第 28 卷 第 5 期
1999 年 10 月

电子科技大学学报
Journal of UEST of China

Vol.28 No.5
Oct. 1999

Development of an On-line Condition Monitoring System Based on Neural Networks

Luo Dehan Lan Wenhui Huang Sheng

(Dept. of Mechanical and Electrical Engineering, Hefei Institute of Economics and Technology Hefei 230052)

Abstract In this paper, the development of an on-line condition monitoring system is discussed based on the neural networks for MK9-5 cigarette machine. This paper gives an introduction of the basic background theory of artificial neural networks. and describes the structure of the condition monitoring system based on neural network. The application of neural network to actual condition monitoring task is also analyzed, concentrating on the work carried out at the MK9-5 cigarette machine.

Key words artificial neural networks; on-line condition monitoring; fault diagnosis; MK9-5 cigarette machine

Condition monitoring is an emerging area for engineering and industrial application. It involves the continuous assessment of the condition of a machine structural component, while still in operation, and allows engineers for an early fault detection, and predictions of any anticipated failure of machinery or a structured component under monitoring. It also involves obtaining real data that give an indication of condition of the machine.

Artificial intelligence has been applied to condition monitoring and a large body of literature existing in this area[1,2]. Knowledge based expert systems may also be used for condition monition, but expert systems are limited, because they have difficulties in analyzing incomplete data, or data which may contain noise. However artificial neural networks (ANNs) emerged as a new method for condition monitoring using real data such as vibration, temperature signals, etc. The application of ANNs in condition monitoring by using the raw measured data has been demonstrated by many researchers[3].

Recognition of machine faults usually requires the intervention of a skilled engineer to undertake the time-consuming and fallible process of comparing current machine conditions with " ideal" conditions via occasion checks rather than constant monitoring. However, in this paper, we present an on-line condition monitoring system based on neural network to solve the problem of fault diagnosis in cigarette machine.

The solution we present here is based on the raw measured data, and shows the feasibility of developing a neural network system which can be used in constantly monitor MK-95 cigarette machine conditions and to provide immediate warnings of faults. Molins company in UK made the MK-95 cigarette machine. It is a high speed and high automatic machine whose construction is very complex. Once some faults appear in the MMK9-5, they may not only cause the machine to stop but also bring danger to operators. It will also take maintenance engineers a lot of time for finding faults reasons and recovering the machine work. In order to make the MK-95 work more reliable and safe, we developed an on-line condition monitoring system based on neural networks for MK-95 cigarette machine. It has been demonstrated that this system is very effective for monitoring the MK-95 faults in production process.

1 Artificial Neural Networks

Neural networks are inspired by knowledge of how human brain and nerve cells operate. Fig.1 shows

Received December 10,1998 and revised April 16,1999

the structure of a typical artificial neuron.

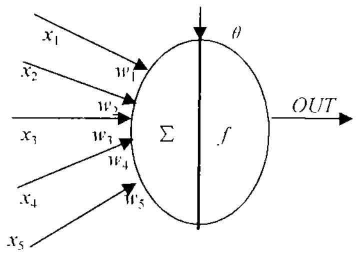

Fig.1 An artificial neuron

Like the biological equivalent, it has three distinct parts: an input tree, a processing unit and an outputs. Inputs and outputs are normally considered as numeric values. The usual operation of the processing unit is to sum the incoming signals from the input tree and the threshold. If the total exceeds the threshold value, an output signal is triggered.

The artificial neural networks (ANNs) are the simple arrangement of a number of richly interconnected processing neurons called nodes, collected together in layers. The nodes in a layer are linked by a synaptic connection called weight to the nodes in the next layer. They take their input (real numbers), and determine their output as function of their input, i.e.

$$OUT = f(net) \tag{1}$$

where, *net* is simply the sum of all the individual inputs (X_i) multiplied by their corresponding weights (W_i), hence

$$OUT = f(net) = f(\sum_{i=1}^{n} W_i X_i + \theta) \tag{2}$$

where, the bias term (θ) is added to shift the sum relative to the origin, and $f(\ )$ is a non-linear activation function, which transforms the sum of the weighted inputs into the output of the node. The type of activation function adapted for the present work is the sigmoid (S-Shaped). A typical multi-layer feed forward network is shown in Fig 2.

