확률신경회로망을 이용한 전력계통의 고장진단에 관한 연구

論 文
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A Study on Fault Diagnosis in Power Systems Using Probabilistic Neural Network

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Abstract - This paper presents the new methods of fault diagnosis through multiple alarm processing of protective relays and circuit breakers in power systems using probabilistic neural networks. In this paper, fault section detection neural network (FSDNN) for fault diagnosis is designed using the alarm information of relays or circuit breakers. In contrast to conventional methods, the proposed FSDNN determines the fault section directly and fast. To show the possibility of the proposed method, it is simulated through simulation panel for Sinyangsan substation system in KEPCO (Korea Electric Power Corporation) and the case studies show the effectiveness of the probabilistic neural network method for the fault diagnosis.

Key Words : Probabilistic Neural Network, Multiple Alarm Processing, Fault Diagnosis

1. Introduction

When faults occur in power systems, an operator in the control center diagnoses the fault and starts recovering the faulted power system after analyzing the alarm information of protective relays or circuit breakers. However, estimation of the fault section is difficult in real systems, especially, for the cases of malfunctions in protective relays and circuit breakers. To provide the uninterrupted power supply of certain quality, the states of protective relays and circuit breakers should be identified in order to take proper action for system restoration. But in the cases of failure operation in protective relays or circuit breakers, fault sections and fault types are difficult to be identified.

From now on, fault diagnosis is heavily relied on heuristic rules of the power system operators. It may lead to malfunctions according to the condition or mood of operators. Therefore, many intelligent systems such as expert systems and neural networks have been successfully applied to the problem of fault diagnosis. Many expert systems, however, are working in a sequential process: it is difficult for these systems to meet the needs of real time information processing [1,2].

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Neural network[3] is system to make use of some organizational principles resembling those of the human brain. Neural network has been applied in some areas where conventional techniques, such as artificial intelligence, do not achieved the desired accuracy. Neural network has a large number of highly interconnected processing elements and usually operate in parallel. Hence, neural network is quick in response time.

Most recently, neural network was used to solve some fault diagnosis problems in power systems [4-9]. In [4], neural network approach is used to diagnose fault of a power substation by identifying different combinations of protective relays and circuit breakers. In [5], the associative memory type is used to solve the fault localization problems in substation. In [6], Handschin proposed the distributed DS-ANN based on an alarm handling system, which can easily distinguish between different faults in case of multiple faults.

In this paper, probabilistic neural network (PNN) is proposed to diagnose faults in the power systems. The proposed systems are capable of identifying the fault section according to the states of protective relays and circuit breaker. To show the effectiveness of the proposed method, the proposed systems have been tested on simulation panel for the fault diagnosis of the Sinyangsan substation in KEPCO and it determines the fault section directly and fast. Hence, the proposed systems will be used as an aid to the operators in power substations.

2. Probabilistic Neural Network

The probabilistic neural network has been used successfully to solve classification problems of a diverse group. Consider the k-category situation in which categories are θ_1, θ_2, $\cdots$, θ_k. Probability density functions (PDFs) for these categories are $f_1(X), f_2(X)$, $\cdots$, $f_k(X)$ where X is an input vector. A priori probability of each category for input vector X is P_1, P_2, $\cdots$, and P_k. Then the Bayes decision rule compares the K values, $P_1f_1(X)$, $P_2f_2(X)$, $\cdots$, $P_kf_k(X)$, and chooses the class corresponding to the highest value.

Bayes theorem provides a method for performing optimal classification to minimize expected risk. The theorem uses a priori probability, loss functions associated with each misclassification and PDFs. Often the a priori probabilities are known or can be estimated correctly; the loss functions require subjective evaluation. However, if the probability densities of the patterns in the classes to be separated are unknown and all that is given are a set of training patterns. Therefore, it is often difficult to determine the PDFs with a high accuracy.

The accuracy of the decision boundaries depends on the accuracy with which the underlying PDFs are estimated. Parzen developed that a class of PDF estimators asymptotically approaches the underlying parent density provided only that it is continuous. Murthy relaxed the assumption of absolute continuity of the distribution function, and Cacoullos has also extended Parzen's results to cover a multivariate case. There is a similarity between parallel analog networks that classify patterns using nonparametric estimators of a PDF and feed-forward neural networks used with other training algorithm proposed by Specht.

