# DETECTION OF SHORTED-TURNS IN THE FIELD WINDING OF TURBINE-GENERATOR ROTORS USING NOVELTY DETECTORS - DEVELOPMENT AND FIELD TEST

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**Abstract - A method for detecting shorted windings in operational turbine-generators is described. The method is based on the traveling wave method described by El-Sharkawi, et. al. [6]. The method is extended in this paper to operational rotors by the application of neural network feature extraction and novelty detection. Results of successful laboratory experiments are reported.**

**Key Words** - Shorted-Turn Detection, Neural Networks, Feature Extraction, Novelty Detection.

## I. INTRODUCTION

One of the most difficult problems in the operation of large synchronous turbine-generators is early detection of shorted turns in the DC-field of the rotor. Not only is the existence of a shorted-turn in the field winding hard to detect, the periodic maintenance required to correct shorted turns may result in expenditures of several hundred thousand dollars. Unfortunately, this expense is incurred even in the case of a wrong diagnosis. This is because the major expense results from the disassembly and assembly of the machine and in the added cost of lost production. Proper localization, and more important, accurate determination of the actual existence of a shorted-turn, is therefore essential to avoid huge unnecessary monetary losses. A general solution to this problem has so far remained elusive.

The machines under consideration are those with two- or four-pole cylindrical rotors. Shorted turns in salient pole rotors are less detrimental to the operation of the machine and, at the same time, easier to detect through the pole-drop test. However, the pole windings in a cylindrical rotor are totally inaccessible for this type of test.

A variety of methods have been proposed for the detection of shorted windings in rotors of large turbine-generators [11, 16]. Some of the more interesting methods are described below.

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For a turbine-generator with a shorted winding, changes in excitation will usually result in changes in vibration level. Unfortunately, there are many other variables in play during the process of changing the excitation making reliable discrimination based solely on vibration almost impossible.

Given the difficulty in reaching a reliable detection decision based on monitoring the vibration of the machine, other methods of detecting shorted turns have been employed. One such method relies on the indirect measurement of the impedance of the rotor field-winding during operation [14]. Unfortunately, this method yields dubious results unless the number of shorted-turns is significant. One positive characteristic of this method is the possible detection of a shorted-turn if this condition disappears at a certain speed. Continuous monitoring of the field resistance during the coast-down operation may reveal an abrupt change in value. This most certainly can be related to an intermittent shorted-turn. However, this method will not provide any help when a constant short is present. Nilsson and Mercurio [12] discuss the use of the pole balance test to detect shorted windings. This test has been inconclusive also due to the large variation present in normal operation.

Some methods detect the flux asymmetry created by a shorted-turn by applying AC current to the field through the collectors and holding a C-shaped pick-up coil across the slot [7]. This method is accurate but can only be performed after removing the rotor from the bore. This is an expensive exercise. In addition, detection of all shorts that tend to disappear when the rotor is brought to stand-still is precluded.

Other methods rely on special design of the stator winding [7]. Flux asymmetries generate circulating currents which can be measured. Although the method has the advantages of being applied to the machine under operation and not being intrusive, it also presents some serious disadvantages. For instance, many machines presently in operation do not have a winding design which lends itself to the application of this method. Redesigning a machine for the sole purpose of detecting shorted-turns is not practical.

Nilsson and Mercurio [13] describe a graphical method using synchronous generator capability curves. The use of the graphical method requires operation of the generator under various conditions to acquire data. This testing requires a great deal of coordination and is not an easy task.

One of the most reliable methods developed to date is based on the direct measurement of the air-gap magnetic flux with the machine in operation [1]. The flux is measured by a pick-up coil installed in the gap. Unfortunately, the presence of these coils in existing machines (and new ones) is rare and installation requires excessive down-time.

Another method relies on neural network models of machines to detect shorted turns [2, 3, 4, 5, 17]. This method requires a mathematical model of the machine or a machine in which turns can be shorted to provide training data for the neural network. The expense of inducing shorts in the rotor windings of large turbine-generators makes this method impractical.

