1-1-1996

Fault Classification Using Kohonen Feature Mapping

Badrul H. Chowdhury
Missouri University of Science and Technology, bchow@mst.edu

Kunyu Wang

Recommended Citation

B. H. Chowdhury and K. Wang, "Fault Classification Using Kohonen Feature Mapping," *Proceedings of the International Conference on Intelligent Systems Applications to Power Systems, 1996*, Institute of Electrical and Electronics Engineers (IEEE), Jan 1996.
The definitive version is available at https://doi.org/10.1109/ISAP.1996.501067

Fault Classification Using Kohonen Feature Mapping

Badrul H. Chowdhury
Kunyu Wang

Electrical Engineering Department
University of Wyoming
Laramie, WY 82071-3295
email: bchow@uwyo.edu

ABSTRACT

Recent applications of neural networks to power system fault diagnosis have provided positive results and shown advantages in process speed over conventional approaches. This paper describes the application of a Kohonen neural network to fault detection and classification using the fundamental components of currents and voltages. The Electromagnetic Transients Program is used to obtain fault patterns for the training and testing of neural networks. Accurate classifications are obtained for all types of possible short circuit faults on test systems representing high voltage transmission lines. Short training time makes the Kohonen network suitable for on-line power system fault diagnosis. The method introduced in the paper can be easily extended to any size power system since the only information required for the NN to function are those that are recorded at substation fault recorders. With fast NN hardware now becoming available, on-line implementation is only a question of economics.

Keywords: Artificial neural network, relaying, fault diagnosis.

1. INTRODUCTION

With the recent advances in learning techniques of artificial neural networks (ANNs), many different architectures of ANNs are being applied to areas of power systems. ANNs show significant potential as alternatives to analytic and even expert system methods. They have been used in security assessment to classify static and transient security states [1]. They have also been used to calculate optimal power flows [2]. ANNs have been used in the area of power system control to decentralize the control of power systems [3] and to design an adaptive control system [4]. Additionally, ANNs have been used to perform electric load forecasting [5].

In the field of fault diagnosis, several implementations of expert systems have also been reported. These implementations have developed knowledge bases of operator experiences coupled with inferencing methods. However, the complexity of the rule base and the inferencing process leads to lengthy path-to-goal times and, as a result, longer times to diagnose faults [6].

More recently, ANN techniques have been used to solve fault diagnosis problems in power systems. The use of neural network based schemes for fault detection and classification is only in its early stages, but it shows great promise for providing the adaptability necessary to sufficiently detect and identify power system faults.

Fault diagnosis is the determination of actual system condition from observable symptoms which might indicate a system failure. Some diagnoses need to be performed without knowing the status of all symptoms during multiple events and are required to select the correct conclusion from among alternatives. When a fault occurs on a transmission line, voltage and current signals develop a transient DC offset component and high-frequency transient components in addition to the power frequency (60 Hz) components. For distance relaying, the fundamental component has to filtered out from the noise spectra and used in the calculation of the apparent impedance. Herein lies the advantage of ANNs in fault detection. The inherent capability of the neural network to correctly predict the output even under noise and/or corrupted input is ideal in such situations where measurement noise can become a significant problem.

These fault-induced transients have frequencies with magnitudes and rates of decay that depend on many factors, such as fault location, fault type and system parameters. Many of these factors are random in nature. Different techniques have been proposed to estimate the phase quantities of the 60 Hz information.

Many fault classification techniques have also been suggested in the literature. Most of these techniques are based on the variation of the voltage or current samples of the three phases or the phasor quantities of the 60 Hz information. A multilayer perceptron method [7] has been developed to detect the presence of arcing faults in which the neural network is configured and trained with data computed from phase current parameters derived using the Electromagnetic Transients Program (EMTP) [8]. Another detection scheme [9] uses the third harmonic components of the residual voltage and current, power, and sequence components of the three phase voltages and currents as input to a single layer perceptron ANN. Another method [10] computes statistics from the phase currents and utilizes these as input to a clustering-based neural network for performing fault diagnosis.

This paper proposes the application of a Kohonen neural network for fault classification. This type of unsupervised network is superior to the conventional backpropagation network in classification tasks. The superiority is in terms of shorter training times. Test results of application of the designed ANN on two simple systems are shown later.

