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The Research on the Fault Diagnosis System of MOA Surge Arresters Based on Wavelet Neural Network

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Abstract: The zinc oxide surge arrester is an important kind of over-voltage protection device in a power system. In this paper, a metal oxide arrester (MOA) fault diagnosis system was designed to ensure the safe operation of transmission lines and electrical equipment of substations. Based on the analysis of zinc oxide surge arrester failure modes, a wavelet neural network was used to establish the MOA final prediction model of the system and a digital signal processor was adopted as the core of the system.

Keywords: digital signal processor; MOA arrester; wavelet neural network

1 Introduction

With the development of the social economy, there are more and more requirements on the quality and the quantity of the power supplying.The zinc oxide surge arrester is an important kind of over-voltage protection device in a power system which has characteristics of a large capacity of flow, fast response and long life, etc. But in its long-term operations under all kinds of over-voltage, being affected with damp, filthy and so on, a surge arrester gradually becomes aging or degradation, which may cause the lost of its protection function, or even more, cause a explosion, leading to a large area blackout accident[1-3]. In the paper, according to the analysis of zinc oxide surge arrester failure modes, a wavelet neural network was used in the design of the MOA fault diagnosis system. The residual life of MOA surge arresters can be predicted which ensures the safe operation of transmission lines and electrical equipment of substations.

2 Zinc oxide surge arrester failure modes

The zinc oxide (ZnO) voltage dependent resistor is a major component of a MOA surge arrester. Failure modes of the MOA surge arrester can be analyzed internally and externally according to the failure mechanism of the voltage dependent resistor and influences of external environments on valve plates.

2.1 Analysis of internal causes

The operation of a MOA will be influenced by some factors such as impulse current, working voltage, transient over-voltage, etc.

If the strength of a impulse current is large enough, the grain boundary barrier layer of a voltage dependent resistor will be distorted irreversibly which cause the failure of a MOA.

The normal working voltage applied on a voltage dependent resistor for a long time may also cause a degradation on the performance of a MOA. Although the amplitude of resistive currents are smaller compared with that of capacitive currents, the power loss will increase with the extension of time which lead to the aging phenomenon in a voltage dependent resistor.

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At the same time, the internal temperature rise due to the cumulatively increased power loss caused by continuous impulse currents will accelerate the aging process.

2.2 Analysis of external causes

The internal resistors of a MOA arrester make its work condition much more complicated in filthy conditions compared with other power equipment. There are mainly three cases when a MOA arrester works in filthy conditions: external flashover, the temperature rise of internal resistors and partial discharge inside a arrester[2-3].

3 The overall scheme design of the on-line MOA zinc oxide surge arrester monitoring system

In order to realize the on-line monitoring of the MOA zinc oxide surge arrester, a DSP processor is used as the core of the system, and the whole system is divided into modular designs with different functions. The overall scheme of the MOA zinc oxide surge arrester fault monitoring system is as show in figure 1. In the system, leakage currents of on-line monitoring modules, resistive currents and the number of lighting strikes are transmitted to photoelectric transducers through short-distance optical fibers. After processed by photoelectric transducers, all data from MOA monitors are converted into wireless signals. Signals are collected and processed, and then transmitted by 485 bus to the DSP for further processing and display.

The DSP system adopts a high-performance 32-bit digital signal processor (TMS320C32) which can improve system abilities of calculation and processing. The TMS320C32 uses PCM encapsulation whose CPU structure is based on registers which can get access to external memories by the 24-bit address bus, the 32-bit data bus and the gating signal. It has rich hardware resources, including a serial port, two clocks, two DMA control channels, 4-level priority interrupt. The processor supports multiple addressing modes with very fast processing speed. The external memory interface of the processor can be extended. Otherwise, the processor adopts the Harvard structure which separate storage spaces of program instructions and data with individual address and data buses. Therefore, data and instructions can be called at the same time, which enhances the processing speed[3].

The resistive current on-line monitor selects a JSH-7 type resistive current on-line monitor which can display leakage currents form all arresters, the value of the resistive current and the number of lighting strikes. The main parameters of the resistive current on-line monitor are as follows: the upper limit of operating peak current 10K A, the lower limit of operating peak current 5A, nominal peak impulse current 10KA, the maximum action number of the counter 10n, maximum peak impulse current 65KA.

The photoelectric transducer converts optical signals into digital signals and sends out signals sin the form of high frequency wireless signals. Its basic parameters are as follows: working voltage: 12V/AC, DC, communication output: high frequency wireless signal, transmission mode to monitor: TS485.

