Int J Adv Manuf Technol (2001) 17:383–391

The International Journal of
Advanced Manufacturing Technology

Intelligent Predictive Decision Support System for Condition-Based Maintenance

R. C. M. Yam[1], P. W. Tse[1], L. Li[1] and P. Tu[2]

[1]Department of Manufacturing Engineering and Engineering Management, City University of Hong Kong, Hong Kong; and [2]Department of Mechanical Engineering, University of Canterbury, Christchurch, New Zealand

The high costs in maintaining today's complex and sophisticated equipment make it necessary to enhance modern maintenance management systems. Conventional condition-based maintenance (CBM) reduces the uncertainty of maintenance according to the needs indicated by the equipment condition. The intelligent predictive decision support system (IPDSS) for condition-based maintenance (CBM) supplements the conventional CBM approach by adding the capability of intelligent condition-based fault diagnosis and the power of predicting the trend of equipment deterioration. An IPDSS model, based on the recurrent neural network (RNN) approach, was developed and tested and run for the critical equipment of a power plant. The results showed that the IPDSS model provided reliable fault diagnosis and strong predictive power for the trend of equipment deterioration. These valuable results could be used as input to an integrated maintenance management system to pre-plan and pre-schedule maintenance work, to reduce inventory costs for spare parts, to cut down unplanned forced outage and to minimise the risk of catastrophic failure.

Keywords: Condition-based maintenance; Deterioration trend; Fault diagnosis; Intelligent predictive decision support system; Neural network; Power plant

1. Introduction

With increased automation and mechanisation, many modern plants have installed flexible computer-controlled automatic and unmanned equipment. Along with the installation of this complex and capital-intensive equipment, maintenance work and costs have increased substantially. Wireman [1] conducted a benchmarking exercise and found that the maintenance cost for industrial firms in the USA has increased by 10–15% per year since 1979. High maintenance costs highlight the need to define clearly the maintenance objectives, to develop and enhance modern maintenance management methods continuously, to integrate maintenance and production activities effectively, and to use intelligent computer-based maintenance systems.

In industry, failure-driven and time-based maintenance are two major maintenance management approaches. Failure-driven maintenance (FDM) is also called run-to-failure maintenance [2]. It is a reactive management approach, where corrective maintenance is often dominated by unplanned events, and is carried out only after the occurrence of an obvious functional failure, malfunction, or breakdown of equipment. Corrective maintenance action can restore an item of failed equipment by either repairing or replacing the failed component. If the equipment is non-critical or is easily repaired, unplanned stoppages of the equipment will cause minimal disruption to production, and FDM could be an acceptable maintenance approach. However, in the case of purely random breakdown of equipment that would have a serious impact on production, an emergency corrective maintenance action is necessary to avoid the serious consequences of failure [3]. The practical implication of emergency corrective maintenance often results in the unpredictable performance in a plant, i.e. high equipment downtime, high cost of restoring equipment, extensive repair time, high penalties associated with the loss of production, and a high spare parts inventory level [4]. Time-based maintenance (TBM) is also called periodic preventive maintenance. In order to slow down the deterioration processes leading to faults, primary preventive maintenance is carried out by periodically lubricating, calibrating, refurbishing, inspecting, and checking of equipment on a regularly scheduled basis. TBM assumes that the estimated failure behaviour of the equipment, i.e. the mean time between functional failures (MTBF) is statistically or experientially known for equipment and machinery degrading in normal usage [5]. TBM also involves minor or major planned shutdowns of systems for overhaul or predetermined repair activities on still functioning equipment. This can prevent functional failures by replacing critical components at regular intervals just shorter than their expected useful lifetime. System overhaul and critical item replacement at fixed intervals are widely adopted by many modern automated plants. Although TBM can reduce the probability of system failure or the frequency of unplanned

Correspondence and offprint requests to: Dr R. C. M. Yam, Department of Manufacturing Engineering and Engineering Management, City University of Hong Kong, Tat Chee Avenue, Kowloon, Hong Kong

emergency repairs, it cannot eliminate the occurrence of random catastrophic failure. Some TBM practices may be out of date and do not cope with the actual operating requirement of the modern automated plant. Most of the maintenance decisions are made by experienced planners according to the original equipment manufacturer's recommendations, the reported breakdown history or failure data and the operating experience and judgement of the maintenance staff and technicians. Under a situation of uncertainty, it is very difficult to plan the maintenance activities properly in advance, and so, very often, the maintenance staff are required to work under "fire fighting" conditions [6].

2. Condition-Based Maintenance (CBM)

Condition-based maintenance (CBM) is a method used to reduce the uncertainty of maintenance activities, and is carried out according to the need indicated by the equipment condition [7]. CBM assumes that existing indicative prognostic parameters can be detected and used to quantify possible failure of equipment before it actually occurs. Prognostic parameters provide the indication of potential problems and incipient faults which would cause the equipment or component to deviate from the acceptable performance level. In maintenance, common problems of equipment are ageing and deterioration. These equipment conditions are useful indicators of possible faults and potential problems before catastrophic failure or damage to equipment occurs. The trend of the deterioration of critical components can also be identified through a trend analysis of the equipment condition data. Maintenance decisions depend very much on actual measured abnormalities and incipient faults, and the prediction of the trend of equipment deterioration.