PNN is composed of input layer, pattern layer, summation layer and output layer. Instead of the sigmoid activation function used for back-propagation neural network, that of pattern layer is as follows.

$$\exp[(Z_i - 1)/\sigma^2] \tag{1}$$

Where, $Z_i = X \circ W_i$

$\circ$: Dot product

X : input vector of a PDF

W_i : weight vector connected to the i-th neuron of the pattern layer.

Assuming that both X and W_i is normalized to unit length, (1) is represented as follows.

$$\exp[-(W_i - X)^t(W_i - X)/2\sigma^2] \tag{2}$$

This is the same form as the estimator of the PDF using the Gaussian weighting function in the multivariate case. The summation layer simply sums the inputs from the patterns units that correspond to the category from which the training pattern was selected. The output units produce binary outputs and classify input patterns.

The network is trained by setting the weight vector in one of the pattern units equal to each of the X patterns in the training set and then connecting the output of this pattern unit to the appropriate summation unit. So a pattern unit is required for every training pattern.

The most important advantage of PNN is that the training speed is fast to instantaneous. So, it can be implemented in real time. PNN also has a generalization capability to new patterns, which is not included in the training set. However, two limitations of the PNN are inherent because (a) the entire training set must be stored, which storage size are large and (b) smoothing parameters σ should be determined appropriately.

3. Probabilistic Neural Network Fault Diagnosis System

When a fault occurs on a power system such as buses, lines, transformers, etc., the protective relays and circuit breakers are generated numerous signals. Some of the signals are transmitted to the control centers. The status of circuit breakers and protection relays can be localizing faults in a power substation. The status of this equipment can be represented by binary signals. A fault situation would, therefore, result in a particular binary symptom pattern for the open/close status of the protective relays and circuit breakers. For example, open/tripped status of circuit breakers is marked as "binary 1" and a closed status of circuit breakers is marked as "binary 0". Also, an operating protective relays are marked as "binary 1" and non-operating protective relays are marked as "binary 0". Hence, a typical training set can be determined. The input neurons represent the protective relay and circuit breaker status. The output neurons indicate a fault section. Therefore, the number of input neurons depends on the sum of the number of protective relays and circuit breakers. The number of output neurons is the same as the number of equipment. By using these data as training set of neural network, on-line fault section estimation can be obtained.

The proposed structure of fault section detection neural network (FSDNN) using probabilistic neural network is shown in Fig. 1. As shown in Fig. 1, the input vector is binary signals using real states of relays and circuit breakers and the output vector is also made up the fault section represented by binary signals.

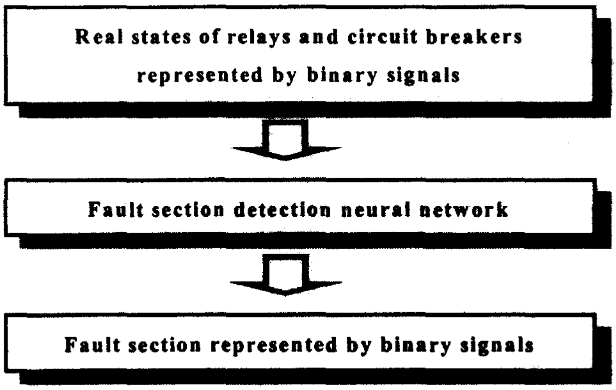

Fig. 1 Fault diagnosis system using probabilistic neural network

4. Case Study

In case study, the Sinyangsan substation in KEPCO used to test the proposed FSDNN using PNN. This simplified power substation is represented Fig. 2, where there are 5 154kV transmission lines, 2 154kV buses, 2 22.9 kV buses, 2 154kV/22.9kV transformers and 8 22.9kV distribution lines. The protection systems have 22 circuit breakers and 71 protective relays.

As shown in Fig. 2, circuit breakers 60-61, 65-66, 40-41, and 45-46 are always closed, and thus, they are not included in the input factor.

For instance, in case of a fault in bus #1, the protective relays of 87/#1 (Differential protective relay), 50/#1 (Instantaneous overcurrent relay), 27/#1 (Undervoltage relay), and 86/#1 (Locking-out relay), which are connected bus #1, have operated and is represented "binary 1". Also, the circuit breakers 6244, 6100, 6133, 677, and 697 have opened. For another instance, in case of a fault in ilkwang distribution line, the protective relays of 51/f1 (Ac time overcurrent relay) and 51G/f1 (Ac time overcurrent ground relay), which are connected f1 (ilkwang distribution line), have operated and the circuit breaker 417 has opened. In these examples, output generated by the PNN that detects the faulted equipment. To avoid a complication of figure, the protective relays are not represented in Fig. 2. Hence, the status of circuit breakers and protection relays can be detecting faults in a substation. Also, the status of this equipment can be represented by binary signals.

