Localization of Winding Shorts Using Fuzzified Neural Networks

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Abstract

Shorted turns in field winding of large turbogenerators are difficult to detect and localize. We propose a technique whereby shorts are detected and localized using an artificial neural network with a fuzzified output. The method is based on injecting two simultaneous and identical waveform signals at both ends of the field winding. Selected features of the received signals are used to train the neural network. Once trained, the neural network can detect and localize short turns in the field winding. The proposed method is verified by a field test on 60 MVA turbogenerator. The results show that the proposed method is quite accurate and efficient.

Keywords: Synchronous Machine, Short Turns, Neural Networks

1. Introduction

Shorted turns in the field winding of large turbogenerators (2 or 4 poles) are a common problem whose detection and localization have remained elusive. Shorts occur primarily from incessant pounding of the rotor copper conductors while the machine is turning in low gear. This low speed operation is designed to avoid the deformation of the shaft that occurs when the rotor remains stationary in the bore for long periods of time.

The pounding of the copper conductors results in the accumulation of copper powder within slots. When the machine is subsequently energized, the copper dust causes arcing between the turns in the slot. Over time, a full short circuit between turns may result. Broken rotor conductors and water intrusion may also cause short turns.

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In many instances, the rotor short turns are speed dependent, i.e., the fault tends to disappear once the machine is brought to standstill. This makes the determination of such a fault difficult.

Methods thus far proposed to recognize the existence of a short-turn in a rotating turbogenerator are based on sensing the increased mechanical vibration or the change in the effective m.m.f. produced by the winding. Such methods are often quite inconclusive.

A promising method requires placement of pickup (search) coils inside the bore area [1]. The passage of leakage flux from each conductor slot induces voltage in the search coils. The amplitude of the voltage is directly proportional to the ampere turns in the slot. Therefore, a reduced voltage is observed when a shorted turn exists. Although this method is reliable, it requires the installation of the pickup coil. This can only be done during a major outage of the machine.

Another method is based on special design of the field windings [2]. The windings of each phase of the generator are divided into two sections connected in parallel. When a shorted turn is present, there is no longer a symmetry between the flux distribution of the two pole faces. The airgap flux density will then contain even harmonics. Equal and opposite even harmonic voltages are induced across the phase windings resulting in circulating currents flowing around the parallel half phase. The shorted winding can then be detected through the measurement of the circulating current. This method relies heavily on winding redesign. This method also provides no information about the location of the shorted turn in the winding [3].

A promising technique that does not require installing equipment inside the turbogenerator uses traveling waves [4-5]. Two traveling waves are sent through the rotor from opposite ends and the signal difference is observed. Due to symmetry, if there is no short, the difference between the two receiving signals is quite small. When a short occurs, the difference between the two received signals can be quite significant. An expert can examine the difference and decide whether the field winding has a short.

In this paper, the traveling wave method is refined to allow for fault localization. A neural network with a fuzzy logic output is used to specify the localization of the short. The developed method is quite general and can be used for localizing short turns in power devices such as transformers and motors.

The proposed detection method was tested in the Southern California Edison facilities on a 60 MVA turbogenerator. The generator has 14 coils with 17 turns per coil. The shorts between windings were intentionally introduced to verify the proposed technique.

2. Description of Proposed System

Figure 1 shows the basic concept of the traveling wave method for fault detection. Two identical signals are injected into the winding from either side and are received on the opposite end. The receiving signals are subtracted to form the *signature signal*, A-B. The frequency of the injected signals should be selected at a rate no greater than about $\frac{1}{10\tau}$, where τ is the travelling time of the field winding which is dependent on winding parameters. The interference between the falling edge of the injected signal and the reflected wave is then essentially eliminated.

