Operation Status Determination of Power Quality Compensatory Equipment Based on Data Analysis

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ABSTRACT

The power supply companies have codes to limit the power quality disturbance from the disturbance source, for example, wind park or arc furnace. To equip the power quality compensatory equipment is the straight way to limit it. However, it is difficult for power supply company to manage the power quality compensatory equipment on the user side. This paper presents an algorithm, based on power quality monitoring data on the grid side, to determine the operation status of the compensatory equipment on the user side for power grid companies. In this paper, the probabilistic neural network is used to classify the operation status of the compensatory equipment, by taking the voltage deviation, three-phase voltage unbalance, total harmonic distortion rate and long-term voltage flicker as the input data of the network, so as to realize the determination of the operation status of the compensatory equipment. The correctness and reliability of the proposed method is verified by the recorded power quality data from a substation in Anhui Power Grid in China.

INTRODUCTION

With the rapid development of power electronic technology, the power quality disturbance sources in power grid are with new characteristics, that is, the disturbance types are various, and the disturbance characteristics are different. The disturbance emission from the typical disturbance sources, such as arc furnace, electrified railway traction stations, photovoltaic power stations, wind farms, etc., is required to meet the relevant national standards or codes proposed by utility before connected to the grid[1-5]. It is a straight way to install the compensatory equipment on the user side to improve the power quality and reduce the disturbance emission from the user side. However, the compensatory equipment is the user's assets, the power supply company cannot know the operation status of the equipment clearly, and it is difficult to know the power quality management situation on the user side accordingly. For power supply company, in order to know the compensation and mitigation condition on the user side, it is necessary to get the information of the operation status of the compensatory equipment.

There is few research on the determination of the operation status of power quality compensatory equipment. The power quality data obtained from on-line power quality monitoring system, is the power supply company's assets. The recorded data is a breakthrough for the research, to determine the operation status of the compensatory equipment. The on-line power quality monitoring system records a set of data every minute or a few minutes, including active power, reactive power, voltage/current harmonics, three-phase unbalance, voltage fluctuation and flicker, etc. These data are closely related to load conditions and the operation status of the compensatory equipment on the user side.

This paper proposes an algorithm to determine the operation status of the compensatory equipment, using the recorded power quality data. The recorded power quality data from grid side are the input of Probabilistic Neural Network (PNN), and the output of PNN is the operation status of the compensatory equipment on the user side. PNN has the advantages of short training time, avoids to produce local optimization, and has high classification accuracy, so it is suitable for pattern recognition of online data.

PROBABILISTIC NEURAL NETWORK

PNN is an artificial neural network based on Bayesian classification rules and estimation method of probability density function of Parzen window[6]. Because of its fast learning speed and strong classification ability, it has been widely used in various fields in recent years.

PNN is a supervised learning algorithm. It needs labelled data as training samples, and then predicts unknown samples through the learning model. It consists of input layer, mode layer, summation layer and output layer. The structure of PNN is shown in Fig.1.

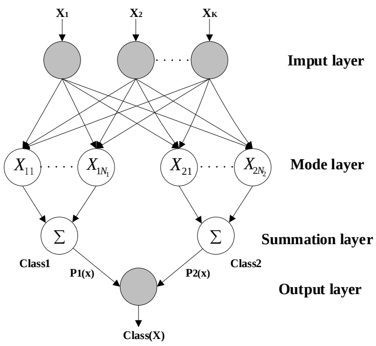

Fig.1 Structure of Probabilistic Neural Network

Input layer

The input layer passes the input data to all neurons of the model layer, and the number of neurons in the input layer equals the dimension of the input eigenvector.

Mode layer

The number of neurons in the model layer equals to the number of training samples. Each neuron has a centre, which is the current training samples. The output of the *j*th neuron in class *i* in this layer is as follows:

$$\Phi_{ij}\left(\boldsymbol{X}\right)=\frac{1}{\left(2\pi\right)^{d/2}\sigma^{d}}\exp\left(-\frac{\left(\boldsymbol{X}-\boldsymbol{X}_{ij}\right)^{T}\left(\boldsymbol{X}-\boldsymbol{X}_{ij}\right)}{2\sigma^{2}}\right) \quad (1)$$

σ is the smoothing parameter of probabilistic neural network, whose value determines the width of the bell curve centred on the training sample points; X_{ij} is the centre of the *j*th neuron in class *i*.

