APPLICATION OF NEURAL NETWORKS TO FAULT DIAGNOSIS

BY

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ABSTRACT

In the past fault diagnosis has been performed by a variety of techniques including parameter identification and knowledge based expert systems. Recent advances in the fields of artificial intelligence and microcomputer technology have brought new techniques to light. One such technique is the artificial neural network. This article looks at how neural networks function and how they have been applied to fault diagnosis problems over the past few years. By analysing the methodology and results obtained from recent research it can be said that artificial neural networks appear to be extremely competent diagnostic tools.

Background

Fault diagnosis is generally performed by the comparison of healthy reference data with data obtained during faulty operation. Operation of a system in a faulty mode will give rise to a deviation of sensor data from the healthy reference data. Close analysis of these deviations can often characterize a particular fault.

In the past this analysis of sensor data deviations has been performed by both parameter identification techniques[1–5] and Knowledge Based System (KBS) approaches [6–11].

Parameter identification techniques involve the generation of a mathematical model of a system to map the inputs onto the outputs. If a system is highly non-linear this process is often very difficult and time-consuming. The real outputs for a set of given inputs are then compared to the model and a difference or residual is generated, using Kalman filtering for example, characterizing the fault. One great disadvantage of this approach is that the mathematical model must fit the process very closely, otherwise residuals are generated during healthy operation giving rise to incorrect diagnosis.

The KBS approach has found widespread application in the field of fault diagnosis. The knowledge base contains a series of *if . . . then* and *and* statements in an attempt to capture an expert's knowledge and experience. This rule structure may then be applied to a problem in the hope that it will emulate the expert's decision making process and arrive at the correct conclusions.

Despite the vast success of this style of approach to practical fault diagnosis, its serious limitations became evident in the early eighties. Building of the knowledge base is both costly, time-consuming and relies heavily on consultation with one or more experts in a particular field.

Because of the often very specific structure of the KB, modifications to account for physical changes in the plant or novel faults are difficult. The occurrence of novel faults or noisy or corrupted data often results in a severe degradation in performance of the system.

Since fault diagnosis is essentially a problem of pattern classification, it is now widely realized that artificial neural networks offer the potential to perform fault diagnosis whilst eliminating the problems discussed earlier.

NEURAL NETWORKS

The advent of neural networks can be dated back to the 1940s. Early pattern classification research was conducted throughout the 60s and 70s but the results had few practical connotations and little attention was paid to real world application.[12] Since then, rapid developments in the field of microcomputer technology have allowed neural networks to be applied in practical situations such as system dynamics modelling, speech, vision[13,26] robotics and fault diagnosis.

Artificial Neural Network Principles

Artificial neural networks aim to mimic the structure of the brain on a very simple level. The microcomputer is a high speed serial machine, whereas the brain runs at a much lower speed but is a massively parallel system. This parallel system is capable of representing and storing knowledge in an accessible way so that it may be applied to problem solving. Perhaps one of the most important features of the brain is its ability to learn by example and reapply the newly acquired knowledge. To enable a microcomputer to behave like the brain it is necessary to analyse the brain's basic structure and then model this on the microcomputer.

The brain structure is highly complex and is generally poorly understood. It consists of about ten thousand million basic units, called neurons (FIG. 1).