A recent study of maintenance management practices shows that there are three major problems facing many modern engineering plants [8]:

1. How to pre-plan and pre-schedule maintenance work for sophisticated equipment under a complex operating environment?
2. How to reduce the high inventory cost for spare parts?
3. How to avoid the risk of catastrophic failure and eliminate unplanned forced outage of equipment or systems?

The analysis of the above problems has shown effective and efficient pre-determinations of when, where, what, how, and who shall maintain equipment systems are very important for cost-effective maintenance. A proper maintenance plan should be prepared at an early stage, well before the equipment problems become critical eventually cause fatal breakdowns. Increasing the percentage of planned maintenance actions can decrease the quantity and value of the spare parts required in the inventory for emergency repairs. Since maintenance faces the problems of inherent deterioration and random failure of equipment, predictive decisions based on condition-based fault diagnosis and the prediction of the trend of equipment deterioration are critical for maintenance decision making and planning processes.

3. The Need for Developing a Decision Support System for Condition-Based Maintenance

A decision support system (DSS) is a computerised information system which contains domain-specific knowledge and analytical decision models to assist the decision maker by presenting information and the interpretation of various alternatives [9]. Work on DSS began in the 1960s [10]. A DSS is intended to enhance individual decision making by providing easier access to problem recognition, problem structure, information management, statistical tools, and the application of knowledge [11]. Such a system is designed to enable the easier and faster generation of alternatives, and to increase the awareness of deficiencies in the decision-making process. It can help the decision maker to make more effective and efficient decisions in complex situations.

A number of computational tools have been developed for DSS such as knowledge base [12,13], analytic hierarchy process [14,15], Petri nets [16], neural networks [17,18], fuzzy logic and fuzzy networks [19,20], and Bayesian theory [21–23]. These computational tools have enabled DSS to become more intelligent by incorporating the normative power of analytical techniques. Today, research into DSS has generally evolved in respect of three perspectives: design, application, and technology [6]. The design perspective places emphasis on the development of methodologies and strategies extending over the whole process from problem recognition and analysis through system specifications to computer implementation. The application issue focuses on the use of DSS by individuals and groups. The technology perspective focuses on man–machine interaction and the development of software environments. The fundamental research issue in building an intelligent decision support system (IDSS) involves linking the domain-specific knowledge of experts with the normative power of analytical decision techniques to improve the quality of decisions.

In the last decade, some research results of DSS for industry-based maintenance have emerged in the literature. First, Rao et al. [24] proposed a concept for an intelligent maintenance support system (IMSS) architecture for air-traffic control in 1990. The primary objective of Rao et al.'s research is to use an interdisciplinary approach to identifying the opportunity for applying existing and emerging technologies to facilitate the automation of maintenance support operations for air-traffic control facilities. The IMSS framework, which includes several individual expert systems, and numerical processing programs, was developed. In 1996, Zhu [25] presented an integrated intelligent management support system with sensor-based condition monitoring for a mining truck. In this system, sensor measurement, data processing, knowledge-based intelligent systems and software implementation are integrated to provide a solid support for maintenance management. Indicative information and early warning about the health of the components in a system are collected through appropriate sensor measurement and monitoring. Tu [26] used a Bayesian probability network to develop a prototype of an intelligent decision support system (IDSS) for a maintenance management system in a textile company. In this IDSS prototype, the cost, quality, and production efficiency were taken into account when making a decision on maintenance activities. The maintenance knowledge of experts was collected and expressed using conditional probabilities, an inference engine for automatic diagnosis has been developed by a Baysian probability network.

After reviewing the current maintenance management practices, we find out that condition-based fault diagnosis and the prediction of the equipment deterioration trend are vital in maintenance management approaches [27]. Condition monitoring, intelligent condition-based fault diagnosis [28] and the prediction of the trend of equipment deterioration need to be integrated to provide a comprehensive decision support for maintenance management [29]. All these encourage us to develop a new framework for an intelligent predictive decision support system (IPDSS), including the prediction of the trend of equipment deterioration, for condition-based maintenance.

4. Intelligent Predictive Decision Support System (IPDSS) for Condition-Based Maintenance

The intelligent predictive decision support system (IPDSS) for condition-based maintenance integrates the concepts of:

1. Equipment condition monitoring.
2. Intelligent condition-based fault diagnosis.
3. Prediction of the trend of equipment deterioration.

Through integrating these three elements, the quality of maintenance decisions could be improved.

