REAL TIME APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR INCIPIENT FAULT DETECTION OF INDUCTION MACHINES

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ABSTRACT

This paper describes several artificial neural network architectures for real time application in incipient fault detection of induction machines. The artificial neural networks perform the fault detection in real time, based on direct measurements from the motor, and no rigorous mathematical model of the motor is needed. Different approaches used to develop a reliable fault detector are presented and compared in this paper. The designed networks vary in complexity and accuracy. A high-order fault detector neural network is discussed first. Then noise considerations are included in more complex fault detector models, since noise is an important factor in the design and analysis of real time fault detector neural networks. Simulation results show that with appropriate designs, artificial neural networks perform satisfactorily in real time incipient fault detection of induction machines.

INTRODUCTION

Rotating machines are manufactured in a wide variety of sizes, but small (less than 10 hp) and medium-size (less than 100 hp) machines are of particular interest. These machines, for economic reasons, receive less periodic maintenance and do not have as many protective features. The importance of incipient fault detection is found in the cost savings which are realized by detecting potential machine failures before they occur [1]. Presently, machines are required to be protected by devices such as circuit breakers or fuses to protect the motor and nearby personnel from injury due to a fault, but they give no warning of potential faults before they occur. Incipient fault detection, on the other hand, allows preventative maintenance to be scheduled for machines which might not ordinarily be due for service. Incipient fault detection may also prevent an extended period of down-time caused by extensive machine failure.

Though rotating machines are usually well constructed and robust, the possibility of incipient faults is inherent due to the stresses involved in the conversion of electrical energy to mechanical energy or vice versa. An incipient fault within a machine will affect the performance of the machine before a failure occurs.

Due to its wide applications, a single phase, medium size induction motor is used in this paper as a prototype rotating machine. The concepts developed for induction motors can be easily generalized to other rotating machines. Two specific faults of single phase induction motors, namely turn-to-turn insulation faults and bearing wear, have been investigated in [6,7]. A turn-to-turn insulation incipient fault in the main winding causes the corresponding equivalent turns, N, of the main winding to change. Bearing wear of the motor is reflected in the damping coefficient B. To determine the most suitable motor measurements for detecting incipient faults, in terms of easy accessibility, reliability and sensitivity, the dynamics of induction motors were analyzed. From the analysis, the steady-state current, I, and the rotor speed, ω, of the motor can be represented by a system of nonlinear algebraic equations, $\underline{f} = [f_1\ f_2]^T$, which are functions of the main winding equivalent turns N and the damping coefficient B :

$$\underline{f}(I,\omega,N,B) = \underline{0}. \qquad (1)$$

For a more detailed induction motor dynamics derivation and analysis, see [6, 7]. Equation (1) does suggest that indications of the condition of the winding and bearings can be obtained from the measurements of the stator current and rotor speed. Indeed, from analysis, the stator current and rotor speed are found to be very sensitive to the changing conditions of the stator winding and the bearings. Moreover, the current and speed are easily accessible and can be measured accurately. Therefore, the stator current and rotor speed were chosen as the variables to be measured for the detection of winding insulation and bearing faults.

However, the mapping between {I,ω} and {N,B} is very complex due to the high degree of nonlinearity of Equation (1). In addition, due to the modeling error induced and propagated through the mathematical derivations, the theoretical solutions of N and B obtained by solving Equation (1) may not agree with their actual values. But this complication can be avoided by using neural networks, in which case neither complex nonlinear equations nor modeling errors would need to be accounted for, and no rigorous mathematical modeling of the machine is necessary. Besides, measurements can be taken directly from the machine itself. Artificial neural networks avoid the need for an accurate understanding of the system dynamics, which is required in other approaches used to estimate the machine parameters to indicate the appropriate machine condition [2—5].

As stated before, the conditions of the main winding and bearing are reflected in the numerical values of the main winding equivalent turns N and the damping coefficient B, respectively. Based on the values of N and B, the condition of the motor is then quantified into three condition levels, namely good, fair and bad. The resulting mapping is $\underset{\sim}{q} : \Re \times \Re \rightarrow Z^2$, where N and B $\in \Re$ (the real number space), and Z = {0.9, 0.5, 0.1} is the condition space representing good, fair, and bad respectively, according to the condition of the motor [6,7].