2. GENERATION OF FAULT DATA

In practice, it is difficult to obtain enough fault cases because the electric utility companies do not always archive all the fault cases or hesitate to make them public. Another problem is that it is not always possible to have all desirable fault cases in a substation. These problems can be eliminated by computer simulations using the well-known simulation package Electromagnetic Transients Program (EMTP).

EMTP simulations were used to obtain fault patterns for neural network training and testing in this study. Extensive simulations were conducted resulting in more than 600 fault cases. All ten possible transmission line fault types (a-g, b-g, c-g, a-b, b-c, c-a, a-b-g, b-c-g, c-a-g and a-b-c faults) were simulated and the following two parameters were varied within each simulation:

- load level (10, 20, 30, 40, 50, 60, 70, 80, 90 and 100 % of full load)
- Incidence angle of the fault occurrence (0, 45 and 90 electric degrees on the phase A voltage waveform).

Normal operation at different load levels were also simulated.

2.1 EMTP

The Electromagnetic Transients Program is a computer program used to simulate electromagnetic, electromechanical, and control system transients on electric power systems [11]. As a digital computer counterpart to the analog Transient Network Analyzer (TNA), EMTP was developed in the late 1960's by Dr. Herman Dommel. Many other capabilities have been added to EMTP since that time, and it is widely used in the utility industry and research institutes.

2.2 Test Systems

The one line diagram of a modeled 230 KV power system is given in Fig. 1

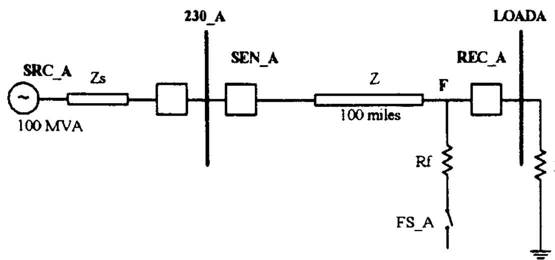


Fig. 1. One line diagram of Test system #1

A second test system, shown in Fig. 2, was also used in the simulations. This system represents a case wherein generating sources are present on either side of a faulted line.

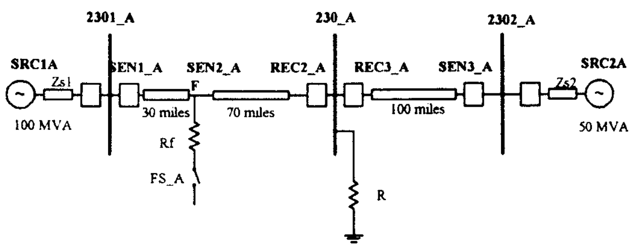


Fig. 2. One line diagram of Test system #2

A total of ten types of faults, viz., three single line-to-ground faults, three line-to-line faults, three double line-to-ground faults, and one three-phase, were applied to the receiving end of the 100-mile long transmission line in Test system #1, one fault at a time. In Test system #2, the fault point (F) was located on the transmission line between Bus 2301 and Bus 230, specifically 30 miles away from Bus 2301. The resulting short-circuit voltages on the 230 KV bus and currents on the faulted transmission line were determined. Results were obtained for loading conditions of 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100 MW on the line. Simulations on Test system #2 were conducted by following the same procedure, but the load resistance was chosen at 353 ohms instead of 529 ohms for the full-load. The point of time (in electrical degrees) on the voltage wave at which the fault was applied to the line was varied. Simulation results have been obtained for the cases of 0, 45 and 90 degrees