4.1 Condition Monitoring

Condition monitoring is defined as the collection and interpretation of the relevant equipment parameters for the purpose of the identification of the state of equipment changes from normal conditions and trends of the health of the equipment. Equipment parameters are a group of characteristics that indicate equipment condition. These characteristics, such as vibrations and temperatures, usually remain stable as long as the equipment is healthy. However, an abnormality in these characteristics may indicate the occurrence of a functional failure. Information on an incipient equipment failure can be obtained from the monitoring of these prognostic parameters.

4.2 Condition-Based Fault Diagnosis and Prediction of the Trend of Equipment Deterioration

Condition-based fault diagnosis is triggered by the detection of an equipment condition that is recognised as a deviation from the expected level. It is the process that detects abnormal problems and faults, recognises and analyses the symptomatic information, identifies and locates the root causes of a failure, obtains the fault development trend, and predicts the remaining lifetime of the equipment.

The intelligent systems used in condition-based fault diagnosis can be divided into three categories [29–31]:

1. Rule-based diagnostic systems.
2. Case-based diagnostic systems.
3. Model-based diagnostic systems.

Rule-based diagnostic systems detect and identify incipient faults in accordance with the rules representing the relation of each possible fault with the actual monitored equipment condition. Case-based diagnostic systems use historical records of maintenance cases to provide an interpretation for the actual monitored conditions of the equipment. The case library of maintenance is required to record all previous incidents, faults, and malfunctions of equipment which are used to identify the historical case that is most similar to the current condition. If a previous equipment fault occurs again, a case-based diagnostic system will automatically pick up the maintenance advice including trouble–cause–remedy from the case library. A model-based diagnostic system uses different mathematical, neural network, and logical methods to improve diagnostic reasoning based on the structure and properties of the equipment system. A model-based diagnostic system compares the real monitored condition with the model of the object in order to predict the fault behaviour.

5. The Need for Machine Condition Prognosis

The essential point of predictive maintenance is to monitor the operating conditions of the machine and keep track of its component failures. Once a fault has developed in one of the components, the condition of the machinery should be monitored regularly so as to avoid emergency breakdown. By monitoring the current operating conditions of the defective machine, some future key symptoms relevant to the deterioration of the machine can be forecast. Equipped with this kind of predictive based condition monitoring system, an advanced alarm can be given when the predicted value, related to the fault symptom, falls within an alarm band. This will help the system operators to take adequate actions to check the condition of the machine and repair the defects prior to a fatal breakdown. Therefore, an effective and efficient predictive-based machine condition prognosis is necessary for modern plants.

Vibration analysis is widely accepted as a tool to monitor the operating conditions of a machine, as it is non-destructive and reliable, and permits continuous monitoring without stopping the machine. Sophisticated techniques and instruments for vibration analysis have been developed and are widely used in industry [32]. For instance, in the case of a fault in gears, a whole family of sidebands may occur in its related spectrum, whereas a ball-bearing fault is characterised by an increase in a whole family of harmonics. Often, a fault developing in a machine will show an increase in vibration level, associated with the fault-related frequencies. The increasing amplitude of vibration may be an indication of a deteriorating machine condition and the rate of increase is proportional to the degree of damage. Therefore, it is possible to predict the trend of deterioration of a particular machine by monitoring its fault-related frequencies.

Experienced operators may use the trend of increasing amplitude of vibration to set up various warning levels, depending on the rate of deterioration of a defective machine. Corresponding to the degree of damage caused by faults, warning levels can be set for alert, high alert, alarm, serious alarm, and damaged, etc. Usually, two types of procedure for setting the alarm levels for spectral vibration are available in industry:

1. Absolute threshold system.
2. Power band system [32].

The absolute threshold system defines the maximum allowable amplitude of any single peak of spectral vibration within each alarm band. The power band system is based on the calculation of the total energy (i.e. "power") within each band. Some reference alarm levels have been recommended by the guidelines issued from various national and international committees, they are the International Standards Organization (ISO), the British Diagnostics Company VCI Ltd, the American IRD and the Canadian government CDMS/MS.

The criteria in the guidelines are very general. Similar machines will not have identical operational behaviours and the operating conditions may also be different [34]. To ensure better reliability, the operator must understand the behaviour of a particular machine and then make changes to the alarm levels according to its components' characteristics and the operating environment. Therefore, the values set for various alarm levels will be relevant to a particular type of machine. Such a scheme can be achieved by using neural networks as they can learn the behaviour of a machine without having the prior knowledge to set up a complex mathematical model. Once a neural network has been trained on the running characteristics of the machine, the warning levels can be adjusted and made uniquely suitable for the machine. Provided with such ability, the alarm warning system becomes more reliable.

5.1 Prediction of the Rate of Equipment Deterioration: An Artificial Neural Network Approach

Once a component is diagnosed as the source of incipient failure, the forecasting function of the fault development trend can be activated to assess the remaining lifetime of the defective component. With this remaining lifetime, planned corrective maintenance action can be arranged in adequate time before a possibly fatal breakdown of the equipment.