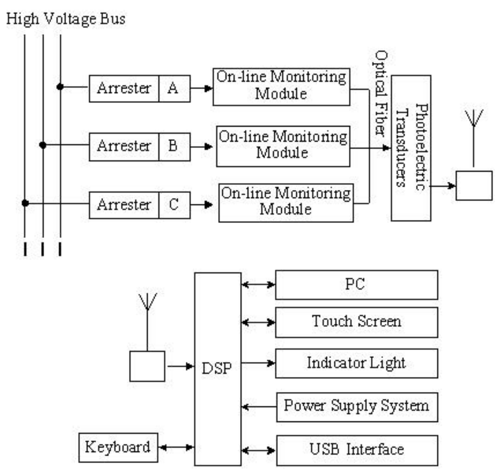

Figure 1: The overall scheme of the MOA zinc oxide surge arrester fault monitoring system

4 Wavelet neural network

The wavelet transform is a powerful signal analysis tool. Multi-resolution analysis of wavelet transform uses a wavelet family to represent signals or functions. Data are decomposed to a series of frequency bands and can be processed and analyzed at different frequency bands to eliminate tedious signals. And then signals are reconstructed[4-6].

Artificial neural network(ANN) is a method that abstracts and simplifies the human brain from the micro structure and functions in order to simulate the human intelligence. Three essential factors that constitute a artificial neural network are neuron, network topology and training algorithm of a network. The ANN has characteristics of massive parallel processing ability, continuous-time dynamics and network global function, etc[7-9].

In the system, wavelet transform are combined effectively with neural network, absorbing the merits of both. Wavelet transform is used to remove noises from signals which can improve generalization ability and fault tolerance of neural network, and increase the learning speed of the neural network.

4.1 The wavelet transform

The wavelet transform has a good time-frequency resolution characteristic, which can represent local features of signals in both time domain and frequency domain.

Assume$f(t)$ is a time signal, $p_j^i(t)$ represents the i^{th} wavelet at the j layer. G and H are the wavelet decomposition filters. G and H are associated with the wavelet function $\psi_j(t)$ and the scaling function $\varphi_j(t)$. The fast decomposition algorithm of the wavelet is

$$\begin{cases} p_j^{2i-1} = \sum\limits_k H(k-2t)p_{j-1}^i(t) \\ p_j^{2i} = \sum\limits_k G(k-2t)p_{j-1}^i(t) \end{cases} \tag{1}$$

In which, $t = 1, 2, \cdots, 2^{J-j}$; $i = 1, 2, \cdots, 2^j$; $J = log_2 N$.

The fast reconstruction algorithm for dyadic wavelet transform is

$$p_j^i(t) = 2\left[\sum_k h(t-2k)p_{j+1}^{2i-1}(t) + \sum_k g(t-2k)p_{j+1}^{2i}(t)\right] \tag{2}$$

In which, $t = J-1, J-2, \cdots, 1, 0$; $i = 2^j, 2^{j-1}, \cdots, 2, 1$; $J = log_2 N$. h and g are wavelet reconstruction filters. g is associated with the wavelet function $\psi_j(t)$ and h is associated with the scaling function $\varphi_j(t)$ [10-11].

Take the voltage signal $u(t)$ for example,

$$\begin{aligned} u(t) &= \sum_{i=0}^{j-1}\sum_{k=0}^{2^{N-j}-1} d_j^{2i}(k)\psi_{j,k}^{2i}(t) + \sum_{i=0}^{2^{j-1}-1}\sum_{k=0}^{2^{N-j}-1} d_j^{2i+1}(k)\psi_{j,k}^{2i+1}(t) \\ &= \sum_{k=0}^{2^{N-j}-1} d_j^0(k)\phi_{j,k}(t) + \sum_{i=1}^{2^{j-1}-1}\sum_{k=0}^{2^{N-j}-1} d_j^{2i}(k)\psi_{j,k}^i(t) \end{aligned} \tag{3}$$

IN which, $\phi_{j,k}(t)$ is the scaling function, $d_j^0(k)$ is the coefficient of the scaling function. $\psi_{j,k}^i(t)$ is the wavelet function, $d_j^{2i}(k)(i > 0)$ is the wavelet coefficient of the $u(t)$. The voltage RMS values on the j scale can be expressed as

$$\int u(t)^2 dt = \int \left[\sum_{k=0}^{2^{N-j}-1} d_j^0(k)\phi_{j,k}(t) + \sum_{i=0}^{2^{j-1}-1}\sum_{k=0}^{2^{N-j}-1} d_j^{2i}(k)\psi_{j,k}^i(t)\right]^2 dt \tag{4}$$