2.3 Results from the Simulations

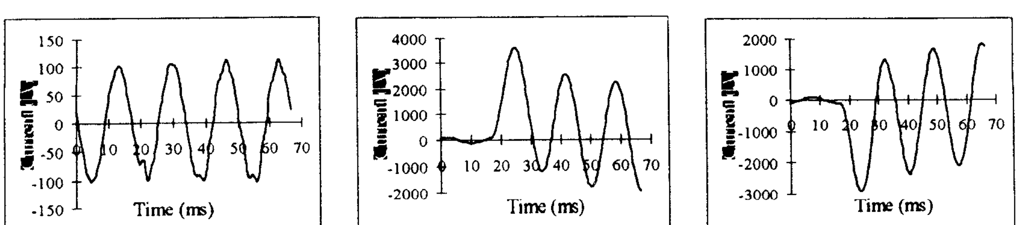
A number of EMTP simulations of various fault events were performed for generating fault patterns to be used for training and testing of the neural network. The sampling frequency was 6 kHz which is as the same as that of digital fault recorder (DFR) in substations. A total number of 620 fault patterns were generated in this way. Also, ten patterns labeled as normal state were generated for each system to represent the steady state (no-fault case) of the power system. Total number of fault patterns used for training was 414. In addition to that, 14 of 20 steady state patterns were provided for the training. Distribution of the patterns according to the fault type is given below in Table 1. The waveforms and the spectra of three phase currents in a line B and C-to-ground fault simulated on Test system #1 is shown in Figs. 3a and 3b respectively.

2.4 Pre-Processing of Fault Data for Inputs to ANN

In order to get the fundamental frequency components of the voltages and currents for the inputs to neural networks used in the fault diagnosis, a Fourier analysis program was used. The spectra of the waveshapes were calculated using a Fast Fourier Transform (FFT). The frequency resolution is limited by the sample size in the time domain. If a two-cycle sample was used, the resolution would be 30 Hz. If the sample was made of one-half cycle, the results would be difficult to interpret since the 60 Hz component itself would not show up. Therefore, a sample size of one cycle was chosen for getting fundamental frequency components. The neutral currents were calculated by adding phasors of the three-phase currents of each fault event.

Table 1. Distribution of fault patterns resulting from EMTP simulation

Fault Type	0 Deg	45 Deg	90 Deg	Test system #1	Test system #2	Number of patterns
a-g	20	20	20	30	30	60
b-g	20	20	20	30	30	60
c-g	20	20	20	30	30	60
a-b	20	20	20	30	30	60
b-c	20	20	20	30	30	60
c-a	20	20	20	30	30	60
a-b-g	20	20	20	30	30	60
b-c-g	20	20	20	30	30	60
c-a-g	20	20	20	30	30	60
a-b-c	20	20	20	30	30	60
normal				10	10	20
Total	200	200	200	310	310	620



(a) Phase A current **(b) Phase B current** **(c) Phase C current**

Fig. 3a. Current waveforms of a BC-G fault

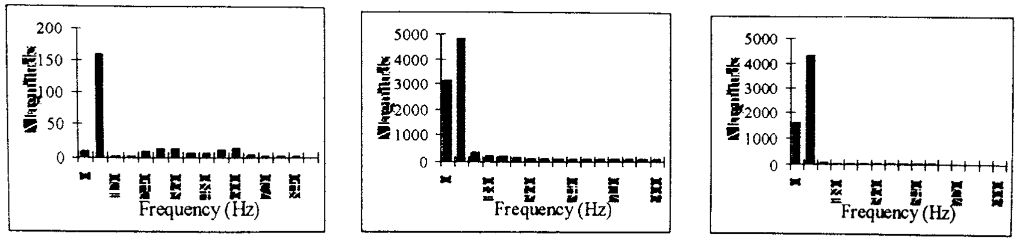


Fig. 3b. Current spectra of a BC-G fault

3. IMPLEMENTATION OF THE ANN

There are many architectures of artificial neural networks (ANNs) associated with different learning methods. The Kohonen network was selected for its excellent pattern classification capability. Table 2 shows an overview of the implementation.

Table 2. An overview of the implementation

Source of data:	Results of EMTP simulations
Input pattern length:	4 currents and 3 voltages of 60 Hz
Sampling frequency:	6 KHz
FFT sample size:	1st cycle after fault occurrence
Fault types to be classified:	All 10 types of faults and 1 normal case
Number of patterns used for training:	414
Number of patterns used for testing:	206

3.1 Neural Network Learning

Uncertainty of relay and circuit breaker tripping signals

Fault diagnosis of power systems is usually based on the tripping signals of relays and circuit breakers. Owing to the uncertainty of data sources, these kinds of signals have not been selected as inputs to the neural networks for fault detection and classification in this study. The information in the alarm messages sent by the Remote Terminal Units (RTUs) is not always reliable. Noise and loss of information may appear at several points between the moment when the fault occurs and the instant at which it reaches the diagnostic system. The most common sources of uncertainty that can be enumerated are given below:

- protective relay failures
- breaker failures
- local acquisition errors
- transmission errors
- inaccurate occurrence time

In order to select the most relevant input features, several different input formats were considered during design and testing of the neural networks. These input formats are summarized in Table 3. Input formats 1 and 2 consist of both prefault and postfault samples, while input formats 3 through 6 contain only postfault samples. Input formats 1 through 4 use fault data in the time-domain. Since the number of neurons in the input layer of the ANN is determined by the length of the input vector (e.g., for the input format 1, the number of neurons in the input layer is 300, while for the input format 2 that number is 600), input neuron requirements are much fewer for formats 5 and 6 which use the fundamental frequency components. The training error rate was noticeably high for input format 5 indicating that there was insufficient distinguishable information present in the data to perform the classification. The data was then pre-processed to add the fundamental frequency components of the neutral currents and voltages of the first cycle of a fault, utilizing a FFT. This processed data is found to contain the most significant information for fault diagnosis. Training was much more satisfactory when using the processed data.

3.2 The Kohonen Self-Organizing Neural Network

In accordance to experimental results, it has been postulated that information in the brain is stored on a two-dimensional surface, and that related information occupies neighboring locations on that surface [1]. Mathematical models describing these self-organizing neural networks have been developed by Kohonen [12]. Throughout this paper, the terms "Kohonen neural network", "Kohonen classifier" and "self-organizing feature map" are used synonymously for this type of network. Fig. 4 shows the Kohonen self-organizing feature map.

Table 3. Input formats of neural networks

Input format	Length of pattern: Sample cycles	Length of pattern: Data domain	Length of pattern: No. of samples	Sample types
1	1/2 cycle prefault, 1st 1/2 cycle fault	time	300	3-ϕ currents
2	1/2 cycle prefault, 1st 1/2 cycle fault	time	600	3- ϕ currents 3- ϕ voltages
3	1st cycle of fault	time	300	3- ϕ currents
4	1st cycle of fault	time	600	3- ϕ currents, 3- ϕ voltages
5	1st cycle of fault	freq	3	3- ϕ currents
6	1st cycle of fault	freq	7	3- ϕ currents, neutral current, 3- ϕ voltages

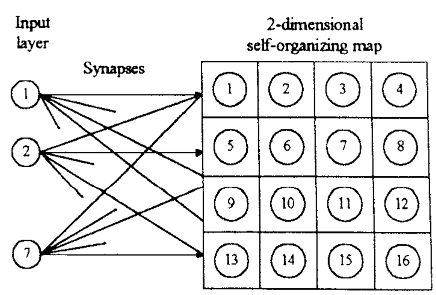


Fig. 4. The Kohonen neural network

There is no target output and no "teacher" for evaluating an error function in these networks. The learning of the synaptic weights is unsupervised, which means that upon presentation of new input vectors, the network determines these weights dynamically such that input vectors which are closely related will excite neurons which are close together or clustered. It is able to separate data into a specified number of categories and therefore capable of acting as a classifier. In the Kohonen network there are only two layers: an input layer where patterns of variables are placed, and an output layer which has one neuron for each of the possible categories or classes.

3.2.1 Training of the self-organizing feature maps

The patterns are presented to the input layer then propagated to the output layer and evaluated. One output neuron is the "winner", that is, the weight vector leading to this neuron is closer, in the input space, to the input pattern than that of any other output neuron. The network weights are then adjusted during training by bringing this weight vector slightly closer to the input pattern. This process is repeated for all patterns for a number of epochs usually chosen in advance.

To function properly, this type of network also depends upon adjusting the weights of "neighboring" neurons during training. Otherwise one neuron could end up winning all of the time. To make this adjustment, the size of the initial neighborhood needs to be specified. The neighborhood size is variable, starting off fairly large (sometimes even close to the number of neurons in the output layer) and decreasing as training progresses. During the last training events, the neighborhood is zero, meaning that only the winning neuron's weights are changed. By that time the learning rate is very small, too, and the clusters have been well defined. The subsequent (small) weight changes only make slight refinements on the cluster arrangements.