The equipment condition and the fault developing trend are often highly nonlinear and time-series based. Recently, artificial neural networks (ANNs) have been used as a new decision support tool because of their potential ability in nonlinear time-series trend prediction. The ability of ANNs to capture and retain nonlinear failure patterns has been researched and documented extensively [35–37]. ANNs have been found to perform better than known classical autoregressive models for the trend prediction of a nonlinear time series [8]. ANN had a rebirth in 1982 after the emergence of some important rediscovered characteristics [35]. Since ANNs differ from traditional statistical techniques in their ability to learn nonlinear features of a time series successfully, they have been widely used in forecasting [38]. According to the Kolmogorov representation theorem, a 3-layer ANN is able to represent an arbitrary function of a system no matter how complex the system is [39]. ANNs often consist of three types of layer: input, hidden, and output. Each layer has a number of simple, neuron-like processing elements called "nodes" or "neurons" that interact with other nodes using numerically weighted connections.

Recent work on forecasting nonlinear, non-stationary and non-Gaussian-type time series also indicates that recurrent neural networks (RNNs) have a better forecasting performance than other methods [8,40,41]. When the RNNs were compared with some of the well-known methods for the prediction of nonlinear time-based trends including vector autoregressive models, Burg algorithms, autoregressive models, bilinear models, and threshold autoregressive models, the results indicated that RNNs have a better forecasting performance than these classical methods and are even better than the feed-forward type ANNs [8].

An RNN is a type of ANN that has closed feedback loops in the network topology [42]. RNNs can store sequential information in the form of historical data and can be used in forecasting. For example, in an RNN, the input nodes are taken as the value of the current condition X_t and values of previous time-series condition (X_{t-1}, X_{t-2}, $X_{t-3, \ldots,}$ X_{t-d}, …, and X_n). The value of the output (X'_{t+1}) can provide a one-step-ahead prediction of a time-series condition, which is a function of the current value X_t and time-lagged values of the previous condition (X_{t-1}, X_{t-2}, …, X_{t-d}, …, and X_n). The predicted value X'_{t+1} of a time series, one-step ahead in the future, is given as:

$$X'_{t+1} = F(X_t, X_{t-1}, X_{t-2}, \ldots, X_{t-d}, \ldots, X_n)$$

where,

d is time lag
X'_{t+1} is the predicted value
X_t is the value of current condition
X_{t-d} is the values of previous condition lagged by time d

A special type of RNN identified by having the smallest root mean square (r.m.s.) errors in prediction is shown in Fig. 1. It consists of one output node, two hidden nodes and six input nodes (one input node with value of current condition X_t, four input nodes with values of previous condition X_{t-1}, X_{t-2}, X_{t-3},

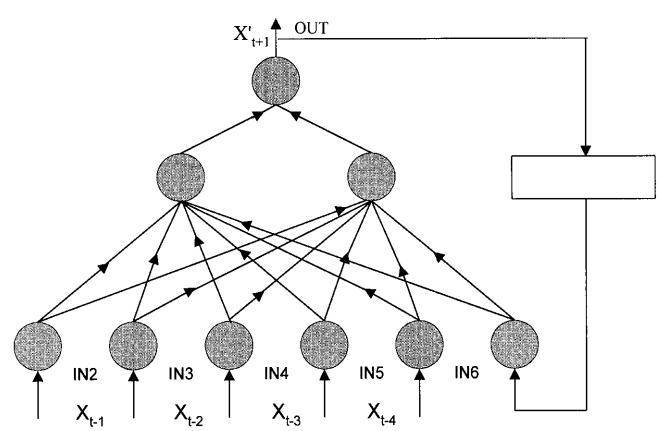

Fig. 1. A type of recurrent neural networks used for fault trend prediction.

X_{t-4}, and one input node fed from the output layer). The output node (X'_{t+1}) presents the one-step-ahead predicted value of the time series:

$$X'_{t+1} = F(X_t, X_{t-1}, X_{t-2}, X_{t-4}, X'_t)$$

where,

X'_{t+1} is the predicted value
X'_t is the previous predicted value
X_t is the value of current condition
X_{t-1}, X_{t-1}, X_{t-2}, X_{t-4} are the values of previous conditions

The prediction of the deterioration trend of defective equipment can be achieved by the learning ability embedded in the RNN. The predicted deterioration trend can indicate the degree of failure and the remaining lifetime of the defective equipment. This prediction provides important information to enable maintenance activities to be planned in advance, so as to avoid an overstock of spare parts and to prevent fatal breakdown.