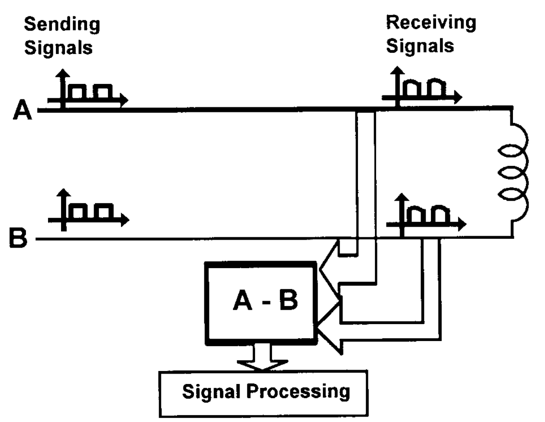

Figure 1. Travelling wave signature signal acquisition

The method's circuitry is depicted in Figure 2. A pulse generator is used to send two signals to the symmetrical circuit. The frequency of the signals is dependent on the winding parameters. The symmetrical circuit receives the two reflected signals and provides the signature signal to a PC-based computer through a *general purpose interface board* (GPIB). Several sampled signals for different short locations are collected for feature extraction and subsequent neural network training. The neural network used in this study is the layered perceptron [6-7]. The output of the neural network is fuzzified to increase the accuracy and the dynamic range of the neural network's output, and also to diminish the effect of noisy measurements [9-12].

The shape of the signature signal is used to perform two functions: 1) detect the existence of a shorted turn; and 2) localize the short. A high frequency sampling device is used to ensure that the entire signature signal is captured. This results in a vector whose high dimension cannot be easily processed by the neural network. Hence, the cardinality of the training data must be reduced without destroying the data's information content [13-17].

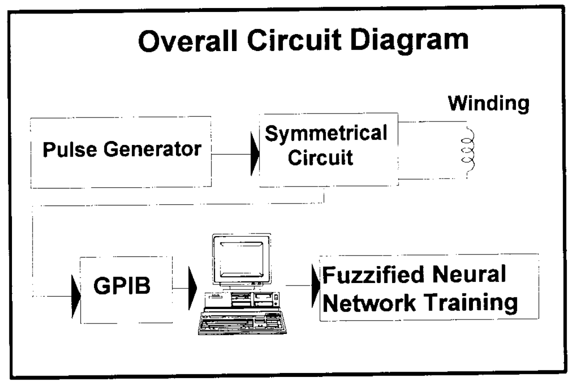

Figure 2. Signature signal circuitry

3. Fuzzified Neural Network

With the introduction of new neural network topologies and efficient training algorithms, neural networks have proven useful in several power applications [7]. The neural network, when adequately designed and trained, can synthesize a useful nonlinear mapping between input and output patterns. This is a key property for short turn detection and localization.

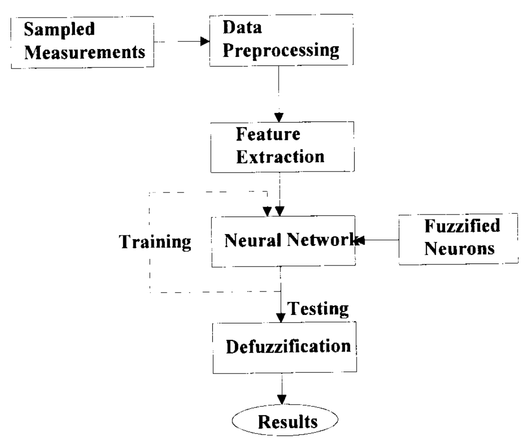

Figure 3. Short turn localization procedure.

Figure 3 outlines the general procedure for short turn detection and localization. The training data acquired by the setup for the signature signal is used for neural network training. Extracted features from the signature signal are used as inputs to train a standard feed forward layered perceptron artificial neural network [8]. The location of the short is coded into a number of output neurons determined by the desired resolution of the short localization. For example, a field winding may be divided into coils and the coils divided into turns.

The location of the short is coded into a number of fuzzy membership functions determined by the desired resolution. In this study 6 membership functions were used. The number of output neurons of the neural network is the same as the number of the fuzzy membership functions as illustrated in Figure 4. The turbogenerator has 14 coils with 17 turns each. The total number of turns is 238. These turns are divided into six groups as shown in the figure. Each output neuron corresponds to the value of the membership function. For a short at turn #75, the membership function (and the NN output) is $[0\ 0.4\ 0.6\ 0\ 0\ 0]^T$.

During testing, the output of the neural net is *defuzzified* where each membership function is weighted by the state of the corresponding output neuron [9-12]. The weighted membership functions are then added and the center of mass (first moment) of the sum is the short location. If, for example, each membership function is of identical shape and has a center of mass C_i, then the (defuzzified) centroid is

$$short\,location = \frac{\sum_i \beta_i C_i}{\sum_i \beta_i} \tag{1}$$

where β_i is the output of the i^{th} output neuron. Other defuzzification methods can also be used [11].