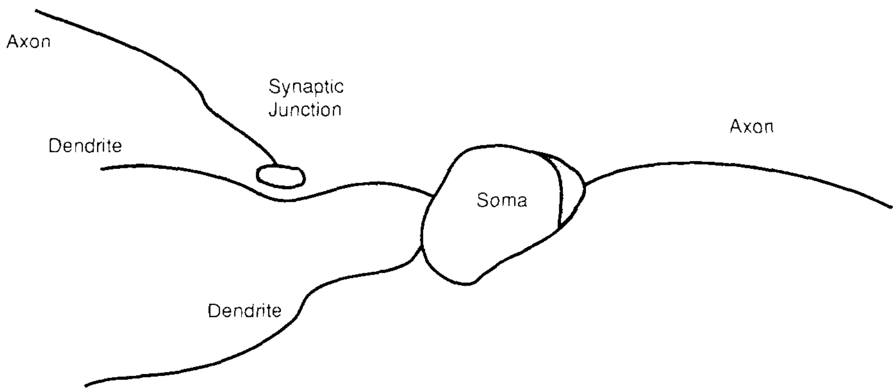

FIG. 1—THE BASIC FEATURES OF THE BIOLOGICAL NEURON

The soma forms the body of the biological neuron and the input and output lines from the soma are the dendrites and axons respectively. The output lines, axons, may in turn be connected to input lines, dendrites, or other neurons via a synaptic junction. This junction is a chemical connection which effectively governs the weighting of the inputs into the dendrite. The dendrite sums its inputs and transmits the resulting potential to the soma. When the potential in the soma rises above a certain critical level the axon produces an output voltage pulse known as an action potential (FIG. 2), and the neuron is said to have fired.

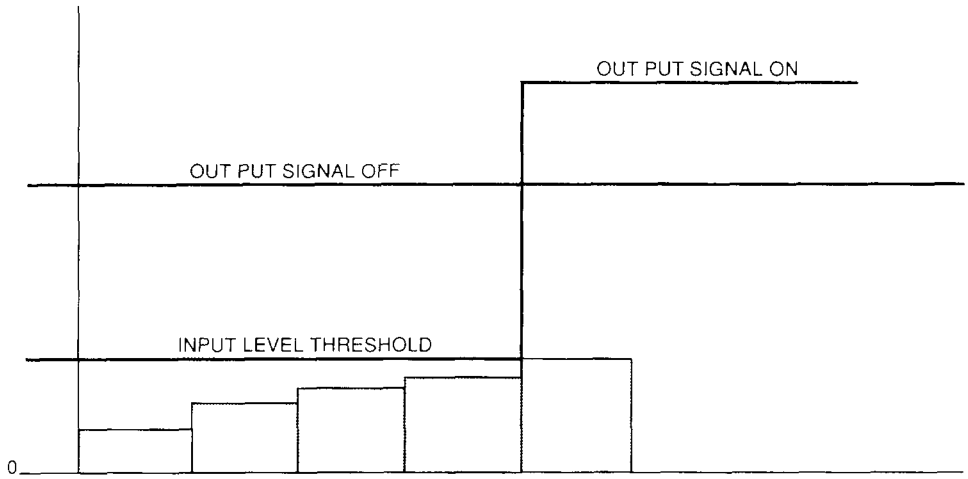

FIG. 2—THE INPUT TO THE NEURON BODY MUST EXCEED A CERTAIN THRESHOLD BEFORE THE CELL WILL FIRE

This basic understanding of how the neuron functions allows the design of a microcomputer model. (FIG. 3) outlines the basic model of the neuron. A number of weighted inputs are applied to the neuron; the neuron adds the inputs and applies a threshold. If the sum of the inputs is greater than the threshold value the neuron fires and an output is produced.

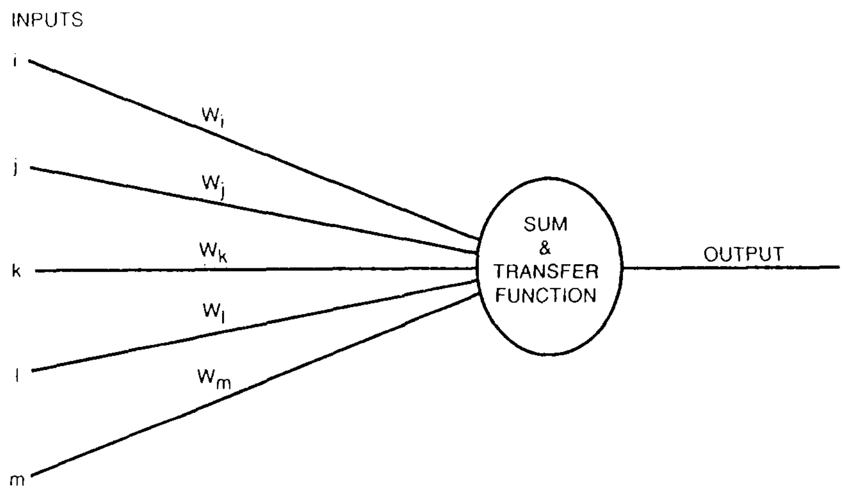

FIG. 3—MICROCOMPUTER MODEL OF THE NEURON

Many of these neurons or nodes may now be linked together to form a network. (FIG. 4) shows a multi layer feed forward network. It consists of three layers of neurons, the input layer, the hidden layer of which there may be one or more, and the output layer.