Based on the analysis presented above, a corresponding high-order artificial neural network structure [6,7,10,11] was designed to output the conditions of the winding and the bearings, given the values of the stator current and rotor speed as network inputs [6,7]. The performance of this network was satisfactorily accurate [6], yet noise was not taken into consideration. Since the detection scheme is for real time application, occasional perturbations and measurement noise need to be considered, as explained in later sections.

LAYERED FEED-FORWARD NEURAL NETWORK

The first use of artificial neural nets dates back to the 1940's. Recently, neural nets have become widely used in many different areas, such as fault diagnosis [6,8,9], system dynamics modeling [12], robotic control and many other areas [13,14,15,16,17]. Neural networks have been proven to be resistant to input and system noises, have learning capability, and can perform in real time [13,14,18]. Because of these useful properties, neural networks are good candidates for the implementation of machine incipient fault detection.

A special type of neural net, called a layered feed-forward neural net, is used in this paper. This network is composed of highly interconnected units (neurons) with a deterministic, monotonic nonincreasing output function. Layered feed-forward neural nets have been successfully used in many applications [8,14,15]. These nets have one or more layers of hidden neuron units between the input and output layers, as shown in Figure 1. An inter-unit connection is typically assigned a numeric weight that modulates the activation passing through the connection.

There can be many layers of hidden units, but every unit must send its output to layers higher than its own and must receive its input from layers lower than its own. Such a network is trained by adjusting the numerical values of the weights between each unit using an algorithm termed "back-propagation" [13,14]. The back-propagation algorithm is conceptually a generalization of the Least-Mean-Squares algorithm. It uses a gradient search technique to minimize a cost function equal to the mean square difference between the desired and the actual net outputs. The net is trained by initially selecting weights and internal thresholds at random and then presenting all training data repeatedly. Weights are adjusted after every trial using external information specifying the correct result, until weights converge and the cost function is reduced to an acceptable value. An essential component of the algorithm is an iterative method that propagates error terms required to adapt weights back from nodes in the output layer to nodes in lower layers.

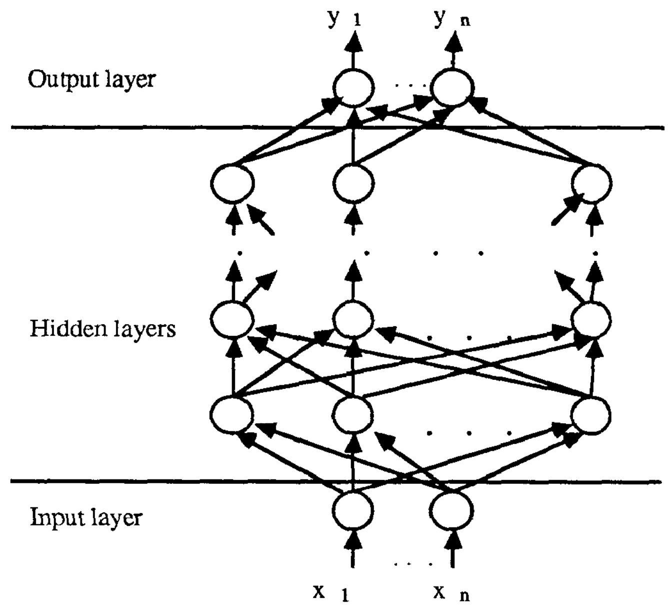

Figure 1 : Basic structure of a multi-layer artificial neural network

DIFFERENT INCIPIENT FAULT DETECTOR ARCHITECTURES

For the initial experiments in the design and training of the neural network, a precisely controllable data source was required. To provide this data source, a computer program was developed to simulate the dynamics of an induction motor [19,20]. The program is able to simulate the motor performance under different fault conditions and generate necessary data to train and test the designed fault detector neural networks.

The fault detector neural network was trained using a set of 224 data patterns obtained from a detailed numerical simulation of the dynamics of an induction motor. The data generated by the simulation covered the whole fault range under consideration. The simulation included the effects of inductance leakage, magnetic saturation, bearing wear, and stator winding insulation faults. The motor was assumed to be operating at a known constant load condition.