In case of the Sinyangsan power substation, the number of input neurons based on the states of protective relays and circuit breakers is 89, which are the sum number of 18 circuit breakers and 71 protective relays. The number of output neurons of the unified fault section based on the equipment is 190. Because, in single fault, 19 output neurons are needed. And, in double faults, 171 output neurons are necessary. Therefore, the number of pattern neuron and summation neuron is 190. Hence, there are 190 training pattern. The reason is that the major disadvantage of PNN that it is requires one neuron for each training set. Table 1 shows main features, which are a component of training data, structure of the PNN, and the number of training samples.

TABLE 1 Structure of PNN and number of training samples

Component of data	Structure of PNN	No. of samples
Single fault and double faults	89-190-190-190	190

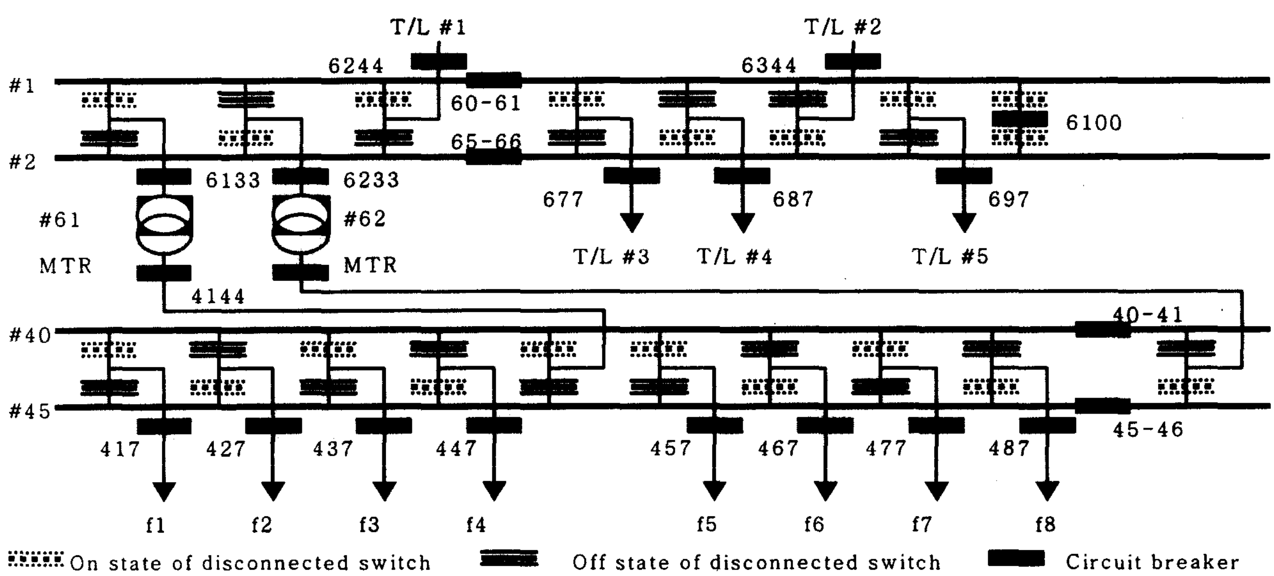

Fig. 2 The Sinyangsan substation system in KEPCO

In this paper, fault section detection of all possible single fault and double faults is considered in the only one PNN.

In training of PNN, input vectors are normalized to unit length and weight vectors between input layer and pattern layer are set by the value of each of the input vector. Also, weight vectors between pattern layer and summation layer and between summation layer and output layer are set to 1. The smoothing parameter σ is determined to 1 by method used NeuralWare Professional Ⅱ. The most major advantage of PNN is that the training speed is fasting to instantaneous. Hence, the training time of PNN takes a few seconds in an IBM PC 586 90 ㎒.

In order to test the performance of the proposed FSDNN using PNN, a total number of 1901 fault patterns with a several error signal, not used during training, was considered. The test data was generated intentionally adding a non-operation and malfunction of protective relays and circuit breakers to the training set.