Training of the neural network for each test system (Test system #1 & #2) was conducted using 207 fault patterns. Trained networks were then used for detection and classification of the postulated faults.

3.2.2 Unsupervised learning and network parameters

The main problem to perform good mapping of the input onto the Kohonen map is one of determination of learning and network parameters. These parameters have been established experimentally by preliminary simulations.

Number of neurons on the Kohonen map

Generally, Kohonen's self-organizing neural network can be applied in two different manners to classification problems. If the number of input vectors exceeds the number of units in the map, the network will cluster similar faults into one unit. The same grouping effect can happen if two inputs are very close in the sense of the chosen distance measure. Otherwise, the neural network will work as a generalizing network, similar to the backpropagation network. In this case, the input vectors will be distributed on a part of the units of the Kohonen map, and the remaining units will represent an interpolation of the surrounding units.

In order to obtain a well-organized generalizing network, the learning parameters must be properly chosen, especially the neighborhood. The winning neuron needs to have a positive influence on its neighbor neurons. The choice of a proper size of neighborhood is dominant for a topologically correct organization of a Kohonen map. After many experiments, a 2-dimensional Kohonen map consisting of 16 units for Test system #1 and a map of 25 neurons for Test system #2 were selected for a total 11 classes.

Number of dimensions of the input vector

The number of components of the input vector is determined by many factors. This was taken to be as small as feasible due to the approximately linear dependence on the simulation time. The comparison of different input formats has been discussed earlier. It has been determined that the input vector will be composed of seven variables (magnitude of Ia, Ib, Ic, In, Va, Vb and Vc) in this study.

The Initial learning gain and neighborhood

The weight updation in kohonen network networks is a dynamic process and is based upon a number of factors, the most important being the learning gain and the neighborhood parameter. Both these parameters change internally to force fast convergence of weights during iterations. Simulations for this study showed that the initial learning gain should be between 0.3 and 0.6, and the initial radius of the neighborhood must be about one-half of the maximal units of the Kohonen map. An initial gain of 0.5 and an initial neighborhood of 8 (12 for the network with 25 output neurons) were used. These two parameters decrease with the progress of training.

Choice of the distance measure

Kohonen himself proposes the scalar product and the Euclidean distance to calculate the similarity between the input and the weight vectors [13]. Due to high computation time of the scalar product, the Euclidean distance method is used for the simulations.

3.2.3 Testing of the trained Kohonen network

The test patterns were randomly carried out to evaluate the performance of the trained Kohonen neural networks. During the testing period, a three-phase and all combinations of line-to-ground, line-to-line and double line-to-ground faults were applied. Tests were performed with fault incidence angles of 0, 45 and 90 degrees, and with different load levels of 30%, 60% and 90% of the full load. The neural network was presented with 103 new fault patterns. The network had never "seen" these patterns before and the task was to classify these new patterns based solely on the previous experience obtained during the training. Results of testing are shown and discussed in the next section.

Based on early test results, modifications and refinements were made to the parameters of the neural networks in order to increase the accuracy of the performance. Table 4 shows the results of tests with different parameters.

The Kohonen maps which show the resulting clusters of the fault type classification are given in Figs. 5 and 6. As noted earlier, the Kohonen feature map developed for Test system 1 has 16 locations and that for Test system 2 has 25 locations. Therefore, a number of locations are not used in the classification. During the recall phase, an incoming faults to be tested for its type will activate the specific output neuron corresponding to its location on the map. It is also worth noticing, in the figures, that faults involving the same phases reside as neighbors.

4. CONCLUSIONS

The ability of artificial neural networks to provide high-speed fault detection and classification in power systems has been demonstrated in this paper. The Kohonen self-organizing network has been developed for fault diagnosis. Test results were shown to be very satisfactory with 100% accuracy.

In the current work, all faults were created using the same fault location. However, fault locations can be included as a variable which means additional simulations would have to be carried out to train the network to recognize such occurrences.

The Kohonen method requires a relatively short training time. When neural networks are applied to power systems for fault diagnosis, they usually need on-line training since there are changes of parameters in power systems from time to time. For on-line training, EMTP simulations are replaced by recorded data at substation DFRs. The method introduced in the paper can be easily extended to any size power system since the only information required for the NN to function are those that are recorded at substation DFR. The simulated Kohonen network could also be implemented on a neural network hardware, which are now becoming available, thereby making on-line implementation a distinct possibility.