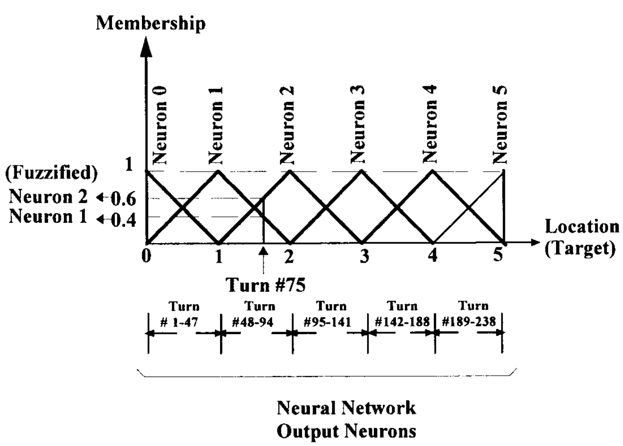

Figure 4. Membership function for the fuzzification mappings.

4. Field Testing

The proposed detection method was tested on a turbogenerator in Southern California Edison Company. The rotor is a 2-pole, 3600 rpm, 60 MVA with 7 concentric coils on each pole. Each coil has 17 turns. Thus the loss of one turn reduces the ampere-turns of that pole by about 0.85%.

The photo of Figure 5 shows the rotor of the turbogenerator and the equipment used for detection. The neural network and fuzzy encoding were implemented by PC software. The hardware is used for the signal generation and acquisition.

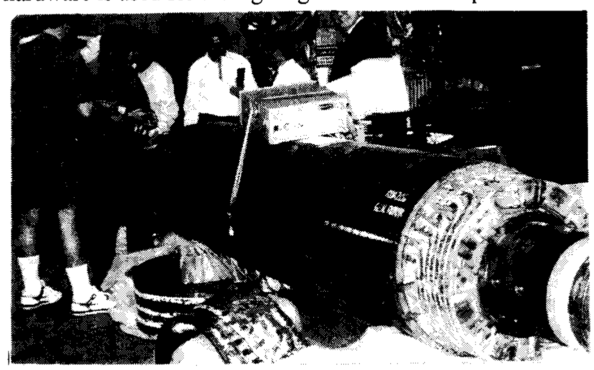
Figure 5: Photo of field test

To train and test the neural network, temporary shorts were introduced between adjacent windings. Two simultaneous signals were then injected from both sides of the field winding. The difference between the two receiving signals is the signature signal. This signal is used to detect and localize the shorted turn. Examples of several sampled waveforms are shown in Figure 6. The horizontal axis represents the time in microseconds and the vertical axis is the magnitude of the signature signals in volts. The signature signal is the difference A-B.

The signature signals are sampled at 5 MHz. If the entire signal is used to train the neural net, the network will certainly suffer from scaling problems and the curse of dimensionality. Feature extraction, rather, must be used to capture the information contents of the signal using small size of data. Some feature extraction methods are based on mathematical techniques [16-17]. Others are based on engineering judgment and heuristics.

Figure 7 shows an expansion of a signature signal. Because of dispersion, the changes in the signal due to different short location near the initial time were the largest. Therefore, we divide the signature signal into two sections: initial and extended. In the initial section, the waveform is divided 4 intervals of 18 microsecond each. The extended section is composed of 4 intervals of 36 microseconds and 5 intervals of 72 microsecond intervals. The area of each interval is

$$Area_i = \int_{t_{i-1}}^{t_i} v(t)\, dt \tag{2}$$

A total of thirteen areas are obtained for each signature signal. These areas are used as the input to the neural network.