Summation layer

The number of neurons in the summation layer is the same as the number of classification categories. The summation layer averages the output of neurons belonging to the same class in the model layer:

$$P_i\left(\boldsymbol{X}\right)=\frac{1}{N}\sum_{j=1}^{N_i}\Phi_{ij}\left(\boldsymbol{X}\right) \quad (2)$$

Output layer

According to the probability estimation of input vectors, the output layer uses Bayesian classification rules to select the category with the maximum posterior probability as the output:

$$Class\left(\boldsymbol{X}\right)=arg\ max\left\{P_i\left(\boldsymbol{X}\right)\right\} \quad (3)$$

OPERATION STATUS DETERMINATION MODEL

Input data

Power quality is usually measured from three aspects: voltage amplitude, voltage waveform distortion and frequency. Compensation equipment is often installed to solve the problem of voltage amplitude and voltage waveform distortion. Voltage amplitude problems include voltage deviation and three-phase voltage unbalance. Voltage waveform distortion includes voltage harmonics distortion and voltage fluctuations and flickers. Therefore, choose voltage deviation V_{DA}, V_{DB}, V_{DC}, three-phase unbalanced voltage V_{S2S1}, total harmonic distortion rate V_{THDA}, V_{THDB}, V_{THDC}, long-term voltage flicker P_{ltA}, P_{ltB} and P_{ltC} as input data of probabilistic neural network[7-10].

Data pretreatment

Different types of data have different dimensions, resulting in incommensurability, and data with large absolute values have a greater impact on training results. In order to eliminate this effect, it is necessary to normalize the data. By expressing the data as the standard value of the limit value under its voltage level, the influence of different magnitudes and dimensions can be eliminated at the same time.

For voltage deviation, using interval data pretreatment equation:

$$u_j=1-\max\left(\frac{x_j}{x_{th1}},\frac{x_j}{x_{th2}}\right) \quad (4)$$

x_j is the actual measurement value of the data. x_{th1} and x_{th2} represent the upper and lower limits of the national standard of the data under a certain voltage level of the measuring point, respectively.

For three-phase unbalance, voltage harmonics and voltage flicker, using the minimum data pretreatment equation:

$$u_j=\frac{x_{th}-x_j}{x_{th}} \quad (5)$$

x_j is the actual measurement value of the data. x_{th} represent the limit of the national standard of the data under the voltage level of the measuring point.

Network Structure Design

Input layer

As mentioned above, the dimension of the input eigenvector is 10. So the number of neurons in the input layer is 10.

Mode layer

The monitoring data used in this paper are recorded every three minutes, and the network is trained with three-day data in the case study. Therefore, the number of neurons in the model layer is 1440. To increase training samples, only need to increase the number of neurons in the mode layer. The smoothing factor σ is usually given by experience. In this paper, $\sigma = 0.1$.

Summation layer

There are two neurons in the summation layer, which correspond to two different operation status of the compensatory equipment: 1. the compensatory equipment is not put into operation (on); 2. the compensatory equipment is put into operation (off).

Output layer

There is only one neuron in the output layer, which corresponds to the classification results.

CASE STUDY

In this paper, recorded power quality data in the power quality monitoring system from a 35kV substation in Anhui Province of China are selected as an example for case study. The disturbance source connected to this substation is a photovoltaic power station. And the compensatory equipment installed by the disturbance source in the substation is static var generator (SVG). The purpose of installing SVG is to compensate the problem of voltage deviation.

An experiment of SVG is carried on in February 2018. The switching actions were recorded as shown in Table.I.

TABLE.I Switching action of SVG

Time	Switching action
2018-02-13 09:32:31.550	On
2018-02-14 11:49:02.145	Off

From Table.I, it can be seen that SVG was on operation from 09:32 on 13th February to 11:49 on 14th February, was off after11:49 on 14th February. In Addition, this SVG was off before 09:32 on 13th February.