The equation above can be approximated as

$$\int u(t)^2 dt = \sum_{i=0}^{2^{j-1}-1}\sum_{k=0}^{2^{N-j}-1} \left[d_j^i(k)\right]^2 \tag{5}$$

The RMS value of the voltage U_{rms} can be written as

$$\begin{aligned} U_{rms} &= \sqrt{\frac{1}{T}\int_0^t u(t)^2 dt} = \sqrt{\frac{1}{2^N}\sum_{i=0}^{2^j-1}\sum_{k=0}^{2^{N-j}-1}\left[d_j^i(k)\right]^2} \\ &= \sqrt{\sum_{i=0}^{2^{j-1}}(U_j^i)^2} \end{aligned} \tag{6}$$

In which, $U_j^i = \sqrt{\frac{1}{2^n}\sum_{k=0}^{2^{n-j}-1}\left[d_j^i(k)\right]^2}$ is the RMS value of the voltage at i^{th} node band of j^{th} layer. In the same way, the RMS value of the current $i(t)$ is

$$\begin{aligned} I_j^i &= \sqrt{\frac{1}{T}\int_0^t i(t)^2 dt} = \sqrt{\frac{1}{2^N}\sum_{i=0}^{2^j-1}\sum_{k=0}^{2^{N-j}-1}\left[d_j^i(k)\right]^2} \\ &= \sqrt{\sum_{i=0}^{2^{j-1}}(I_j^i)^2} \end{aligned} \tag{7}$$

In theory, measured signals can be decomposed into different frequency bands by wavelet packet transform. Actually, there are some various noise interference in operations. Therefore, general methods can not distinguish the time domain features clearly. Wavelet packet transform has space localization property, that is to determine wavelet packet transform at one point by local information near the point. Wavelet coefficient will also change when the signal mutations occur, and the wavelet coefficient at the point differs form those of stable points. Through the feature the time when a signal mutates can be identified and then measured signals can be analyzed.

4.2 Neural network

A multi-layer feedforward neural network(BP neural network) is used in the system. It is composed of a input layer, a hidden layer and a output layer. Weights are adjusted through back propagation to make a good mapping relation between

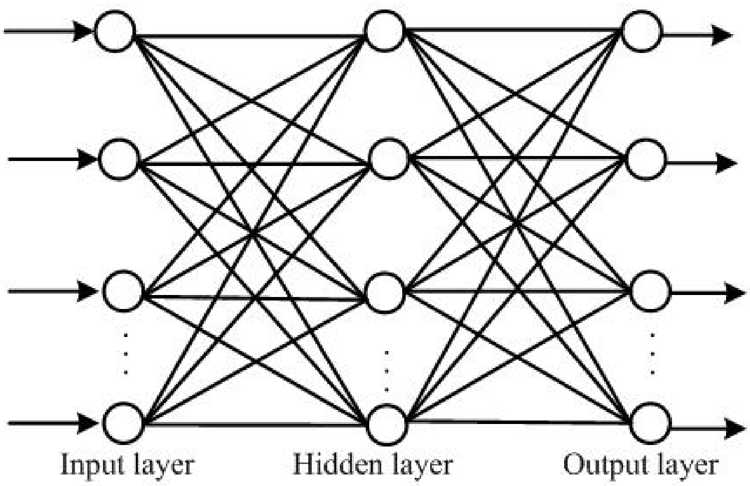

Figure 2: Three-layer BP neural network

The structure of the BP neural network established in the system is as shown in figure 2. The learning process is composed of two processes of forward propagation and error back propagation[8-9].

The neural network is used to establish the final prediction model of a MOA. Four macro status indicators, aging, failure, damp and filthy, are used in fault predictions of a MOA. each of macro indicators has corresponding evaluation indexes.

