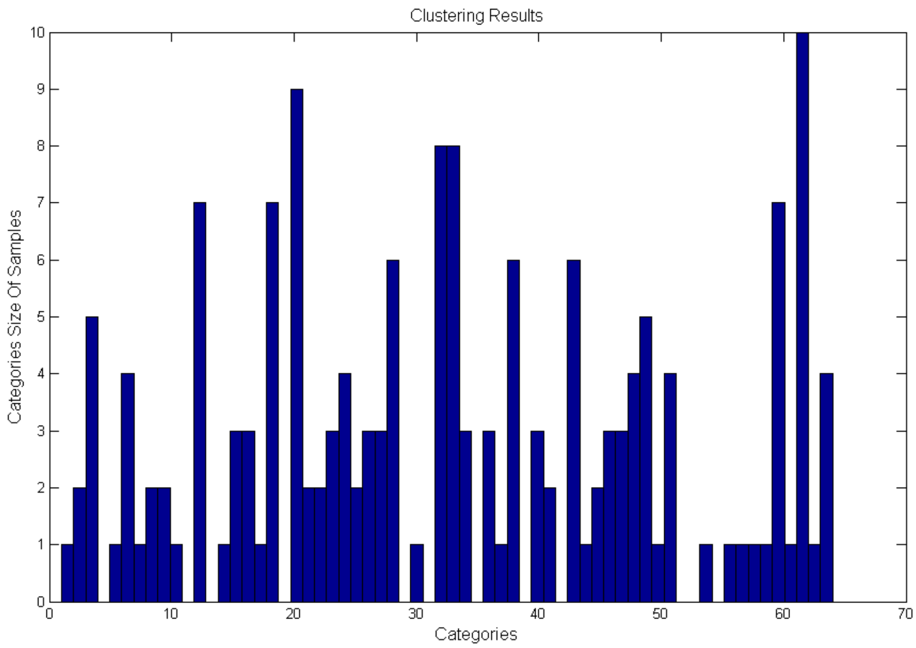

Figure 9-B. Clustering of data

Among the 64 classification frameworks in the figure above, the number of some categories is 1 or even 0, indicating that the dispersion of data does not reach this scale. Considering that the relative error rate scale has 5 areas in steps of 0.2 from 0~1, and $r_{n2} \le r_{n1}$ can be deduced from formulas (4) and (5), combined with the above dispersion degree, reduce the network scale to 3×5, draw a more intuitive cellular topology, and draw the data center points as follows:

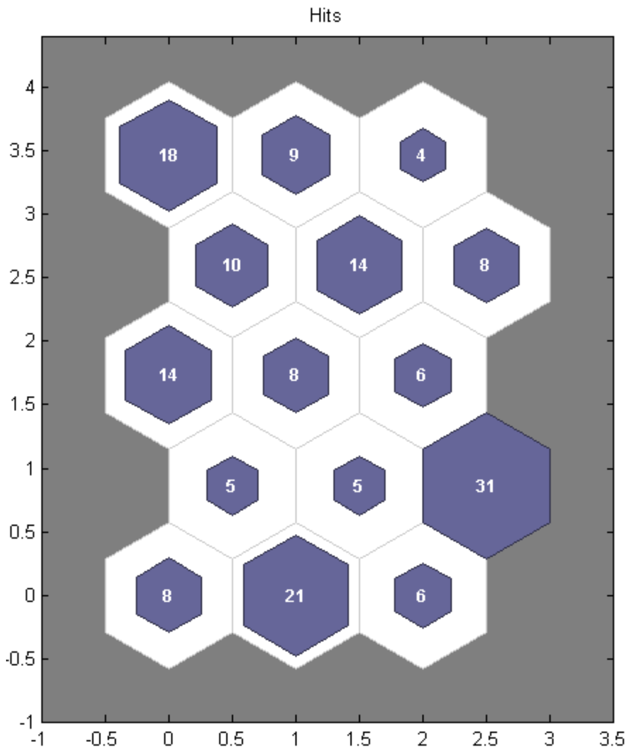

Figure 10-A. 3×5 cellular topology network clustering

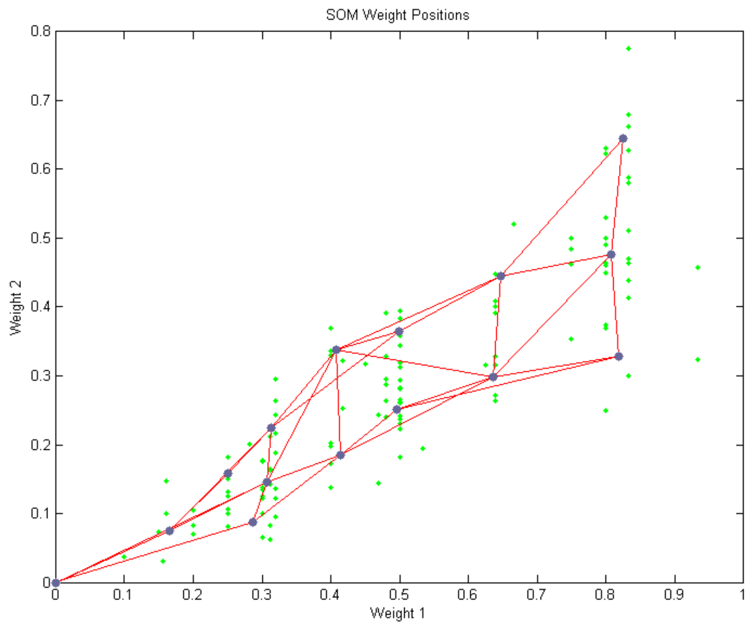

Figure 10-B. 3×5 cellular topology network center point drawing

The gradient formed by the connecting line of the central point does not reflect the health trend of a single pressure gauge, but several radial networks provide the threshold division radius of the health status of the pressure gauges in use.