Table 4. Testing results of Kohonen neural networks for Test system #1 with modification of parameters

No. of neurons in output layer	Initial Neighbor-hood	Initial learning gain	Training epochs	Performance Accuracy
16	8	0.5	50	100%
16	10	0.5	200	81.82%
16	15	0.5	200	63.64%
18	9	0.5	200	100%
25	8	0.5	200	86.00%
25	10	0.5	200	93.00%
25	12	0.5	200	93.00%
25	13	0.5	200	93.00%
25	14	0.3	200	95.00%
25	18	0.3	200	77.82%
25	24	0.5	200	78.82%

#1 C-A	#2 CA-G	#3	#4 A-B-C
#5	#6 B-C	#7 BC-G	#8
#9 B-G	#10	#11 C-G	#12 Normal
#13 A-G	#14	#15 AB-G	#16 A-B

Fig. 5. The Kohonen self-organizing map of classified faults for Test system #1

#1 B-C	#2 BC-G	#3	#4	#5
#6 B-G	#7	#8	#9 C-G	#10
#11 Normal	#12	#13 A-G	#14	#15
#16	#17 CA-G	#18 C-A	#19	#20
#21	#22 A-B-C	#23	#24 A-B	#25 AB-G

Fig. 6. The Kohonen self-organizing map of classified faults for Test system #2

5. REFERENCES

[1] D. Niebur and A. J. Germond, "Unsupervised Neural Network Classification of Power System Static Security States," Proc. Third Sym. on ESAP, Tokyo, Japan, 1991, pp. 336 -342.

[2] H. Mori, N. Kitani and S. Tsuzuki, "Optimal Power Flow Calculation using the Hopfield Net Proc. Third Sym. on ESAP, Tokyo, Japan, 1991, pp. 328-335.

[3] A. Tan and M. Etezadi-Amoli, "Decentralized Control of Power Systems using Neural Networks and Transient Energy Function," Proc. 1993 North American Power Sym, Washington, DC, October 1993, pp. 329-335.

[4] D. J. Sobajic, Y.-H. Pao and D. T. Lee, "Autonomous Adaptive Power System Control," Proc. Third Sym. on ESAP, Tokyo, Japan, 1991, pp. 351-357.

[5] N. S. Moharari and A. S. Debs, "A Rule-Based Artificial Neural Network Approach for Electric Load Forecasting," Proc. 1993 North American Power Symposium, Washington, D.C., October 1993, pp. 145-150.

[6] Kwang-Ho Kim and Jong-Keun Park, "Application of Hierarchical Neural Network to Fault Diagnosis of Power System," Proc. Third Sym. ESAP, Tokyo, Japan, 1991, pp. 323-327.

[7] S. Ebron, D. Lubkeman and M. White, "A Neural Network Approach to the Detection of Incipient Faults on Power Distribution Feeders," IEEE Trans. on Power Delivery, Vol. 5, No. 2, April 1990, pp. 905-914.

[8] "EMTP Book – Version 1.0," EPRI Report EL-4541, Vols. 1-2, prepared by Systems Control Inc., 1986.

[9] A. M. Sharaf, L. A. Snider and K. Debnath, "Third Harmonic Based Detection of High Impedance Faults in Distribution Systems using Artificial Neural Networks," Proceedings of the 1993 North American Power Symposium, Washington, D.C., October 1993, pp. 315-321.

[10] K. L. Butler and J. A. Momoh, "Neural Network Based Classification of Arcing Faults in a Power Distribution System," Proceedings of the 1993 North American Power Symposium, Washington, D.C., October 1993, pp. 322-328.

[11] S. F. Mauser and T. E. McDermott, "Electromagnetic Transients Program (EMTP) Primer, Electric Power Research Institute (EPRI), EPRI EL-4202, Final Report, Palo Alto, California, 1985.

[12] T. Kohonen, "Self-Organized Formation of Topologically Correct Feature Maps," Biol. Cybernetics No. 43, 1982, pp. 59-69.

[13] T. Kohonen, Self-Organization and Associative Memory, 2nd Edition, Springer-Verlag, New York, 1988.