The method proposed in this paper is based on the traveling wave method described by El-Sharkawi, et. al. [6]. Square pulses are injected into both ends of the device windings simultaneously. The pulses travel through the windings and reflect from a variety of circuit elements such as impedance mismatches and winding asymmetries. The difference between the reflected pulses is measured and amplified to produce a signature signal. Using the recorded signature signals and a fuzzified neural network, faults are not only detected but located with a reasonable degree of certainty. The equipment is very portable and the test requires little time. Tests performed so far have indicated reliable detection of shorted turns.

The major disadvantage of the method of El-Sharkawi, et al. [6] is that a neural network must be trained. The rotor windings must be accessible for the introduction of shorts between adjacent windings. The signature signals under shorted-turn conditions must then be collected to provide known inputs for network training. While the rotor is in operation, the windings can not be shorted due to the high cost of dismantling the machine and the danger of damage to the equipment and thus no data is available for training.

Therefore, only signatures for healthy windings are available for operational rotors. The use of the signature signal concept is thus proposed for detection of shorted turns in operational machines using novelty detection. The method can be applied to both a running and a still rotor, eliminating the problem of detecting intermittent shorted-turns.

Section II describes the use of a novelty detector to detect shorted-turns in turbine-generator field windings. Section III describes the results of laboratory and field experiments which demonstrate the successful detection of shorted turns in operational equipment.

## II. DETECTION OF SHORTED TURNS IN OPERATIONAL TURBINE-GENERATORS

The detection of shorted turns in operational rotors can be accomplished using the traveling wave method and novelty detection. The detection of faults for a rotor which is in operation is made much more difficult due to the presence of noise caused by the brushes, the mechanical variations during rotation, and the presence of the excitation source in the rotor circuit.

The brushes of a turbine-generator connect the excitation source to the slip rings and supply power to the rotor. The motion of the brushes and the current flowing through the brushes causes arcing. The arc noise is measured by the acquisition hardware. It corrupts the signature signal. A study of brush noise was performed on a small laboratory machine and found not to be a difficult problem since the frequency spectrum of the noise is well separated from the signature signal spectrum. The noise can simply be removed by frequency domain filtering or by averaging many signatures.

The rotation of the rotor causes the windings to shift as the rotor turns. The signature signal is dependent on the physical characteristics of the rotor windings and thus the signature signal will not be identical when measured at different points in the rotational cycle. The shifting windings will cause a low frequency stochastic component to appear in the signature signals. Removal of the rotational effects has not been attempted due to the complexity. The stochastic component, however, is dealt with in the novelty detection algorithm.

The excitation source provides another path for the pulses of the signature signal acquisition system. The added path will greatly change the reflected signals and thus change the signature signal from the dismantled rotor case. As long as the excitation windings are symmetrical from the perspective of the injected pulses, the ability to detect faults will not be hindered.

All of the modifying effects described above prevent the use of training examples collected while the rotor is dismantled to detect shorted turns while the rotor is operating. Since inducing shorted turns in an operational rotor is prohibitively expensive, the concept of a novelty detector must be used for the detection of shorted turns. An unlimited number of signatures can be collected for a healthy rotor in operation. When a shorted-turn fault occurs in the rotor, the signature signal will change. The change in the signal produces a novel signature and will be detected by the algorithm described below.

### *A. Signature Measurement*

The acquisition of signature signals for operational rotors is similar to the acquisition of signature signals for dismantled rotors [6]. The addition of blocking capacitors in series with each pulse generation path is required to protect the measurement circuits from the high excitation source voltage present on the brushes during operation. The pulses are not significantly affected by the capacitors and thus measurement of the signature signals is not affected.

Since the signature signals will be corrupted by noise, many collected waveforms will be averaged to produce a single signature. Averaging of the signals will remove any noise with zero mean such as brush noise. The number of signals averaged depends on the standard deviation of the noise and the degree to which the noise is to be removed. For noise outside the bandwidth of the signature signals, a lowpass frequency selective filter is used. Different rotors produce signature signals with different frequency contents. Therefore, the signature signals and the undesired noise frequency spectrums must be analyzed for each rotor type.