4.3 The design of the wavelet neural network

It can be found through the analysis of the wavelet transform and the neural network that the wavelet transform has a good time-frequency local characteristics and the neural network has features of self-learning, self-adaption, robustness, fault tolerant and generalization ability. The combination of the wavelet transform and the neural network in fault diagnosis system has a good development prospects. There are two ways of the combination. One is to preprocess signals with the wavelet transform, which is to extract features of signals with wavelet analysis before they are sent to the neural network for further processing. The other is to establish a wavelet neural network, in which the nonlinear excitation function of neurons (eg. Sigmoid function) is replaced by nonlinear wavelet basis. In this way, the wavelet transform and the neural network can be combined effectively with a full inheritance of both advantages[11-12]. The latter method is adopted in the paper. Excitation functions at hidden nodes of the neural network is replaced by wavelet functions, and threshold is replaced by translation and scaling parameters of the wavelet. The inputs of the wavelet neural network are not instantaneous discrete values but functions or processes varied with time. At the same time, a time accumulation operator is added which makes the wavelet neural network can process two-dimensional information of time and space. The adaptability of the wavelet neural network for solving practical problems is increase greatly. It is very important to select a proper wavelet function because its the excitation function of the wavelet neural network. If the excitation function and the input function has a certain similarity, a good expression of signals can be achieved. Otherwise, the wavelet function should satisfy not only allowable conditions, but also regularity conditions, in order to get a better local performance in the frequency domain.

The measured signals of a real metal oxide arrester (MOA) are more complicated. For verifying the effectiveness and the universality of the method, we select unpredictable random sequences with white noises and bandwidth to simulate nonlinear load harmonic signals in power systems.

$$x_j(t) = \alpha x_j(t-1)(1 - x_j(t-1)) + e_j(t) \tag{8}$$

In which, $e_j(t)$ is the Gaussian white noises. Continuous eight discrete data are fitted to form a sequential function as the input function of the neural network and the ninth data is taken as a output. The input function and the connection weight function of the multi-resolution wavelet process neural network are expanded into triangle base functions which have 6 forms. Assume the learning error precision of the network is 0.001, the maximum numbers of iterations is 5000. The previous three hundreds data are used as training samples. Learning iterations are converged after 1989 times iterations. The curve of learning errors is as shown in figure 3.

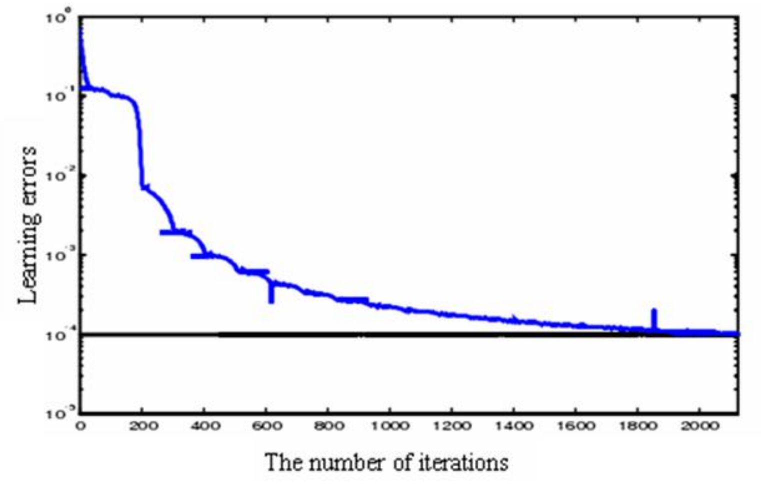

Figure 3: The curve of learning errors

In order to test the generalization ability of the wavelet neural network after the learning, 100 groups non-training samples are used to test the network. The average relative error of predicts of the network is 0.53%.

The prediction results of wavelet neural network based on multi-resolution are as shown in figure 4.

Multi-resolution wavelet neural network is essentially to project primitive functions onto wavelet basis at different frequencies respectively, and to get information of primitive functions at different frequencies. In the wavelet neural network, every wavelet neurons and scale neurons correspond to an input channel of raw data and complete its filter function.

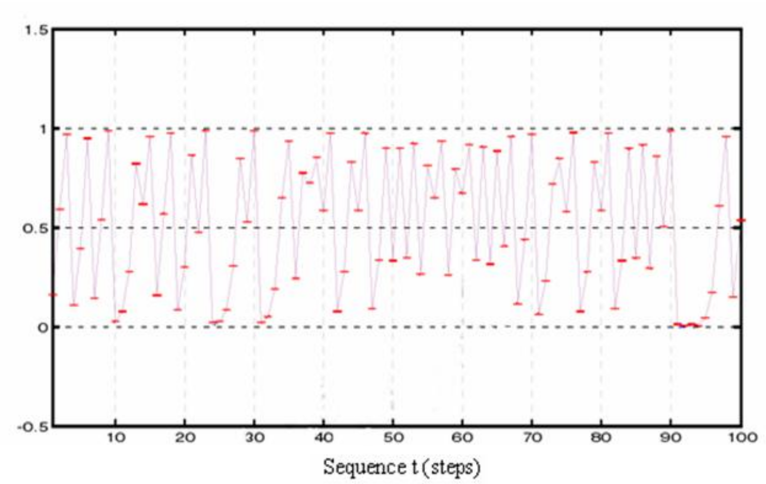

Figure 4: The prediction output of the wavelet neural network based on multi-resolution