Again, the competitive neural network algorithm is designed. According to the "New", "Old" and linear data forms defined when looking for the baseline, combined with the usual evaluation methods of "Good", "Medium" and "Bad", the threshold categories are divided into three corresponding ones. Finally, when the number of iterations is 2200, while the learning rate and learning radius decreasing adaptively with the number of iterations, the more rigorous clustering results are as follows:

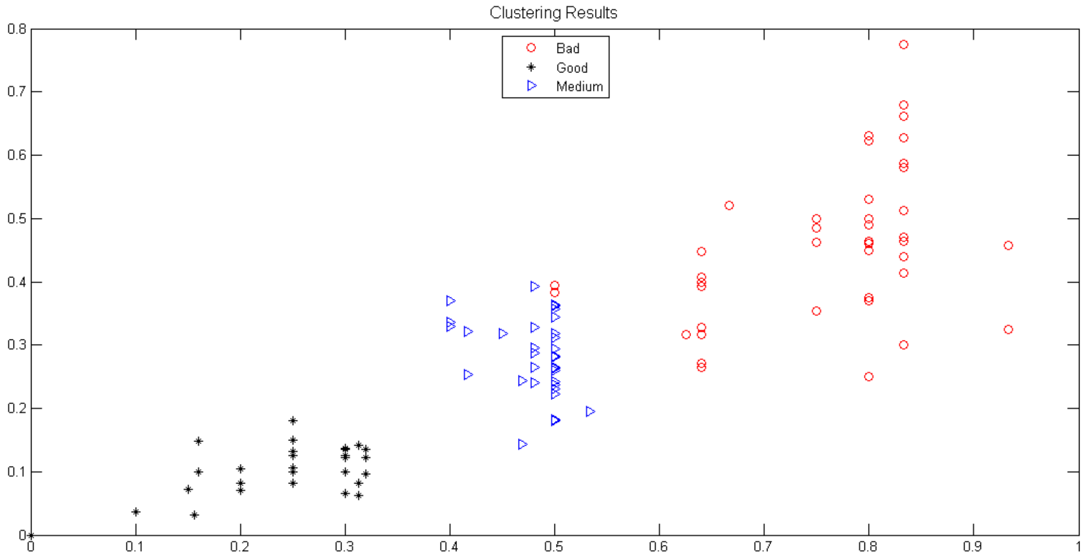

Figure 11. Clustering center point of competitive neural network

So far, the health threshold division of the pressure gauge has been completed.

4.3 Result analysis

Taking the pressure gauge as the starting point, this paper designs the sample data system and brings it into the BP neural network algorithm training to confirm the baseline of health status, and uses SOFM neural network to find the clustering and distribution characteristics. Finally, the algorithm is designed to realize the division of health threshold shown in Figure 11. The specific analysis process is as follows:

(1) The batch algorithm realizes the attribute differentiation of pressure gauge with 84% success rate, as shown in Figure 6; However, Figure 7 shows that with the iteration breaking through 1000 times, the sum of squares of errors tends to be stable, thus guess the algorithm is limited; By observing the distribution map, it can be seen that the data distribution of some old gauges intersects with the new gauges, guess that the linear indivisibility of the data is one of the factors affecting the accuracy;

(2) The optimization algorithm successfully achieves 92% accuracy, but figure 8 shows that it is difficult to continue to improve the algorithm to achieve 100% discrimination ability, the data samples are presumed to be the key reason;

(3) The classification accuracy of the algorithm practice is only 37.7%, but figure 9-A shows that the overall distribution of the test data is highly similar to the training data, and the "wrong" classified data is not a gross error; When the measured data is returned to the serial optimal algorithm as training data for reiteration, it is found that the result fluctuates greatly, and the accuracy is directly related to the sampling data of the current old gauges.

The above situation shows that with the increase of the measured number of pressure gauges in use, the linearly inseparable data is also increasing. It is inferred that there is no logic problem in the design and implementation of the algorithm itself, the accuracy depends on the good amount of data in the old gauges, and there is a baseline for the health status of the pressure gauges in use.

Therefore, SOFM network is introduced to draw the center point, as shown in Figure 10-A/B. The figures reflect the clustering of data quite well. At the same time, several radiation networks of the central points also indirectly prove that the health status can be measured by quantitative threshold. In order to fully demonstrate this assumption, SOFM algorithm is designed again, and the threshold is successfully divided into "Good", "Medium" and "Bad".

To sum up, it is concluded that the health status of the pressure gauge in use can be quantified, and different thresholds can be divided by algorithm to represent the health level.

5. conclusion

In this paper, the health status of the pressure gauges in use of our enterprise is quantified by introducing the neural network algorithm. The research results have excellent generalization ability, and can be nested and analyzed for other types of instruments in use. The research results can be directly used as a direction guide for evaluating the calibration cycle of pressure gauge, and also provide an excellent auxiliary means for the in-situ-calibration of instrumentation.

Of course, due to the incomplete sampling coverage in this paper, there is a certain deviation between the drawing of clustering threshold and the actual situation prediction, and it has not been extended to all kinds of instruments for actual measurement. In the next step, we will continue to explore the algorithm design, continuously enrich the simulation means, improve the accuracy of the algorithm, and make continuous in-depth breakthroughs in the metrology support work.

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