### *B. Novelty Detection*

A novelty filter, as defined by Kohonen [10], is a system which extracts the new, anomalous, or unfamiliar part of the input data. Neural networks have been applied to novelty filtering [9, 15]. The novelty filter neural network operates as an associative memory where the neural network, normally a two layer feed forward network, is trained to identify the inputs [8]. During training of the network by back propagation, the output of the network is forced to repeat the input. The output layer must thus have the same number of nodes as the input. During operation of the network, the inputs are presented and the output produces the values corresponding to the training input which resembles the current input. The novelty is then the difference between the current input and the output produced by the network. The difference signal is then compared with a threshold using some form of distance function. Use of neural networks for detection of shorted windings is difficult due to the high dimension of the signature signal and the noise characteristics. The neural network must be able to learn all signature signals for healthy operational rotors.

Measurements can easily be made for healthy rotors. Data collected when the machine is new or immediately after maintenance or cleaning increases the chance that data for a healthy machine is being gathered. Since many "good" signals can be measured, a statistical view can be obtained about the signal. The basic assumption is that the signal will vary significantly when a fault is present. A signal space boundary can then be computed and if a signature signal lies outside the boundary, the machine is considered faulty.

### *C. Computation of Detection Threshold*

The first operation performed on the signature signals is the removal of the mean. Since the signature signals are sampled and converted to an array of digital numbers, each signal can be considered a discrete vector or a point in the signal space. The average signal is computed by summing all healthy rotor signatures as vectors and dividing each component by the number of healthy signature signals used in the sum. The average vector, called the prototype signature, is subtracted from each signature signal to translate the signature signals toward the signal space origin.

The signal space is then partitioned into two regions: one for healthy rotors and one for faulted rotors. Due to the stochastic nature of the signature signals, the region corresponding to healthy rotors will extend away from the origin. A surface separating the two regions must be defined to enclose the healthy region. Any translated signature signals outside the detection surface will be assumed to represent a rotor with a fault.

The simplest detection surface is a hypersphere. The largest Euclidean length of the translated healthy signature signals is used as the threshold. The region for healthy rotors is inside the resulting hypersphere. Any signature signal outside the hypersphere will represent a faulted rotor. The detectors decision is made according to

$$\begin{array}{lll} Fault = True & if & \|x-\bar{x}\| > T \\ Fault = False & if & \|x-\bar{x}\| < T \end{array} \tag{1}$$

where $x$ is a signature signal, $\bar{x}$ is the prototype vector and T is the detection threshold or radius of the hypersphere. This method could potentially produce a detection algorithm with a high rate of missed detections. For example, if the translated healthy signatures all lie on a line, the sphere will enclose all the points but will have a great deal of space with no healthy signature signals nearby. A signature signal for a faulted rotor may lie within the hypersphere but not on the line and thus no fault would be detected.

A more accurate detection boundary can be defined using hyperellipses. The hyperellipse can be oriented in any direction and thus would not contain large empty spaces unless the healthy region consisted of multiple disjoint subregions. A signature matrix $X$ is formed by using the healthy translated signature signals as the columns. The correlation matrix $C$ is formed by

$$C = X\,X^T \tag{2}$$

The eigenvectors of the correlation matrix $C$ define the principle axes of the hyperellipse [8]. Each translated healthy signature signal is rotated into a new space by vector multiplication by the eigenvectors.

The use of the full signature matrix results in a large computational burden. The signature signals obtained for laboratory experiments have typically contained a minimum of 500 samples. The correlation matrix would then contain $500^2$ = 250000 elements. Computing the eigenvectors of such a large matrix can be difficult especially on the small personal computers used for data acquisition. For this reason, a neural network feature extraction method [15] is used to reduce the dimension of the signature signals before construction of the correlation matrix.