The weights of the network were trained using the popular back-propagation [13,14], pattern-update algorithm. The network stopped training when the average one-norm error of the whole training set was smaller than 0.05, or when the change of the weight value of each interconnection between the network layers was less than 1E-6 [6].

The design, analysis, and results of the different fault detector models used in this paper will be discussed in the following sections. First, the Incipient Fault Detector Artificial Neural Network (IFDANN) will be presented. Then a slightly more complicated fault detector model, namely, the Multiple Sampling Inputs Incipient Fault Detector Artificial Neural Network (MS-IFDANN), will be discussed. Finally, the Noise Filter Artificial Neural Network-Incipient Fault Detector Artificial Neural Network (NF-IFDANN) will be presented. The performance of each network design will then be analyzed and compared.

INCIPIENT FAULT DETECTOR ARTIFICIAL NEURAL NETWORK MODEL (IFDANN)

As discussed previously, the stator current, I, and the rotor speed, ω, of the motor are the variables to be measured in order to determine the condition of the main winding equivalent turns, N, and the damping coefficient, B, which in turn will indicate if incipient faults exist within the motor in question. It has been shown that, by expanding the input space from two dimensions (I, ω) to five dimensions (I, ω, I^2, ω^2, I*ω), the accuracy of the Incipient Fault Detector Artificial Neural Network (IFDANN) is increased [6], leading to the design of high-order neural networks [6,11]. It has also been shown that the more hidden nodes are used, the better the performance of the fault detector neural network [6]. As shown in Figure 2, the original IFDANN used in this paper was designed to include 5 input nodes (I, ω, I^2, ω^2, I*ω), 8 hidden nodes, and 2 output nodes (conditions of N and B, respectively). Assuming *ideal, non-noisy* measurements, the average performance of such a fault detector is 98.8 % accurate for the prediction of the condition of N and 99.1 % accurate for B. These results are satisfactory for most fault detection purposes.

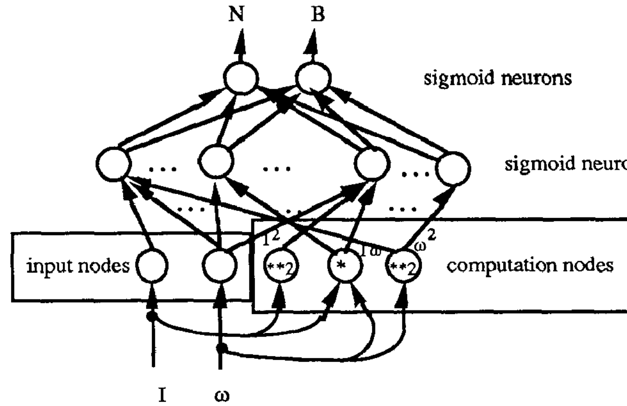

Figure 2 : Configuration of the original model of the high-order fault detector neural network

However, despite the satisfactory performance of this fault detector for *ideal, non-noisy* measurements, in real time applications motor measurements are likely to be contaminated with noise. Therefore, methods to make the fault detector neural network resistant to noise are considered and analyzed in the following sections, leading to the design of more complex fault detector neural network models.

MULTIPLE SAMPLING-INPUTS INCIPIENT FAULT DETECTOR ARTIFICIAL NEURAL NETWORK MODEL (MS-IFDANN)

Artificial neural networks have been widely used partly because of their multi-input parallel processing capability. A large number of input variables can be simultaneously fed to a multi-input neural network. Despite the increase in the number of input nodes, the computation time of the network remains the same because neural nets perform parallel processing. That is, all the neuron computations within one layer are computed simultaneously, so that the computation time of the network depends only on the number of layers present in the network and not on the number of nodes or neurons per layer. Thus, increasing the number of input nodes does not affect the neural network processing speed. Taking advantage of this parallel processing capability, the Multiple Sampling-Inputs Incipient Fault Detector model (MS-IFDANN) was designed.