5 Software design

The purpose of the MOA arrester fault diagnosis system is to get the real descriptions of operating states of relevant power equipment through analysis and processing of original operating state data. In the design, several factors are needed to be taken in consideration on the premise of meeting function requirements of the system: the readability of the software, the extensibility of functions, the update of the system.

A modular structure is easy for realizing data sharing, improving system efficiency and making system maintenance. Hence, a modular design method is adopted in the software design. Kingview 6.55 is used in the design. The MOA arrester fault diagnosis system is mainly composed of the main interface, the whole current waveform interface, the harmonic wave interface, relative data report from interface, and so on. The function module structure of the software system is as shown in figure 5.

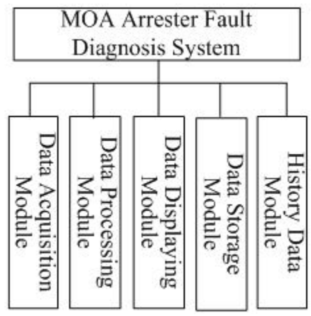

Figure 5: The module structure of the software in the MOA arrester fault diagnosis system

6 Conclusions

The zinc oxide surge arrester is an important kind of over-voltage protection device in a power system. In the operation of a MOA, it is affected by over-current, over-voltage, damp, and filth for a long time, which make the MOA aged or degraded gradually, and even damaged. In the paper, according to the analysis of zinc oxide surge arrester failure modes, a wavelet neural network was used to remove noised from signals, and a neural network is adopted for establishing the final predicting model. A MOA fault diagnosis system is designed based on the digital signal processor. The residual life of MOA surge arresters can be predicted which ensures the safe operation of transmission lines and electrical equipment of substations.

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References

[1] Lingguo Meng. Study on On-line Monitoring and Analysis System of ZnO Arresters. Shandong University master degree thesis. 2012.

[2] Lili Jiang. Design of Based on DSP and ARM MOA Monitro. Ann. Beijing Jiaotong University master degree thesis. 2007.

[3] Dianhong Zang. Research on On-line Monitoring Equipment of Metal Oxide Surge Arrester Based on DSP. China University of Petroleum master degree thesis. 2009.

[4] Huijuan Yang and Jianqiu Zhang. Multi-sensor data reconstruction algorithm based on wavelet and data fusion. *Journal of Fudan University(natural science edition)*, 44(1)(2008):161–165.

[5] Bing Zhao. The Application of Wavelet Threshold De-noising in Power Load Management Terminals. *Computer Technology and Development*,19(7)(2009):206–209.

[6] Xiaoyong Zhou and Yinzhong Ye. Application of WaveletAnalysis to Fault Diagnosis. *Control Engineering*,13(1)(2006):70–73.

[7] Shu Tang, Dong Liu and Yixin Yin. Information fusion method based on rough set and neural network. *MicroComputer Information*,23(18)(2007):89–91.

[8] Anbing Zhang, Jun Sun, Jinxiang Gao and Xipan Li. TS-BT neural network modeling and its application. *Journal of Hebei University of Engineering*,24(1)(2007):89–91.

[9] Tianshu Liu. Improvement Research and Application of BP Neural Network. Dongbei Agricultural University master degree thesis. 2011.

[10] Weiwei Ning, Yuan Pei and Liyan Liu. Harmonic Analysis Methods of Power Systems Based on Neural Network with Fourier Basis Function. *The Power System Protection and Contro*,36(12)(2008):39–42.

[11] Yu Chen. Application of Wavelet Multi-resolution Algorithm to Harmonic Monitor in Electric Power System. *Computer Measurement & Control*,16(10)(2008):1493–1495,1518.

[12] Heji Yu, Changzhen Chen and Sheng Zhang. Intelligent Diagnosis Based on Neural Network. Metallurgical Industry Press. 2002.