The feedforward neural network is trained to reproduce the input vectors at the output. However, a hidden layer containing a small number of nodes is used. If a linear network is used, the resulting operation can be shown to correspond to a projection onto a linear subspace. The dimension of the subspace corresponds to the number of nodes in the hidden layer. The activation values of the hidden nodes then correspond to the extracted features of the signature signals. To improve the performance of the linear network, the inputs are scaled to be within the interval [0, 1].

If the signature space is imagined to be three dimensional, the projection performed by the neural network can be viewed as a projection onto a plane. The hyperellipse detection boundary would then lie on the plane. Figure 1 shows this idea.

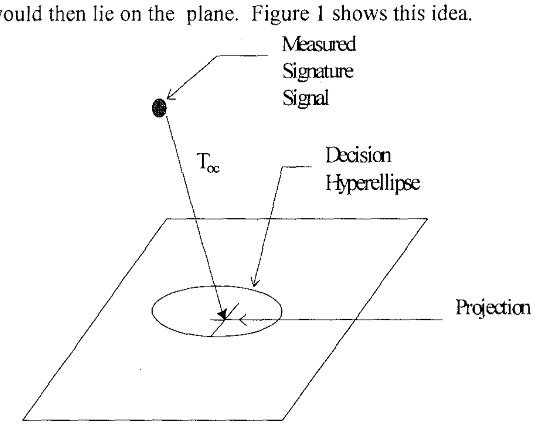


Figure 1: Simplified view of the projection of a signature onto the hyperellipse. The measured signature is shown to be projected onto the hyperellipse but to be significantly removed from the projection plane.

One problem created by the neural network projection is that the projection of a shorted winding signature may be inside the resulting hyperellipse. To resolve this problem, the magnitude of the orthogonal complement is computed for each healthy signature.

Since the training of the network will not be prefect, all signals will have a small orthogonal complement. The orthogonal complement can be computed by subtracting the network output from the input vector. The maximum Euclidean vector magnitude of the orthogonal complements of all healthy signatures can be stored to identify which vectors are potentially outside the detection surface. Let the maximum magnitude be given by $T_{OC}$.

The threshold calculation process now consists of translated healthy signatures which have been reduced to a smaller dimension. Since the signatures are scaled between zero and one and may not be centered about the origin, a new prototype is calculated for the reduced data and removed from all healthy, reduced signatures. The correlation matrix can then be constructed and the eigenvectors, $E$, easily calculated. The eigenvectors correspond to the axes of the hyperellipse. By forming the dot product between the eigenvectors and the signatures, the ellipse can be oriented along the coordinate axis making ellipse calculations much easier.

The next step involves calculation of the size of the ellipse or the actual detection boundary. A hyperellipse with minimum volume which encloses all healthy signatures is desired. This is done using the following procedure. First, all ellipse coordinates are set to the distance to the farthest healthy signature forming a hypersphere. Then, for each coordinate, the minimum size which encloses all the signatures is computed by

$$a_j = \max_{\vec{x}} \left\{ \frac{x_j}{\sqrt{1 - \sum_{\substack{i=0 \\ i \neq j}}^{N-1} \left( \frac{x_i}{a_i} \right)^2}} \right\} \tag{3}$$

where $N$ is the number of healthy signatures, $a_j$ is coordinate $j$ of the hyperellipse, and $x_j$ is component $j$ of the signature. The maximum is taken over all healthy signatures. The hyperellipse coordinates must be less than the maximum magnitude used to initialize the coordinates and each coordinate is independent of the others. Thus, the above procedure will result in the desired minimum volume hyperellipse.

The test to determine if a signature is within the hyperellipse is another simple calculation. The value $B$ given by

$$B = \sum_{i=0}^{N-1} \left( \frac{x_i}{a_i} \right)^2 \tag{4}$$

is tested to determine whether the signature is inside or outside the detection boundary

$$\begin{aligned} &Fault = True \quad && if \quad B > 1 \\ &Fault = False \quad && if \quad B < 1 \end{aligned} \tag{5}$$

*D. The Detection Algorithm*

The hyperellipse detection process can be summarized by the following algorithm. Let $\vec{x}$ be a newly recorded signature to be classified.