Suppose that measurements are taken every sampling time Δt, and that the measurements at time i are represented as $\underline{z}(t_i)$. By letting $\underline{y}(t_i) = [I\ \omega\ I^2\ \omega^2\ I*\omega]^T$ be the actual value of the signals to be measured and $\underline{v}(t_i)$ be the corresponding measurement noise, the measurement $\underline{z}(t_i)$ on $\underline{y}(t_i)$ becomes

$$\underline{z}(t_i) = \underline{y}(t_i) + \underline{v}(t_i).$$

Note that the values of I and ω are direct measurements from the motor, while the values of I^2,

ω^2, and $I*\omega$ are calculated from I and ω during real time fault detection. Without loss of generality and for simplicity of notation, we assume that the five input variables (I, ω, I^2, ω^2, $I*\omega$) are all direct motor measurements.

The measurement noise is assumed to be i.i.d. Gaussian white noise with the following statistical properties :

$$E\{\underline{v}(t_i)\} = \underline{0} \qquad \forall\ i$$
$$E\{\underline{v}(t_i)\ \underline{v}(t_j)^T\} = \underline{R}\ \delta(t_i - t_j) \qquad \forall\ i,j$$
$$\mathrm{Cov}\{\underline{v}(t_i)\ \underline{y}(t_j)^T\} = \underline{0} \qquad \forall\ i,j$$

where δ represents the Kronecker delta function; $\underline{R}$ is a diagonal matrix representing the noise variance matrix of $\underline{v}$; E{.} represents the expectation value, and Cov{.} represents the covariance matrix. With the motor problem under consideration, the sampling time is chosen such that $\underline{y}(t)$ is a "slowly" time-varying signal (compared to the sampling time used). By letting τ_y be the fastest time constant of $\underline{y}(t)$, then $\tau_y << n\ \Delta t$, and all signal values within a sampling widow can be well approximated by a constant $\underline{y}_k$, i.e. $y(t_i) = \underline{y}_k$ for $k \le i \le k\text{-}n\text{+}1$.

The input layer of the MS-IFDANN model is basically an expansion from the input measurements at time t_k to n consecutive measurement at times t_k, t_{k-1}, .., t_{k-n+1}, obtained with the aid of a tapped-delay line. The sampled input signal is applied to a string of delay boxes, each delaying the signal by one sampling period. At any given instance of time, n sets of input measurements (where n is the sampling window size) are fed to the MS-IFDANN. Figure 3 shows an overview diagram of the MS-IFDANN model. The hidden layer and output layer structures remain the same as discussed before.

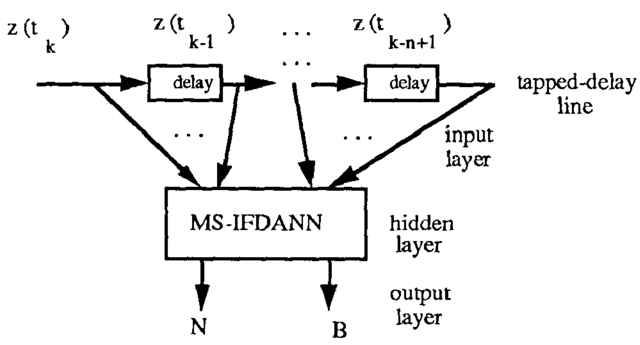

Figure 3. Overview diagram of the Multiple Sampling-inputs Incipient Fault Detector Artificial Neural Network model (MS-IFDANN)

This scheme increases the robustness of the fault detector neural network to noisy inputs because the condition of the motor is now determined based not only on the current measurements but also on the past n-1 measurements. The noise effect of each measurement fed to the detector is suppressed by the multiple inputs of the neural network.

Figures 4 and 5 show the accuracy of the fault detector under different noise levels and for different numbers of multiple sampling inputs. Note that all the data used are normalized between 0 and 1. The noisy data were Gaussian white noise with a variance value of 0.5. The noise level indicates the fraction of the Gaussian white noise that was added to the actual motor measurements in the fault detection simulation. Also note that the MS-IFDANN model with 5 inputs is actually the IFDANN model discussed in the previous section.