Fig.2 shows the variation trend of average value of three-phase voltage deviation on 13th February. It is obvious that the voltage varied to 35.67kV when SVG is off before 09:32 on 13th. After SVG was put into operation, the voltage recovery to about 35.1kV, the problem of voltage deviation is mitigated.

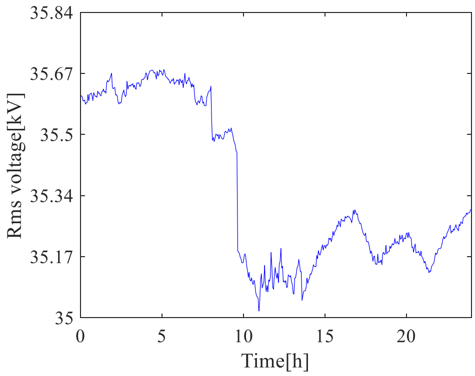

Fig.2 The variation trend of voltage deviation on 13th February

Data pretreatment

In this paper, the recorded data from 11th February to 13th February are pretreated and as the input into PNN for training. PNN is run by the newpnn function of MATLAB/Simulink.

The monitor records data every 3 minutes, so there are 480 sets data records every day. According to the requirement of national standard in China[7-10], choose the following data as the input data, including maximum within 3 minutes of voltage deviation, and the 95% probability value within 3 minutes of three-phase unbalance, total harmonic distortion and long-term flicker. Due to the limited space, only part of the data on 13th February is shown.

Table.II shows the recorded data before pretreatment. Voltage deviation, three-phase unbalance and total distortion rate of voltage harmonics are listed in percentage. For example, at 09:21 on 13th February, the voltage deviation for three phases are 5.378%, 5.863%, 6.709%, respectively, the three-phase voltage unbalance is 0.206%, the total harmonic distortion rate for three phases are 1.25%, 1.2%, 1.25%, and the long-term voltage flickers are 0.054, 0.051, 0.046.

Table.III shows the recorded data after pretreatment. Since the voltage level of the substation is 35 kV, the national standard limits of voltage deviation, three-phase unbalance, total harmonic distortion rate and long-term flicker of voltage in the pretreatment equation are ±10%, 2%, 3% and 1, respectively[7-10]. For example, by substituting the data at 09:21 on 13th February into (4) and (5), the pretreated voltage deviation for three phases are 0.462, 0.412, 0.329, the pretreated three-phase voltage unbalance is 0.897, the pretreated total harmonic distortion rate for three phases are 0.583, 0.6, 0.583, and the pretreated long-term voltage flickers are 0.946, 0.949, 0.954.

The last column in Table.III is listed as the operation status of the known training data. 1 represents that the compensatory equipment is on, and 2 represents that the compensatory equipment is off.

TABLE.II Part of input data before pretreatment

Time	V_{DA} (%)	V_{DB} (%)	V_{DC} (%)	V_{S2S1} (%)	V_{THDA} (%)	V_{THDB} (%)	V_{THDC} (%)	P_{ltA}	P_{ltB}	P_{ltC}
09:21:00.000	5.378	5.863	6.709	0.206	1.25	1.2	1.25	0.054	0.051	0.046
09:24:00.000	5.554	5.701	6.453	0.243	1.26	1.21	1.26	0.054	0.051	0.046
09:27:00.000	5.363	5.753	6.486	0.21	1.27	1.22	1.27	0.054	0.051	0.046
09:30:00.000	5.21	5.812	6.439	0.281	1.28	1.23	1.29	0.054	0.051	0.046
09:33:00.000	5.086	5.629	6.47	0.133	1.28	1.24	1.29	0.054	0.051	0.046
09:36:00.000	5.167	5.592	6.363	0.209	1.22	1.19	1.25	0.054	0.051	0.046
09:39:00.000	3.405	4.035	4.83	0.219	1.19	1.18	1.24	0.054	0.051	0.046
09:42:00.000	3.413	4.134	4.677	0.303	1.12	1.12	1.19	0.054	0.051	0.046
09:45:00.000	3.51	4.061	4.593	0.338	1.07	1.08	1.15	0.054	0.051	0.046
09:48:00.000	3.368	4.085	4.524	0.35	1.09	1.08	1.15	0.054	0.051	0.046