1. Center $\vec{x}$ by subtracting the prototype, $\bar{x}$, from the raw signal.

   $$\vec{y} = \vec{x} - \bar{x}$$

2. Propagate the centered signature through the neural network and record the activation values of the hidden nodes and the output nodes.

   $$\vec{z} = N_h(\vec{y})$$

   $$\vec{b} = N(\vec{y})$$

3. Compute the magnitude of the orthogonal complement by subtracting the neural network output from the centered signature and compute the vector magnitude.

   $$M = \left\| \vec{b} - \vec{y} \right\|$$

4. Rotate the reduced dimension vector into the hyperellipse space using the eigenvector matrix $E$.

   $$\vec{c} = E^T \vec{z}$$

5. Determine if the rotated vector is within the hyperellipse by using equations (4) and (5) with $c$ in place of x.

   $$B = \sum_{i=0}^{N-1} \left( \frac{c_i}{a_i} \right)^2$$

   $$\begin{aligned} &Fault = True \quad && if \quad B > 1 \\ &Fault = False \quad && if \quad B < 1 \end{aligned}$$

6. If the vector is within the hyperellipse (Fault = False), test the orthogonal complement. If the magnitude of the orthogonal complement is greater than the threshold, declare a fault.

   $$\begin{aligned} &Fault = True \quad && if \quad M > T_{oc} \\ &Fault = False \quad && if \quad M < T_{oc} \end{aligned}$$

The process of detection can also include human evaluation. Rather than a strict Fault/NoFault answer, the algorithm can also produce a value representing the distance from the detection boundary. For example, using the hyperellipse, a display of the value $D=B-1$ could provide additional information. If $D$ is less than zero, the signature is inside the hyperellipse. If $D$ is near zero, however, a fault may yet be present. Or, even if $D$ is positive indicating that the signature is outside the hyperellipse, the signature may represent a healthy signature. Recording a number of signatures and observing the distance from the boundary for each signature will give the added information needed to make a more accurate prediction of the state of the rotor windings.

## III. LABORATORY TESTS

*A. Transformer*

The easiest test for the shorted winding detection algorithm makes use of an autotransformer. The autotransformer wiper arm is used to induce shorts between groups of windings but is not connected to the transformer otherwise. The autotransformer is then a coil of approximately 250 turns of copper wire similar to a winding in a turbine-generator. Insulating the wiper arm from the winding results in unshorted windings.

A set of 80 signatures was collected without an induced short and used to train the detector. An additional 39 signatures were collected for test purposes.

By rotating the autotransformer wiper arm, shorted turns were induced into the windings at arbitrary locations. The location of each signature was recorded, however, for later identification. The wiper arm contact spanned approximately ten turns and signatures were collected at approximately the ten turn interval. Several signature signals were gathered at each location, and several independent rotations were performed. The resulting 190 shorted turn signatures were applied to the detection algorithm.

The detection algorithm correctly classified 178 of the 190 signatures. The 12 shorted turn signatures which were incorrectly classified as healthy signatures were found to be located very near the center of the windings. The presence of a shorted-turn in the center of the windings has been known to be a problem for the twin signal sensing method. Since the detection method relies on asymmetry of the windings, if a short occurs at the center, the windings will still be symmetric and detection of the shorted turn will not be possible. Due to noise in the signature signals, even signatures slightly away from the center were classified as healthy. The 39 healthy signatures which were not used for training the detector were all correctly classified. A total of 229 signatures were tested and 217 were correctly classified for a correct classification rate of 94.8 percent.

### *B. Field Tests*

The shorted-turn detector was tested on a 60 MW generator at Southern California Edison's Highgrove Power Station. The station, located in Edison's territory, comprises four steam turbine generators. The station's design offers ready access to the machine. The generators are two-pole, hydrogen cooled machines. The DC rotor field windings are fed from rotary exciters attached to the shaft of the outboard end of the machine. Access to the generator's collector rings, and to the exciter's commutators are readily attainable through hatches on both sides of each machine.