For instance, in case of a single fault in T/L#1, the protective relays of 87ST(T/L#1), 64(T/L#1) and 50(T/L#1), which are connected T/L#1, have operated. The circuit breaker 6244 has also opened. But, in case of non-operation in 64(T/L#1) and malfunction in 87ST(T/L#2), the proposed FSDNN detected accurately fault section. For another example, the protective relays of 87ST(T/L#1), 64(T/L#1), 50(T/L#1), 87ST(T/L#2), 64 (T/L#2) and 50(T/L#2) and the circuit breakers of 6244 and 6344 are working in case of a double fault in T/L#1 and T/L#2. However, the proposed method detects also accurately fault section in case of non-operation in 6244.

The overall results are summarized according to the testing data in Table 2. As shown in Table 2, the detection ratio is 100% for the all test fault patterns.

To show the real effectiveness of the proposed fault diagnosis system, simulation panel, which can generate multiple alarms, is designed. Fig. 3 shows the fault diagnosis system using simulation panels. There are alarms representing the status of protective relays and circuit breakers and switches that can represent on/off status of each alarm.

When faults occur, the status of protective relays and circuit breakers in the simulation panel are transmitted to the fault diagnosis system through 8255 I/O port.

According to this on-off status of protective relays and circuit breakers, the proposed FSDNN determines the fault section directly and fast. Hence, this system can be used as an aid to the operators in power substation.

Fig. 4 shows initial display of fault diagnosis system.

TABLE 2 Composition of testing patterns, number of testing data, and detection ratio

Fault type with error signal		No. of data	Detection ratio(%)
Single Fault	In case of one failure breaker(non-operation)	30	30/30 (100%)
	In case of one failure relay(non-operation)	71	71/71 (100%)
	In case of one failure device(malfunction)	500	500/500 (100%)
	In case of two failure relays	200	200/200 (100%)
Double Fault	In case of one failure breaker(non-operation)	100	100/100 (100%)
	In case of one failure relay(non-operation)	300	300/300 (100%)
	In case of one failure device(malfunction)	500	500/500 (100%)
	In case of two failure relays	200	200/200 (100%)
Summation		1901	1901/1901 (100%)

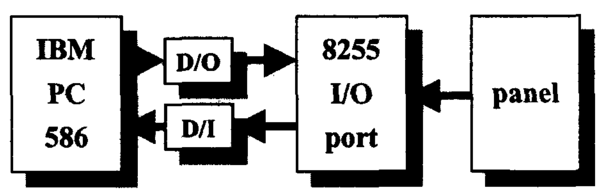

Fig. 3 Fault diagnosis system using simulation panel

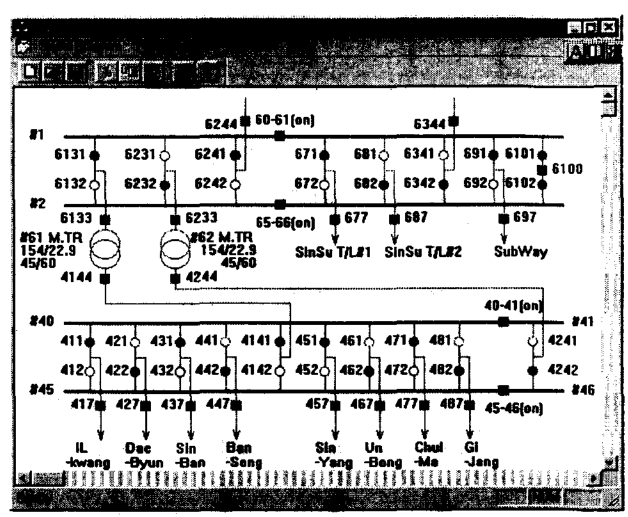

Fig. 4 Initial display of fault diagnosis system

5. Conclusions

In this paper, the PNN method for fault diagnosis in a power substation is proposed. The fault section detection of all-possible single fault and double faults is considered in the only one PNN. The performance of detection ratio is 100% for the all test fault patterns. Also, the training time of PNN takes a few seconds.

Although the proposed FSDNN has been used for a power substation, it can be applied to power system operation centers. Hence, the proposed system can be used as an aid to the operators in detecting fault section even though failed protective relays and circuit breakers exist.

To use a fault diagnosis system using PNN in real power systems, more case studies are necessary.

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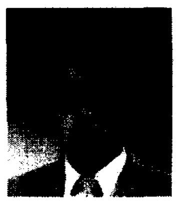

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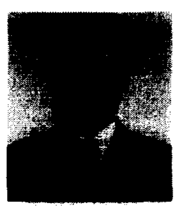

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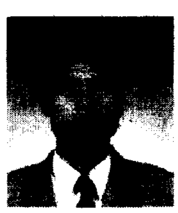

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