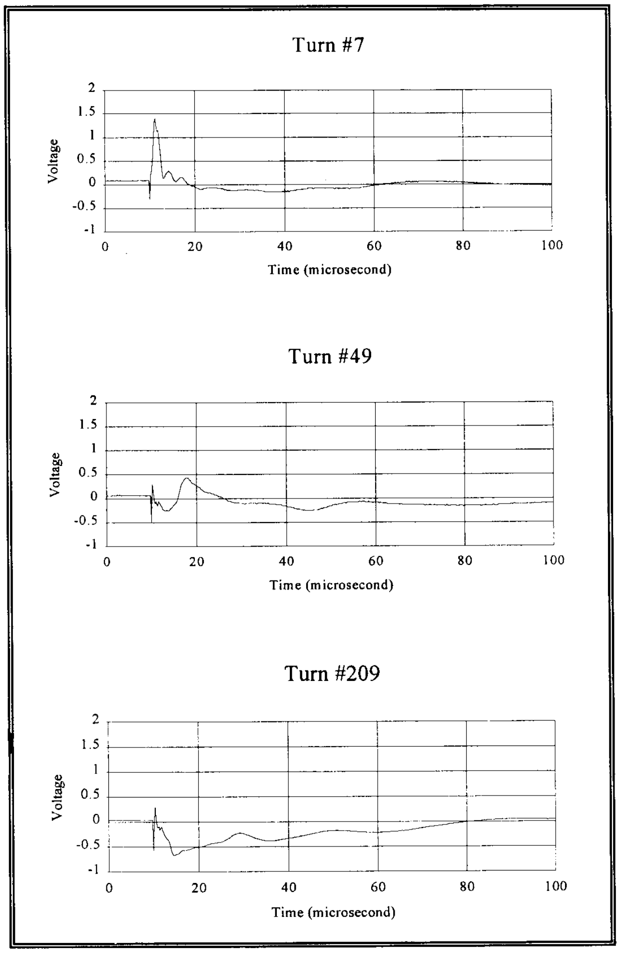

Figure 6. Samples of signature signals.

A total of 67 training patterns were collected by shorting adjacent turns at several locations within the field winding. A neural net with one hidden layer, thirteen input neurons, four hidden neurons and six output neurons was used. This architecture gave a lower test error than other architectures. The network was trained by using the standard back-error propagation method.

After training, the neural net was tested for 60 short locations taken at random points. None of the test data was used during training. The test results are listed in the Table 1.

As seen in the table the proposed technique is highly accurate and very robust. In all test cases, the coil with shorted turns was accurately identified. Moreover, the shorted turns were all localized to within a few turns.

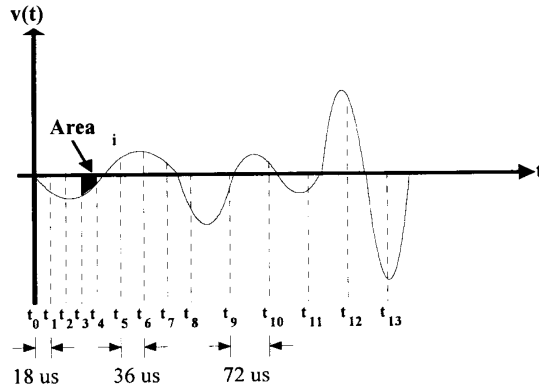

Figure 7. Features extracted from signature signal

Table 1. Field test results.

NN Structure	
Input Neurons	13
Hidden Neurons	4
Output Neurons	6
Patterns	
Training Patterns	67
Testing Patterns	60
Test Results	
Percentage of Accurate Identification of Coil	100%
Maximum error in short localization	± 7 turns (± 3%)

5. Conclusions

A method to detect and localize shorted turns in the field winding of turbogenerator was developed and verified. The procedure is based on neural network and fuzzy logic technology. When tested on a 60 MVA turbogenerator, the method was accurate and robust.

Acknowledgment

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Discussion

N. Iwan Santoso (Siemens Corporate Research Inc., Princeton, NJ): I would like to congratulate the authors for their interesting application of neural network approach to diagnostic and allocation of shorted turns in field windings of large turbogenerators.

Our experience in motor diagnostic using neural network approach show that it requires sufficient normal and fault data for training the network, before the network can give a reasonable good performance during testing. Moreover, the trained network is not usually transferable for diagnosing another similar machine because of characteristic differences between those machines.

Based upon these investigation, two questions come to mind:

1. Is extensive measurement for obtaining the necessary training data required for each individual machine? Is generalization between machines for this particular problem is possible?
2. Considering the large difference between time of measurement and time of failure, the characteristic of the winding may have change significantly. How robust is the performance of the network to this type of changes?

Comments and suggestions from the authors would be most appreciated.

Manuscript received February 14, 1994.

L.L. Lai and K.H. Chu, (Energy Systems Group, City University, London EC1V 0HB, England, UK): The neural network (NN) has capability of nonlinear mapping, parallel processing and learning. On the other hand, the fuzzy logic technology is characterised as extension of binary Boolean logic. The fuzzy logic is a class in which transition from membership to non-membership is gradual rather than abrupt. Both the NN and fuzzy logic have some difficulties. The NN can produce mapping rules from empirical training sets through learning, but the mapping rules in the neural network is not visible and is difficult to understand. On the other hand, since the fuzzy set does not have learning capability, it is difficult to tune the rules. In order to solve these difficulties, recently, much research has been trying to integrate the fuzzy logic technology and NN.