In ANNs, input information is presented to the first layer that passes the information on to the next layer via a set of connection weights. Some of neurons fire to produce a new pattern which is passed on the next layer and so on until an output emerges from the last layer of the network. This output pattern is considered the networks solution. The output derived from any input is determined by the many connection weights within the network.

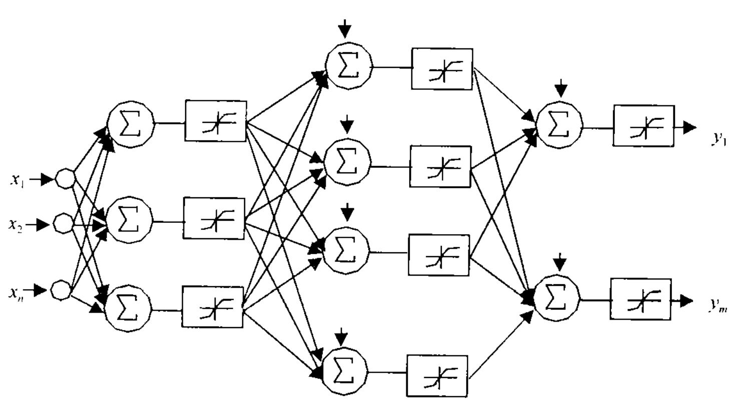

Fig.2 A typical multi-layer feed forward network

The first step in using an ANN is to train it. The type of training is a supervised learning method. The kind of training algorithm used here is the back propagation algorithm. It is commonly used to train the multi-layer feed forward network. In this kind of learning, the inputs and the desire outputs are known. During the training, a set of inputs are applied to the network, then the resultant outputs are compared with those of the desired ones. The error is then propagated backwards via the network, and the training algorithm uses it to adjust the value of the weights on the neural connection in multiple layers. This process is repeated until the reduced to an acceptable error value.

2 System Structure and Signal Processing

2.1 System Structure

The purpose of the research described in this paper was to demonstrate the feasibility of using neural network to monitor machine faults. Fig.3 shows the schematic presentation of the condition monitoring used. It consists of several sensors, a signal conditioner, a charge amplifier, a 486 PC/AT computer, etc. An accelerometer was mounted on the main gearbox of machine for detecting vibration signal, and connected via the charge amplifier to the computer. Two temperature sensors were mounted heating plate for measuring garniture temperature, and connected to the signal conditioner. Six infra-red sensors and two inductive proximity sensors were fitted to different positions for detecting machine status, that is the paper broken, break out of rod, the tobacco higher or lower, the machine over speed, and so on. The computer collected above signals via a sampler, and processed them for monitoring machine status.