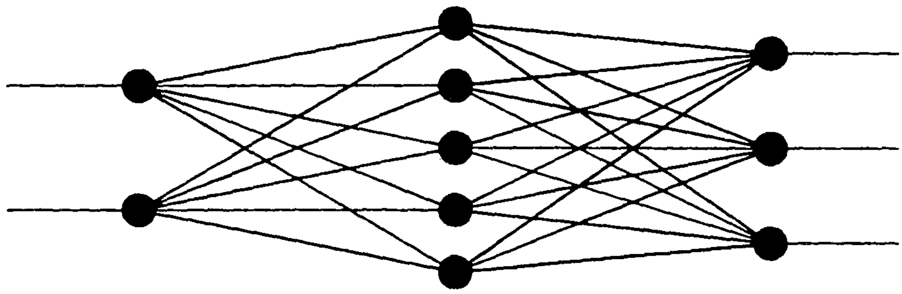

FIG. 4—MUTLI-LAYER FEED FORWARD NETWORK

Learning in Artificial Neural Networks

Probably the most important attribute of the neural network is its ability to learn by example and progressively improve its performance. The learning process can be categorised into two basic classes. Supervised and unsupervised.

Supervised Learning

For a network to undergo supervised learning it must be presented with pairs of training data, in the form of inputs and desired outputs. During training the features extracted from the example data will be entered into the input layer of neurons. The consequent results will feed through the network until they reach the output layer. The results will then be compared with the desired output. Through the implementation of a training algorithm, back propagation for example, the weights in the network may be manipulated so as to reduce the error between the output from the network and the desired output. This process is repeated until the network outputs are close enough to the desired outputs. The final weights obtained characterize the mapping of the inputs onto the outputs; it can be said that the input/output relationship is described by the weighted connections between each layer of neurons.

Unsupervised Learning

Unlike supervised learning, only input training data is required by the network in unsupervised learning. Implementation of the training algorithm will again adjust the weights in the network to characterize the input/output relationship but this time the network is trained to produce the same output for similar inputs. This process allows the network to group or *cluster* inputs which exhibit similar properties. This technique proves most useful in the realms of fault diagnosis since the network does not need to be trained to recognize every possible fault. Providing the network has been given a sufficient variety of training data it is possible for the network to classify a novel fault simply by virtue of the fact that it does not closely match any of the clusters derived during training.

NEURAL NETWORKS APPLIED TO FAULT DIAGNOSIS

The aim of this section is to give an overview of research in the field of neural networks applied to fault diagnosis. This area of work began in the late 1980s and is currently one of the fastest expanding research topics.

Research work conducted to date on both process plant[14–19] and machinery[20–25] has produced several systems which are in commercial operation today[16–20]. Other programmes of research which are not yet technically mature are also producing some very promising results.

Process Plant Fault Diagnosis

By far the most popular research field has been in chemical process plants. The relatively new approach of neural networks stems from earlier work, mentioned in reference 17, by Rich and Venkatasubramanian 1987, Venkatasubramanian and Rich 1988, Shum *et al.* 1988, Finch and Kramer 1988 and also Watanabe and Himmelblau[21], to mention only a few.

Work by Venkatasubramanian and Chan[18] demonstrated how a neural network approach may be substituted for an expert system approach. It showed how a fault tree may be utilized by a neural network to diagnose process faults. The work also investigated the effects of network training and hidden layer architecture by evaluating the accuracy of diagnosis. This work was extended further to analyse how the neural network would perform on multiple faults, noisy data and novel faults. The research revealed that the neural networks recall to trained single faults was nearly perfect at 98%. It was also discovered that multiple faults comprising of single trained faults could be diagnosed successfully whilst diagnosis of totally novel single faults was poor.

It was concluded that the network performed well under novel conditions that were similar to those encountered during training but network performance deteriorated under totally novel conditions. The work also proved that neural networks have the ability to function successfully even in the presence of noisy input data. These findings are also reinforced by research work carried out by Hoskins *et al.*[14]

Watanabe *et al.*[21] also investigated the effects of altering the network topology and the degree of network learning. Further to this, it was discovered that a two-stage network structure could not only diagnose a particular fault but could also class the degree of severity of the fault.