TABLE.III Part of input data after pretreatment

Time	V_{DA}	V_{DB}	V_{DC}	V_{S2S1}	V_{THDA}	V_{THDB}	V_{THDC}	P_{ltA}	P_{ltB}	P_{ltC}	type
09:21:00.000	0.462	0.414	0.329	0.897	0.583	0.6	0.583	0.946	0.949	0.954	1
09:24:00.000	0.445	0.43	0.355	0.879	0.58	0.597	0.58	0.946	0.949	0.954	1

09:27:00.000	0.464	0.425	0.351	0.895	0.577	0.593	0.577	0.946	0.949	0.954	1
09:30:00.000	0.479	0.419	0.356	0.86	0.573	0.59	0.57	0.946	0.949	0.954	1
09:33:00.000	0.491	0.437	0.353	0.934	0.573	0.587	0.57	0.946	0.949	0.954	2
09:36:00.000	0.483	0.441	0.364	0.895	0.593	0.603	0.583	0.946	0.949	0.954	2
09:39:00.000	0.66	0.596	0.517	0.89	0.603	0.607	0.587	0.946	0.949	0.954	2
09:42:00.000	0.659	0.587	0.532	0.848	0.627	0.627	0.603	0.946	0.949	0.954	2
09:45:00.000	0.649	0.594	0.541	0.831	0.643	0.64	0.617	0.946	0.949	0.954	2
09:48:00.000	0.663	0.592	0.548	0.825	0.637	0.64	0.617	0.946	0.949	0.954	2

The data from 11th February to 16th February are input into the trained PNN to be classified, and the classification results are compared with the known correct results. Define classification accuracy rate (*CAR*) as (6):

$$CAR = \frac{C}{480} \tag{6}$$

C is the number of correct results in one day. The denominator is the total number of results per day, which is 480 in this case. The classification accuracy rate is shown in Table.IV.

From Table.IV, we can see that the classification accuracy rate is 100% on 11th, 12th, 15th and 16th February when there is no switching action. On 13th and 14th February, due to a delay between SVG starting he SVG working effectively, there is a lag of power quality improvement after the SVG was starting, so the change of power quality data have a certain delay compared with the action of SVG switch. Thus, there are a few misclassification. However, the correct rate of all the classifications is more than 95%, which is within acceptable range.

TABLE.IV Accuracy of classification results

Date	11th Feb	12th Feb	13th Feb	14th Feb	15th Feb	16th Feb	Total
Accuracy	100%	100%	99.58%	95.83%	100%	100%	99.24%

For further analysis, the classification results and correct results of 13th February are shown in Fig.3. The blue line represents the correct result, and the red line represents the classification result by the proposed method. The changes of blue line from 1 to 2 represents that SVG was put into operation. The change of the red line is delay about two sample points (6 minutes) than that of the blue line, which is consistent with previous analysis.

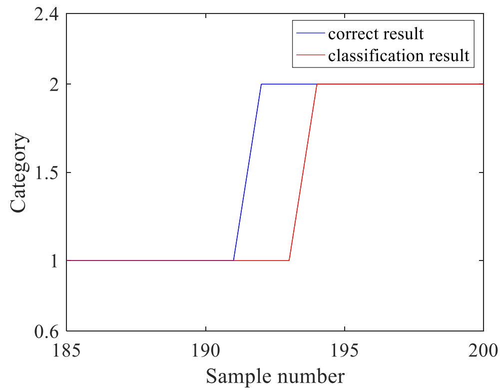

Fig.3 Result contrast on 13th February

CONCLUSION

In view of the complex power quality disturbance sources and the difficult management of the power quality compensatory equipment on the user side in power grid, this paper proposes an algorithm to determine the operation status of compensatory equipment based on power quality monitoring data.

This paper uses the steady-state power quality data set as the input data of PNN to recognize the operation status of the compensatory equipment.

The proposed method is verified by the measured data from a substation in Anhui power grid of China. The case study shows that the proposed method in this paper can accurately identify the operation status of compensatory equipment, provide effective theoretical and data support for the management of compensatory equipment and improvement of compensation scheme, and has high engineering value and practical universality.

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