As expected, the fault detector neural network yields greater accuracy as the size of the sampling window increases, even for large noise levels. That is, the robustness of IFDANN increases as more past measurements are included in the inputs of the fault detector. The more inputs to the fault detector, the less susceptible it becomes to increasing noise levels.

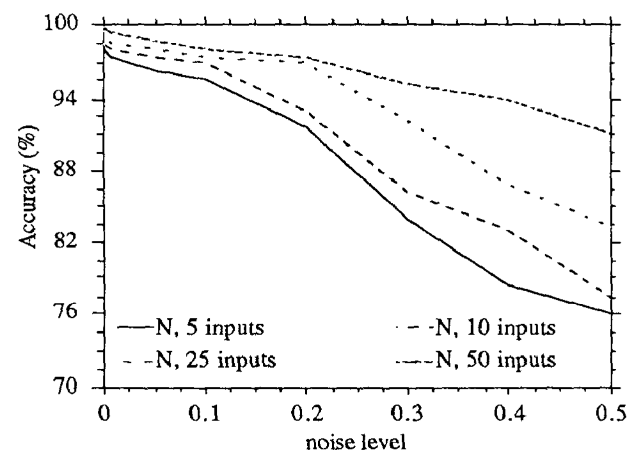

Figure 4 : Accuracy of the MS-IFDANN model, as a function of the number of inputs, for the detection of the condition of N under different noise levels

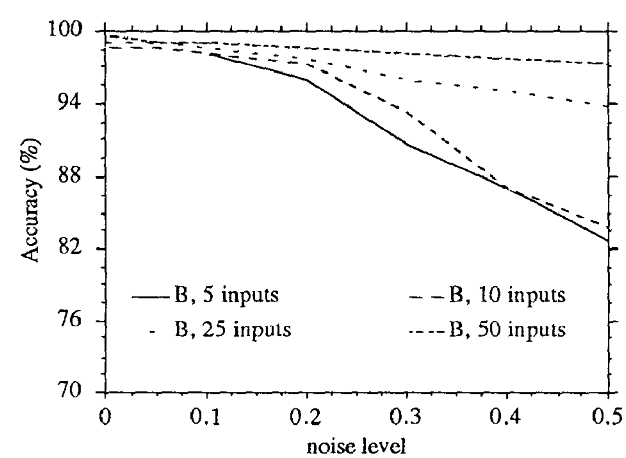

Figure 5 : Accuracy of the MS-IFDANN model, as a function of the number of inputs, for the detection of the condition of B under different noise levels

MODULAR FAULT DETECTOR ARTIFICIAL NEURAL NETWORK MODEL

The trend of artificial neural network applications is toward the design of neural network modules that perform specific tasks. For certain applications, a user can combine several neural networks, each with a specific task or function, to meet the needs of the application. In this paper, the modularized fault detector neural network (NF-IFDANN) to be considered is composed of two parts: a Noise Filter Artificial Neural Network (NFANN), and an Incipient Fault Detector Artificial Neural Network (IFDANN). Under the new scheme, real time measurements are collected and fed to NFANN to filter out the noise that may be present in the measurements. Then the filtered data, i.e., the outputs of NFANN, are fed to IFDANN for incipient fault detection. As before, the IFDANN of the modularized fault detector model is the high-order neural network, with 5 inputs (I, ω, I^2, ω^2, $I^*\omega$), 8 hidden nodes, and 2 outputs (conditions of N and B, respectively) designed in [6].

Figure 6 presents an overview of the *filter-detector* network structure, where n(t) is the measurement noise; i(t) and ω(t) are the real time measurements of rms current and average rotor speed of the motor respectively; $i_f(t)$ and $\omega_f(t)$ are the filtered versions of i(t) and ω(t), and N_c and B_c indicate the conditions of stator winding and bearings respectively.