6. Condition-Based Maintenance Decision Making in a Power Station

An electricity supply company, which is one of the largest modern single coal/oil-fired power stations in the world, has a total electrical generating capacity of over 4000 megawatts (MWI). In the past, the primary aim of this power station was to produce electricity with very high availability and reliability of equipment, and to achieve high thermal efficiency. However, in recent years, owing to the commissioning of new power stations and the slow down of the economy in the area, the demand for electricity has levelled off and spare generating capacity is increasing. The challenge of the more market-oriented competitive environment forces this company to become more conscious of the role of maintenance management for better equipment performance and quality of production. Moreover, the results of a benchmarking program conducted in the company show that high maintenance cost is caused by the high inventory level of spare parts, the unplanned outage cycles and the sophistication of maintenance planning and scheduling. These problems are also very common for other modern plants. In order to solve these problems, maintenance decisions should be made in advance, based on a comprehensive consideration of equipment operating conditions, intelligent condition-based fault diagnosis, and a prediction of the rate of equipment deterioration.

Actual maintenance operations (i.e. corrective maintenance action) before the specific planned outage should only be considered when the risk of failure is unacceptably high before the next planned overhaul. The specific forced outage time should fit into the available production schedule, so that unexpected maintenance work should be deferred to off-peak production, as much as possible. Planned overhaul of the total system should be performed only when it is really necessary. Overhaul intervals should be adjusted to fit into the production plan.

A defective planetary gear train of one the motor-pump houses installed in the power generation plant has been used for verifying RNNs in fault trend prediction. As shown in Fig. 2, the rotating wheel of the planetary gear (coupled to the motor shaft on the upper side) has 27 teeth and runs at 744 r.p.m. Each of the four planet gears has 36 teeth, and the annulus ring (coupled to the gear case) has 101 teeth. The output speed of the shaft at the lower side is stepped down to 157 r.p.m.

If the motor shaft is rotating in a clockwise direction, the lower shaft connected to the pump turns in an anticlockwise direction with the annulus ring remain stationary. Severe vibration had been observed at the toothmeshing frequency around 260 Hz and its harmonics. The gear train finally broke down and an overhaul had to be carried out, costing over $2 million and 200 man-hours for the replacement of a new gear train. Therefore, a system which can predict the life span of the gear train and avoid fatal breakdown is desirable.

The data of the operating conditions of the gear train were collected at two different periods of time, from January 1995 to February 1996, and then from March 1996 to April 1997. A total of 110 sets of data had been selected at equal intervals from each period. The sets of data were used to verify the ability of the RNN in forecasting the deterioration rate of the defective gear train. From each period, 65 sets of data were used for training the RNN and 45 sets of data were used for validation. An RNN, with a structure similar to Fig. 1, except the number of input nodes had been decreased to 4 nodes denoted as X_t to X_{t-3}, was used to forecast the one step ahead value, X_{t+1}.

After successful training, the 45 sets of data used for validation were fed into the RNN to predict the future fault trend occurring at the toothmeshing frequency of the defective gear train. The time series of the actual fault trends occurring at the toothmeshing frequency, at two different period of time, was compared with the series predicted by the RNN and plotted in Figs. 3 and 4. The root-mean-squared error in prediction using the validation data is less than 4.834×10^{-5}. Since deviation between the actual and the predicted fault trends is small, the RNN is capable of predicting the future rate of deterioration. Notice that in Fig. 4, the vibration level of the fault trend had dropped back to normal after a major overhaul of the gearbox.

RNNs can trace the deterioration rate of the gearbox, which can provide an early alarm when the predicted condition of the gearbox falls to a predefined dangerous level. With the early alarm, the planned corrective maintenance action can be arranged to be fitted into the normal pump operation cycle without interrupting the normal production. Maintenance activities can be carried out in accordance with the deterioration rate of the equipment condition and the degree of damage caused by potential faults.

7. Maintenance Operations Supported by the IPDSS

Figure 5 shows the operations of an IPDSS model, maintenance advice given according to the equipment condition. When the equipment operates under normal conditions, only minimal routine maintenance is required. When the monitored equipment parameters reach base level the equipment goes into a degrad-