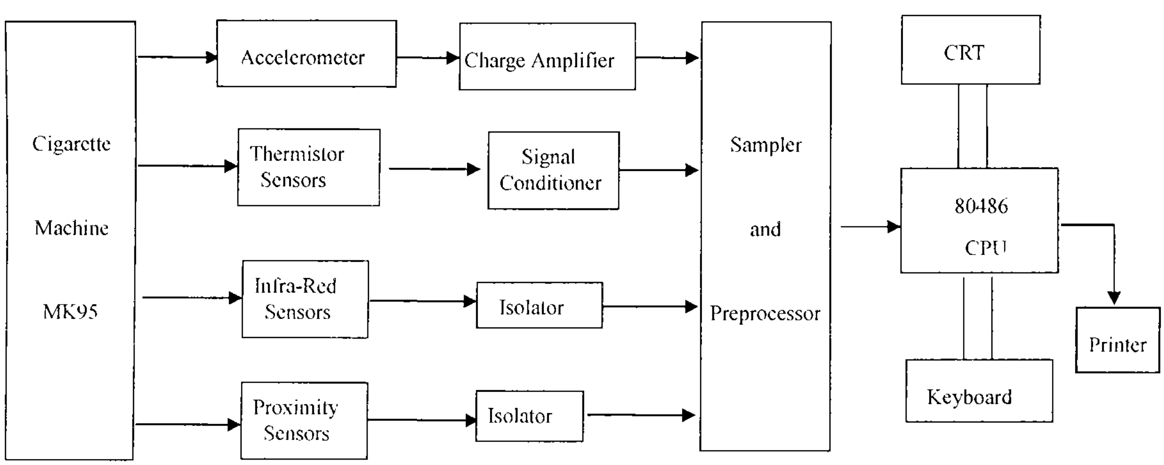

Fig.3 Schematic diagram of the condition monitoring system

2.2 Signal Processing

Condition monitoring data that will form the input vector to a neural network must come from various measured sources, such as the vibration signal, temperature signals and machine status signals etc. All signals detected by sensors were pre-processed. The real time domain vibration signal was first amplified by the charge amplifier, then was transferred to the sampler and preprocessed by FFT program. The temperature signals were first conditioned by signal conditioner, and processed by pre-processor, then were gotten by the computer. The discrete signals detected by the infra-red sensors and inductive proximity sensors were first shaped and electric isolated, then sent to the computer. The computer extracted key information from above data and formed input vectors of the neural network.

The signals for "good condition" and "faulty" of machine were transferred to the computer. A program was used to treat the measured data as an input vector set to the back propagation networks.

The output vectors must be representative of the type of information required by maintenance engineers. They were defined through a process of testing and discussion with maintenance engineers as to how they would like the information presented to them. The condition monitoring system was performed both with real data acquired from the machine, some of which had known conditions from inspection, and also with artificially generated data to examine the network's performance in identifying particular defect types. The network output classifications were compared with known condition data, and also with the classification of the condition monitoring engineers. Training data sets were constructed from real data collected from cigarette machine, where the target output could be confidently generated as a result of known machine condition due to inspection.

The input vectors and output vectors were formed by inspecting cigarette machine and consulting with maintenance engineers for training neural network, shown as follows:

Input vectors	Target output vectors
(0,0,0,0,0,0,0,0,0,1)	(0,0,0,1)
(0,0,0,0,0,0,0,0,1,0)	(0,0,1,0)
(0,0,0,0,0,0,0,1,0,0)	(0,0,1,1)
(0,0,0,0,0,0,1,0,0,0)	(0,1,0,0)
(0,0,0,0,0,1,0,0,0,0)	(0,1,0,1)
(0,0,0,0,1,0,0,0,0,0)	(0,1,1,0)
(0,0,0,1,0,0,0,0,0,0)	(0,1,1,1)
(0,0,1,0,0,0,0,0,0,0)	(1,0,0,0)
(0,1,0,0,0,0,0,0,0,0)	(1,0,0,1)
(1,0,0,0,0,0,0,0,0,0)	(1,0,1,0)

The research has shown that 10 dimension-input vectors can express the key parameters of MK-95 cigarette machine and have enough information for monitoring the machine conditions. The 4 dimension output vectors can give faults expression of MK-95.

2.3 Neural Network Trained

A neural network model has been developed for condition monitoring of the cigarette machine. This network is based on the multi-layer feed forward network architecture, using the back propagation training algorithm. The use of back propagation allows the adjustment of weights in the neural connections in multiple layers. The raw measured data form the input vector to the back-propagation network. The network used here is the three layers. There are 10 neurons in the input layer, 6 in hidden layer and 4 in output layer.

The raw measured data that form the input vector to ANNs were first preprocessed. The 10 most energetic components were extracted. From these values, the training and test files were created. The output node codes were assigned for each condition of the machine.

The network was trained to produced a non-zero response only at the appropriate node when it was presented with the training data and zero else where. In order to measure the accuracy (goodness of fit) of the network, during the learning stage, the normalized root mean square (RMS) error was calculated in ever 600 iteration. During the training, the root mean square (RMS) error is calculated. This error is then propagated backwards through the neural connections, and the process is repeated until the RMS error is within a threshold. Fig. 4 shows the normalized root mean square (RMS) error of the back propagation network during learning, which was introduced to compare the target outputs of the network with those

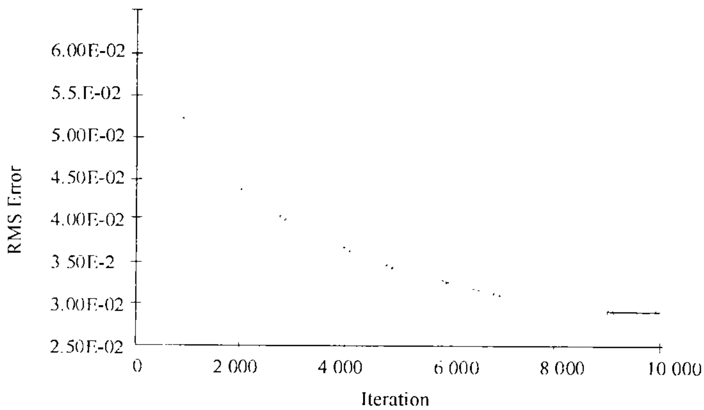

Fig.4 RMS during the training of the network

actually obtained. It can be seen that (RMS) error for Fig.4 is 0.036. The training was highly successful and the network gave a binary number of one at the appropriate node when presented with the training set.