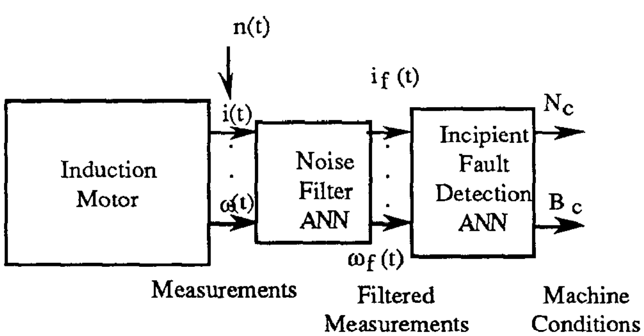

Figure 6 : Block diagram of the modularized NF-IFDANN fault detector model

A moving measurement average noise filtering scheme is implemented in an artificial neural network structure and used in the NFANN module. By letting the sampling window size be n, then the k-th sampling window Z_k contains the measurements

$$Z_k = \{ \underline{z}(t_k), \underline{z}(t_{k-1}), \ldots, \underline{z}(t_{k-n+1}) \}.$$

The n sets of consecutive measurements, z_k, z_{k-1}, ..., z_{k-n+1}, are fed to NFANN simultaneously after they are collected with the aid of a tapped-delay line. The average value $\hat{\underline{z}}_k$, defined as

$$\hat{\underline{z}}_k = \frac{1}{n} \sum_{i=1}^{n} \underline{z}(t_{k-i+1}),$$

is then the output of NFANN, which in turn is the input to IFDANN. The measurement noise remaining at the output of NFANN can still be shown to be Gaussian white with variance reduced by a factor of $1/n^2$ [7]. Figure 7 shows a diagram of the structure of NFANN.

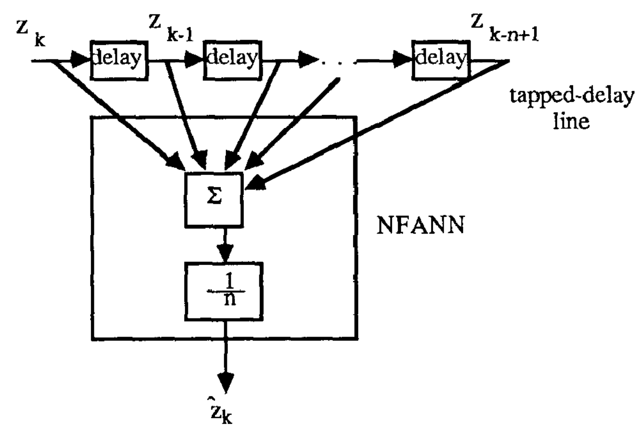

Figure 7 : Structure of the Noise Filter Artificial Neural Network (NFANN)

NF-IFDANN was tested with simulated real time induction motor measurements, with random Gaussian measurement noise (as used in the MS-IFDANN model) included in the testing data. The performance of the NF-IFDANN architecture is shown in Figures 8 and 9. Simulation results show that, in general, the larger the size of the sampling window, the better the performance of the NF-IFDANN fault detector, similar to the results obtained from the MS-IFDANN model.

An interesting observation from the simulation results is the fact that, for the detection of the condition of N, small-level noise added to the actual motor measurements slightly increases the accuracy of the network (Figure 8). The authors of the paper suspect that this behavior is caused by the discretization of the output values of the training data, which might have induced uncertainties at the boundary fault conditions. Thus, a little random Gaussian noise actually helps the network to better detect boundary conditions in some cases. A more detailed analysis on the effects of the random Gaussian noise on the fault detector accuracy will be performed in the near future.

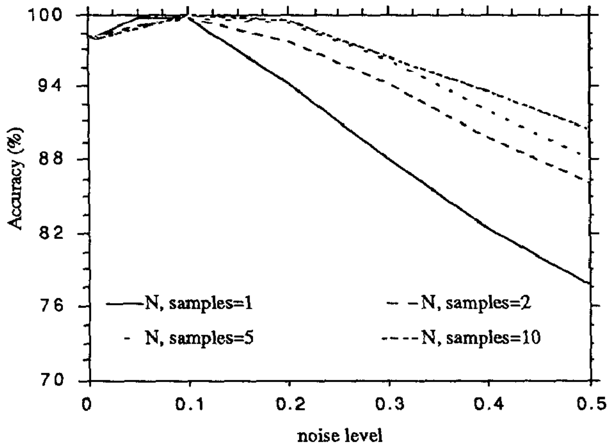

Figure 8 : Accuracy of the NF-IFDANN model, as a function of sampling window size, for the detection of the condition of N under different noise levels