The four generators are almost identical units. This fact allows comparison tests to be performed between the different machines. Therefore, the shorted-turn detector was also applied to a second unit, and the waveforms were compared with those obtained in the first one.

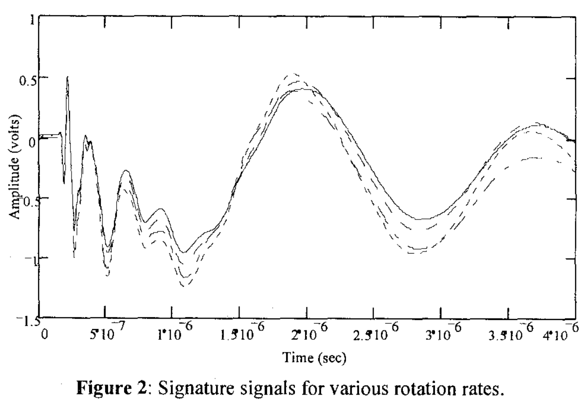


**Figure 2**: Signature signals for various rotation rates.

In several stages, the rotor of the first machine was brought up to full speed with the excitation connected and thus providing power to the rotor. The voltage applied to the rotor is proportional to rotation speed. Figure 2 shows plots of the signature signal at several different speeds. The solid line represents no rotation, the dotted line represents a very slow rolling rate, the dashed line represents 1800 rpm, and the dash-dot line represents 3600 rpm. All of the signature signals are seen to be quite similar especially in the early portion. As the rotation speed increased, the signature signals became more unstable, as if being modulated by a low frequency signal.

Signatures from a second machine were recorded by connecting the measurement leads directly to the slip rings. The rotor was not rotating during this test. Figure 3 shows the signatures for both machines under this condition. The two signatures are very different implying that the machines are different or that one machine has shorted turns. The resistance to ground for the second machine, measured before the experiment began, was found to be much lower than the resistance for the first machine. It is not clear that the resistance to ground should have such an impact and further studies are indicated.

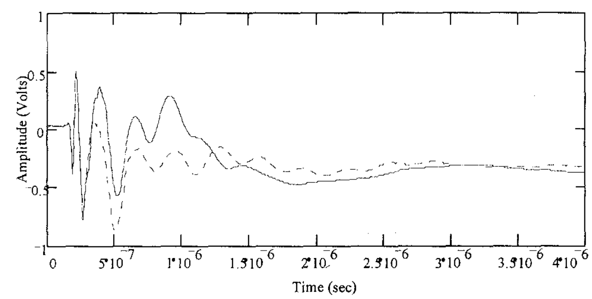


**Figure 3**: Signature signals for two different machines. The measurement leads were connected directly to the slip rings.

The signature signals collected during the experiment demonstrate that detection of shorted rotor windings may indeed be possible while the rotor is in operation. Several tests are required to improve the detection accuracy. Since the signature signals for the two similar machines were different, a test should be conducted on two machines which are known to have identical rotors and excitation sources and known not to have shorted rotor windings. The resulting signatures will verify whether the detection process will require sets of signatures for all machines before shorted turns can be detected or if a single set of signatures for a given machine type will be sufficient.

As pointed out by Nilsson and Mercurio [13], machines direct from the factory may have shorted turns. However, as additional turns are shorted, the signatures will change and the shorted turns will be detected.

## IV. CONCLUSION

The method presented in this paper for the detection of shorted windings in large turbine-generators shows great promise. Shorted windings can be detected in rotating machinery and other equipment containing symmetrical windings. The method makes use of the twin signal sensing method to provide a signature for healthy windings. A neural network is used to extract features from the signature data and thus reduces the dimension of the data. A novelty detector is then used to determine if a shorted turn is present.

Due to the inability to induce shorts between rotor windings of an operating turbine-generator, complete testing and verification of the detection algorithm has not been completed. However, based on the performance shown for the dismantled rotor case by El-Sharkawi, et al. [6] and the signals gathered for operational turbine-generators, shorted turns should be detectable with great accuracy.

## V. ACKNOWLEDGMENT

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## VII. BIOGRAPHIES

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