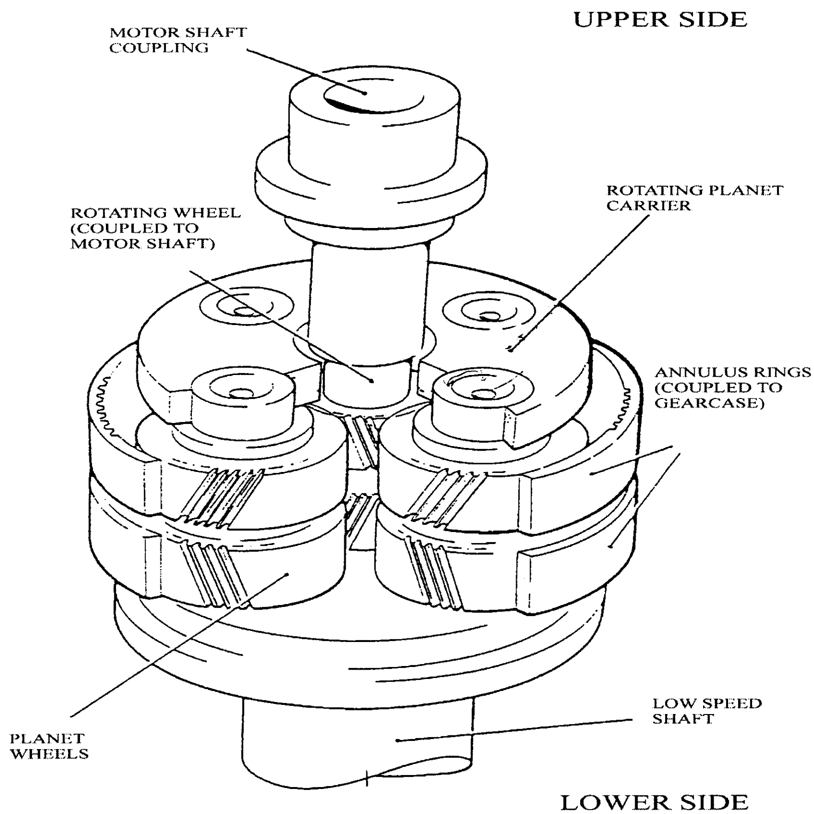

Fig. 2. A planetary gear train.

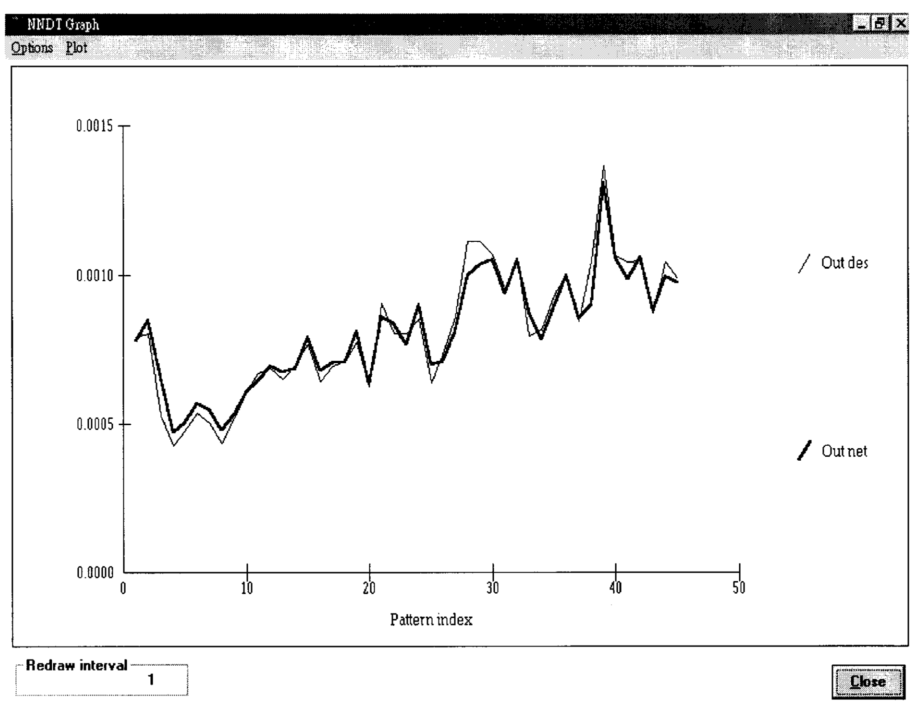

Fig. 3. Comparison of the predicted and the actual fault trends when the gearbox started deteriorating. ——, actual trend; ——, trend predicted by RNN.

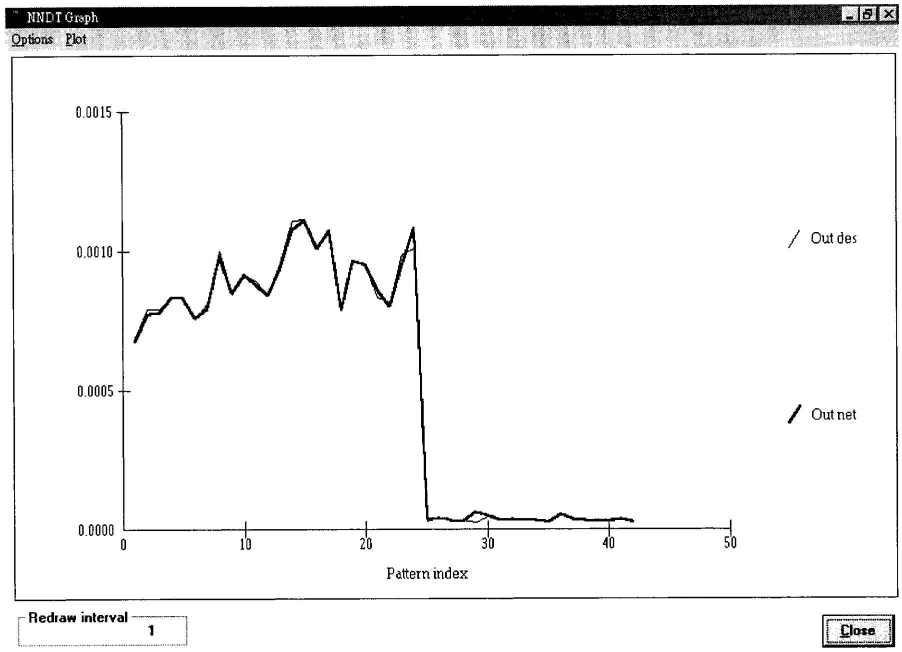

Fig. 4. Comparison of predicted and actual fault trends before and after a major overhaul of the gearbox. ——, actual trend; ——, trend predicted by RNN.