The authors are to be congratulated for an interesting paper in this area. It would be appreciated if the following points are clarified:

The neural network should respond to new patterns not originally included in the training set. A common feature of any neural network is its capability to produce good response to a pattern which is not covered by the training set. If a neural network fails to do this, it is not acceptable at all. Would the authors explain how do they obtain the training data and testing data? Would it be true that the two sets are in fact very similar in this case and therefore the accuracy is so high. as reported in the paper.

There must be certain parameters that tend to indicate a short circuit on the winding. Could the authors confirm that the parameters that they have used are the most important one. Are there any other parameters that have been considered as well?

The discusser interests in the methodology that the authors used to construct the training set. The choice of input dimension and the content of the training set play an important role in the network learning capabilities. The training set should be large enough to provide evidence for generalisation. Could the authors explain in detail how to use the 'fault locations' for the training set? Are the authors happy to confirm that this fuzzified neural network has generalised the problem?

Could the authors explain in detail how to deal with the scaling problem? It is not fully clear to the discusser from the paper and this is a very important matter for training and testing neural networks.

Manuscript received March 4, 1994.

M. A. El-Sharkawi, R. J. Marks, and **I. Kerszenbaum**:

In Response to Dr. Lai and Mr. Chu: The points raised by Lai & Chu are good ones. We thank them for making them.

Cross validation of a trained neural network is of fundamental importance. Care must be taken so that the neural network does not memorize. We report in the paper that cross validation was made with 60 test cases. With reference to Figure 5, training data was taken corresponding to shorts imposed at the far end of the rotor — the end where the people are standing. The test data, on the other hand, was generated by imposing shorts at the other end. If testing was performed from data taken at the same location as the training data, the results of the neural network performance would be nearly meaningless. This point should have been made in the paper and we thank Lai & Chu for bringing it to our attention.

Choosing features from raw data is an important component in the training of a neural network. All of the raw data cannot be used in the training due to the curse of dimensionality. In preliminary studies, we tried a number of different feature sets —including use of characteristics of the signal signature (i.e. magnitude and location of the largest peak). We found, in our studies, that the method described in the paper gave the best performance. Feature selection remains more of an art than a science. We cannot claim the features we used are optimal. Indeed, there exists no method we know of to ensure optimality. The best that can be done is to find better and better feature sets.

Our intent of using the fuzzified output was to increase the dynamic range and corresponding accuracy of the fault location. Note that the curse of dimensionality does not apply to the output of the neural network. As with the choice of the features, we tried a number of different output fuzzy parameterization and found that the architecture described in the paper performed to the desired precision.

Lai & Chu asked how we determined that the cardinality and distribution of the training set were sufficient for successful neural network training. A training signature signal was taken for a short imposed at each of the rotor's turns. This was a sufficient distribution simply because the resulting trained neural network generalized well—to 100% accuracy. Indeed, a more sparse sampling could have also performed well. We have not investigated this since downed rotor time is quite expensive. However, this may be a worthy investigation.

In Response to Dr. Santoso: We are appreciative of the insightful comments of Dr. Santoso.

The DC-field winding of a turbo-generator is essentially different from that of an induction machine. DC-field windings tend to have only a dozen or so of coils. Most field windings (turbo-generators) have two to four poles. Regardless of the machine's size and ratings, the general geometry of the windings does not change significantly between different machines. Therefore, we are led to believe that training of a neural network in a particular configuration (two or four-pole winding; number of coils; etceteras) will be sufficient to discriminate correctly for a family of machines. We believe the neural network will have to be trained on perhaps no more than a few machines to provide coverage of most of the machines in use. However, this is an area that requires the availability of more rotors for test. We will appreciate any manufacturer or customer in possession of large turbo-generators which will facilitate the testing of rotors, when available, with this device.

We do not believe degrading of the insulation has any influence on this particular test. Our device can only detect a shorted-turn once it has occurred. We have found the limit for detection of a shorted-turn is about ten to fifteen ohms between the turns. Unfortunately, the test will not detect a worsening insulation condition. This still relies on conventional insulation tests.

Manuscript received April 11, 1994.