After the successful training of the network, the test files were created. They were used to perform condition monitoring on the machine running. It can be seen from testing results that the network gave a binary number of "1" at the corresponding output node, which were assigned for the particular machine condition, and the fault resulting classification was very good.

3 Conclusion

The work carried out at factory shows that a successfully trained back propagation network can perform analysis of some condition monitoring data successfully. The condition monitoring system not just monitors the status of the machine, but also recognizes the type of fault occurring in machine. It can successfully perform fault classification for the cigarette machine.

In the practical terms, ANNs based condition monitoring has proved to be very effective in continuous machine monitoring, which is an extremely valuable technique for the area of factory maintenance, and can generate significant financial benefits.

Further development is on going at our work. The author aims to develop a system which has high degree of automation of the data analysis function in condition monitoring, which will assist maintenance engineers to make maintenance decision with a high degree of confidence.

References

1 Chan E H P. Application of neural network computing in intelligent alarm processing. IEEE conference PICA'89, Seattle, 1989

2 Mayes I. Use of neural networks for on-line vibration monitoring. Proceedings of the Seminar on the Application of Expert System in the Power Generation Industry, Institute of Mechanical Engineers Headquarters, London, 1993

3 Harris T. Neural network and their application to diagnostics and control. Proceedings of 4th International Congress on Condition Monitoring and Diagnostic Engineering Management (COMADEM), Nimes, France, 1992

基于人工神经网络的在线设备状态监测系统的研究

骆德汉* 郎文辉 黄 胜

（合肥经济技术学院机电系 合肥 230052）

【摘要】 研究了基于人工神经网络在线设备状态监测系统，简要介绍了人工神经网络的基础理论，描述了基于人工神经网络在线设备状态监测系的结构和工作过程，给出该系统对卷烟机 MK 9-5 的状态监测和故障诊断的结果。实验结果表明，将多层前馈人工神经网络用于设备在线状态监测具有较好的效果，并可对设备故障进行可靠诊断。

关 键 词 人工神经网络； 在线状态监测； 故障诊断； 卷烟机MK9-5

中图分类号 TP18； TP306.3

· 科研成果介绍 ·

驻厂军代室网络管理信息系统

主研人员 陈雷霆 龚 杰 袁宏春 王建国 李志伟 李毅超 周小华 黄克军 等

驻厂军代室网络管理信息系统包含网络系统和管理信息系统：网络系统是面向地域分散、站点较多客观情况而建立的一个光集线器为中心的光纤星结构，具有网络共享打印、网络文件共享及网络远程透明访问等功能；管理信息系统主要包括办公室管理、计划管理、成本管理、技术管理、热加工组管理、冷加工组管理、装试组管理及破璃组管理 8 个分系统。

保密视频会议系统

主研人员 敬万钧 潘泽友 秦志光 朱长如 李国华 何世达 刘锦德 曾启铭 许 胜 尚晋钢

保密视频会议系统是具有保密措施的会议系统，它为及时、高效的工作创造了条件。其优点如下：

1）该系统工作平台为 SGI INDY 工作站，UNIX 操作系统，通过 FDDI 主干网运行，实现了语音、图形、图像和视频图像点对点的实时交互；

2）该系统创造性地实现网上传输的声音、图形、图像白板数据实时 DES 加密/解密，对所存贮的白板文件作数学签名；

3）该系统所提供的视频功能，使交谈双方能清晰地了解对方的环境及表情，增强了对交流信息的理解；

4）该系统所提供的电子白板功能完善，集图、文、声、像于一体，构成了一个丰富媒体信息的综合会议环境，其语言注释功能大大地增强了系统使用的有效性。

· 科 卞·

1998 年 12 月 10 日收稿

* 男 40岁 博士 副教授