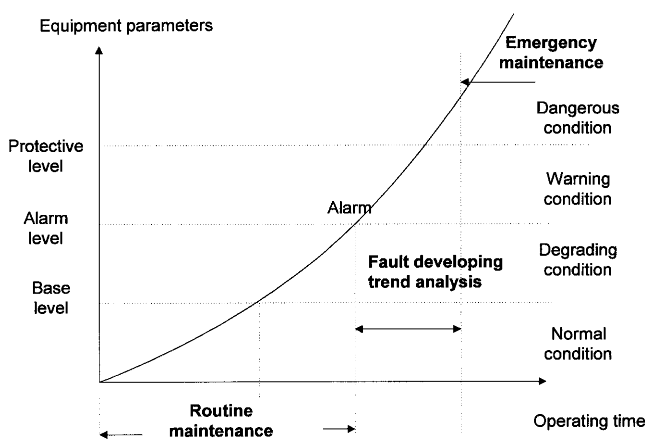

Fig. 5. Maintenance advice is made in accordance with equipment condition.

ing condition, which may subsequently cause functional failure. Fault developing trend analysis should be carried out, this analysis can indicate the possible problem areas in which an incipient fault has occurred or is likely to occur. Under a degrading condition, no special maintenance action is required and more condition monitoring should be carried out to avoid an emergency event. When the monitored equipment parameters exceed the alarm level, alarms will be activated to alert operators and maintenance staff, indicating that a warning condition has occurred. The case-based diagnostic system of the IPDSS will then be activated to look for a similar situation from the case library of maintenance. If an equipment fault occurs again, the case-based diagnostic system will automatically pick up the maintenance advice with trouble–cause–remedy from the maintenance case library. If the warning for a condition does not occur in the maintenance case library, IPDSS will activate the rule-based or model-based fault diagnostic system. The rule-based diagnostic system can detect and identify incipient faults according to the rules representing the relations of each possible fault and the actual monitored equipment condition. The model-based diagnostic system improves diagnosis reasoning based on the structure and properties of the equipment system which include mathematical, neural network, and logical methods. Once a component is diagnosed as the source of incipient failure, the prediction of the trend of the equipment deterioration can be activated to assess the remaining life time of the defective equipment. The result of the prediction will then be used to arrange the planned corrective maintenance action before the equipment fails so as to avoid possible fatal breakdown. When the monitored equipment parameters reach the predefined protective level, the equipment will cause sudden or nearly complete shutdowns, this is the result of a catastrophic fault in the equipment. Under this dangerous condition, emergency corrective maintenance action will be initiated immediately.

8. Conclusion

Some initial concepts of IPDSS for condition-based maintenance have been introduced in a power station. The trial experiment has indicated that the IPDSS approach and, in particular, its prediction is useful to enhance the efficiency of the maintenance function for a large complex automated engineering plant. IPDSS can reduce maintenance costs by preparing appropriate remedial actions before possible fatal breakdown of equipment. Equipment problems can be detected before they become critical, and prior to major overhauls.

Repairs can be carried out at a convenient time to avoid loss of production. With the successful implementation of IPDSS, the duration between major outages for overhauls can be extended and the overhaul may be required only on a need basis. Early indication of failure provides more time for proper maintenance planning and scheduling. It can often help to reduce significant damage to equipment. IPDSS can also facilitate spare part inventory management to avoid premature part replacement and overstocking of unnecessary spare parts. In addition, IPDSS can also help to reduce the magnitude or frequencies of maintenance activities.

Acknowledgement

This paper is based on the findings of the research project "Decision Support System for Equipment Diagnosis and Maintenance Management: An Artificial Intelligence Approach" funded by the Strategic Research Grant of the City University of Hong Kong.