More recent study by Venkatasubramanian *et al.*[17] investigates the implementation of a neural network on a more complex chemical process plant. The main difference between this and previous work is that the faults to be investigated affect almost all of the network inputs, making the derivation of fault-symptom relationships a difficult task. The work completed on noisy input data was taken further to include faulty sensor data. Again it was found that diagnosis of single trained faults and multiple faults was successful. The network also demonstrated its robustness in the presence of both noisy and faulty sensor data.

Machinery Fault Diagnosis

The application of neural networks to machinery fault diagnosis has generated a great deal of interest from industry and educational establishments in the past couple of years. Research work is currently being conducted by Lloyds register[7], MJA Dynamics, SD Scicon[20] and RAE Pyestock, among others.

Study by Ray[22] showed how a two-layer neural network may be integrated with a KBS. This off line approach interrogated the user in order to determine what symptoms were present on the machinery. The user would classify whether the symptom was present, likely present, unknown, likely absent or absent. These five classes were represented by numbers between +1 and −1, present and absent respectively.

These numbers formed the inputs to the neural network. The resulting diagnosis took the form of a list of causes and their relative weightings, higher weightings inferring a greater probability. Although this system gave a correct diagnosis approximately 75% of the time it was found that for some symptoms too many causes were being generated sometimes with weightings of a similar size. Ray suggested that these problems could be attributed to insufficient data and the systems generalization performance could be increased by the addition of hidden layers. Another good example of how neural networks can be integrated with other techniques is the work carried out by Healey, Bahrke and Navarrete[23]. This work demonstrated how Kalman filters can produce inputs to neural networks which perform on line machinery diagnostics for underwater vehicles.

Several other papers such as Chow *et al.*[24] and Dietz[25] outline neural network fault diagnosis techniques. Chow investigates the implementation of a neural network to detect incipient faults in single phase squirrel cage induction motors. Here significant detail is given regarding choosing and filtering of the input signals to the network and the importance of computer simulations during network training.

Most study to date has concentrated on fault diagnosis during steady state conditions. However work by Lloyds Register (Hobday *et al.*[7]) on gas turbines has shown that diagnosis is easier if the transient behaviour is analysed. Transient data has many advantages over steady state data because fault symptoms are exaggerated or amplified. This means that instrumentation accuracy is less critical and earlier fault detection and diagnosis becomes possible. Hobday has also been involved with a project to convert the Diesel Engine Expert Diagnostic System, DEEDS, formerly a KBS into a neural network system. Present work at Lloyds Register is concerned with using well established TV techniques from RAE Pyestock together with neural networks to perform fault diagnosis of marine diesel engines.

CONCLUSION

The conclusions drawn from past research suggest that fault diagnosis using the neural network approach has the potential to be very successful. It is now widely realized that neural networks have the ability to out-perform KBS and parameter identification techniques.

It is evident that the approach to the implementation of the neural network and the conclusions drawn regarding its performance are often very similar irrespective of the diagnosis task. These apparent trends in recent research can be summarized as follows;

(*a*) Neural networks offer a realistic alternative to KBS.
(*b*) Computer simulation of the process and its faults can provide invaluable information for the development of a neural network approach.
(*c*) Network topology and training is critical to the performance of the network, in terms of training times and accuracy of diagnosis.
(*d*) The most widely used training method is the back propagation algorithm.
(*e*) Most process faults can be diagnosed with either one or two hidden layers.
(*f*) Diagnosis of faults which the network has been trained on is very successful.
(*g*) Neural networks can generalize and diagnose multiple faults comprising single faults on which the network has been trained.
(*h*) Neural networks prove to be robust classifiers in the presence of both noisy and faulty sensor data.

(*i*) Neural networks offer no user transparency, making the insight into the problem solving process impossible.
(*j*) Unlike KBS, neural networks suffer a graceful degradation in performance when faced with incomplete data sets.
(*k*) Choice of the input data is possibly the most important stage in the development of a neural network diagnostic system.

The Future

Having identified that neural networks have a promising future when applied to diagnostic problems the RN Engineering College intends to apply neural network techniques to condition monitoring and fault diagnosis of marine diesel engines. The next stage in the work is to establish fault/symptom relationships by both computer simulation and test bed experimentation. It is hoped that the results from this will lead to the successful implementation of a neural network approach.

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