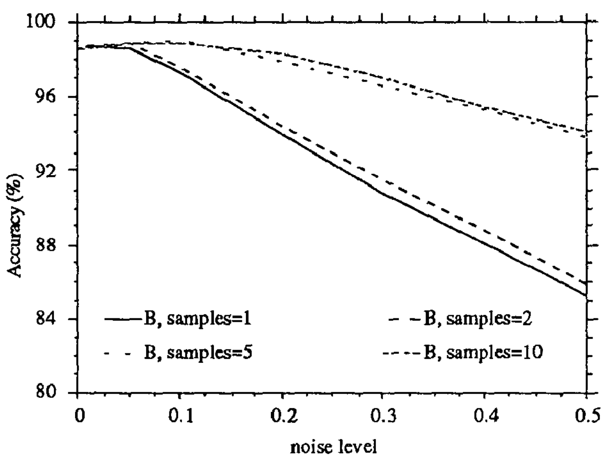

Figure 9 : Accuracy of the NF-IFDANN model, as a function of the sampling window size, for the detection of the condition of B under different noise levels

COMPARISONS AND FUTURE RESEARCH

Figure 10 shows a comparison of the accuracy achieved by both the MS-IFDANN and NF-IFDANN fault detector architectures under different noise levels, when equivalent inputs are used, namely, 50 inputs for MS-IFDANN and a sampling window size of 10 for NF-IFDANN. Simulation results show that the original IFDANN model can be modified to yield satisfactory results even under very noisy environments, with an average accuracy of 91% for the prediction of the condition of N and 95% for B, at a noise level of 0.5. It can be observed that MS-IFDANN yields higher accuracy for the prediction of the condition of B, while NF-IFDANN performs better for the prediction of the condition of N. It can also be observed that for large noise levels, the accuracy of predicting the condition of N is always lower than that of the condition of B for both fault detectors.

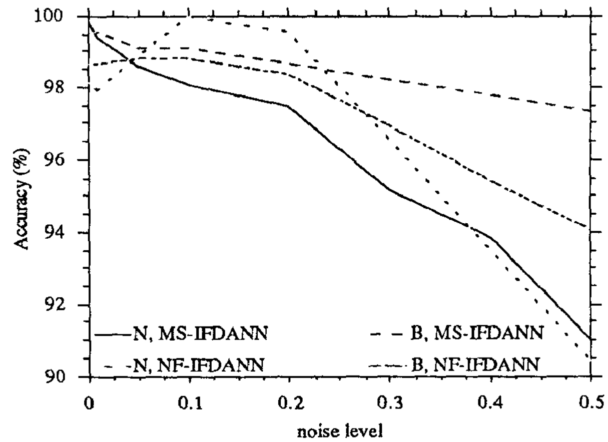

Figure 10 : Comparison of the accuracy between the MS-IFDANN and NF-IFDANN models under different noise levels

Even though the performance of NF-IFDANN is similar to that of MS-IFDANN, NF-IFDANN is a more flexible model and can be modified easily to meet the user's needs due to its modularity. The authors of this paper are currently searching for methods to improve the performance of NF-IFDANN, and further results will be reported in the future, along with a more rigorous analysis of the different fault detector structures discussed in this paper.

CONCLUSION

This paper develops a real time application of artificial neural networks for incipient fault detection of induction machines. The fault detector neural network performs the detection based on direct measurements from the motor, avoiding the complication of nonlinear equations and modeling errors. It has been shown that with some additions and modifications of the conventional layered feed-forward neural network, satisfactory results can be obtained from the designed fault detector neural networks discussed in this paper. For real time applications, noise effects were considered, and structurally simple and satisfactorily accurate fault detector neural networks were designed. Satisfactory results show a promising future for the use of artificial neural networks for incipient fault detection in rotating machines.

ACKNOWLEDGEMENT

This project is funded by Electric Power Research Center project grant 5-31067, North Carolina State University.

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