References

1. T. Wireman, "World class maintenance management", Industrial Press, New York, 1990.
2. John Moubray, Reliability-Centered Maintenance, 2nd edn, Industrial Press, New York, 1997.
3. Benjamin W. Niebel, Engineering Maintenance Management, 2nd edn, Marcel Dekker, New York, 1996.
4. Albert H. C. Tsang, "Conidition-based maintenance tools and decision making", Journal of Quality in Maintenance Engineering, 1(3), pp. 3–17, 1995.
5. I. B. Gertsbakh, Models of Preventive Maintenance, North-Holland, 1977.
6. Y. Tu, "Decision support system for equipment diagnosis and maintenance management: An artificial intelligent approach", Research Proposal, City University of Hong Kong, HK, 1995.
7. British Standards Institution, BS3811:1993, British Standard Glossary of Maintenance Management Terms in Terotechnology, 1993.
8. P. Tse and D. Atherton, "Prediction of machine deterioration using vibration based fault trends and recurrent neural networks", Transactions of the ASME: Journal of Vibration and Acoustics, 121(3), pp. 355–362, 1999.
9. Huaiqing Wang, "Intelligent agent assisted decision support systems: Integration of knowledge discovery, knowledge analysis, and group decision support", Expert System with Application, 12(3), pp. 323–335, 1997.
10. M. Klein and L. B. Methlie, Expert Systems: A Decision Support Approach, Addison-Wesley, New York, 1990.
11. M. Santana, "Managerial learning: A neglected dimension in decision support systems", Proceeding: The 28th Annual Hawaii International Conference on System Sciences, vol. 4, pp. 82–91, 1995.
12. A. Borden, "Designing and maintaining decision-making processes", AGARD Conference Proceedings 545, Paris, France, pp. 3/1–6, May 1993.
13. M. T. Liberatore and A. C. Stylianou, "Using knowledge-based systems for strategic market assessment", Information and Management, 27(4), pp. 221–32, October 1994.
14. T. L. Saaty, "Multicriteria decision making", The Analytic Hierarchy Process, RWS Publication, USA, 1990.
15. M. A. P. Davies, "A multi-criteria decision model application for managing group decisions", Journal of the Operational Research Society, 45(1), pp. 47–58, 1994.
16. C. Kocourek, "A Petri net based design decision support system", Proceedings of the IASTED International Conference, Applied Modeling and Simulation, Vancouver, BC, Canada, pp. 108–14, July 1993.
17. A. R. Hurson, S. Pakzad and B. Lin, "Automated knowledge acquisition in a neural network based decision support system for incomplete database systems", Microcomputers in Civil Engineering, 9(2), pp. 129–43, 1994.
18. T. S. Quah, C. L. Tan and B. Srinivasan, "A fuzzy neural-network decision support systems for bond trading", Proceedings of International Symposium on Artificial Intelligence, The Artificial Intelligence Technology Transfer Conference, Monterrey, Mexico, September, pp. 20–24, 1993.
19. A. Ishikawa, "The new fuzzy Delphi methods: Economization of GDS (group decision support)", Proceedings of the Twenty-sixth Hawaii International Conference on System Science, Wailea, HI, USA, vol. 4, pp. 255–264, January 1993.
20. C. P. Schrunder, J. E. Gallertly and J. R. Bicheno, "A fuzzy, knowledge-based decision support tool for production operations management", Expert System, 11(1), pp. 3–11, 1994.
21. P. G. W. Keen, "Value analysis: Justifying decision support systems", Management Information Systems Quarterly, 1980.
22. E. Charniak, "Bayesian networks without tears", AI Magazine, 12, pp. 50–64, 1991.
23. V. M. R. Tummala and W. Ellis, "Minimum expected loss estimators of scale and shape parameters of the Weibull distribution", IEEE Transaction on Reliability, R-35, pp. 212–215, 1986.
24. M. Rao, C. Theisen and J. T. Luxhoj, "Intelligent system for air-traffic control", The Proceedings of the 5th IEEE International Symposium on Intelligent Control, vol. 2, pp. 859–63, 1990.
25. X. Zhu, "Sensor-based condition monitoring and predictive maintenance: An integrated intelligent management support system", Intelligent Systems in Accounting, Finance and Management, 5, pp. 241–258, 1996.
26. Y. L. Tu, "Integrated maintenance management system in a textile company", International Journal of Advanced Manufacturing Technology, 13, pp. 453–462, 1997.
27. P. Tse and K. W. Tam, "Intelligent machine condition prognostic system for maintenance management and scheduling", Proceedings of 1999 International Conference on Advanced Manufacturing Technology '99, Science Press, New York, pp. 996–1000, 1999.
28. P. Tse, D. Wang and D. Atherton, "Harmony theory yields robust machine fault diagnostic system based on learning vector quantization classifier", Journal of Engineering Applications of Artificial Intelligence, 9(5), pp. 487–498, 1996.
29. P. Tse, "Neural networks based robust machine fault diagnostic and life span predicting system", PhD thesis, The University of Sussex, UK, 1998.
30. Robert Milne, "Strategies for diagnosis", IEEE Transaction Systems, Man and Cybernetics, 17(3), May, pp. 333–339, 1989.
31. Karen L. Butler, "An expert system based framework for an incipient failure detection and predictive maintenance system", Proceedings of the International Conference on Intelligent Systems Applications to Power Systems (ISAP-96), 1, pp. 321–326, 1996.
32. Bruel and Kjaer, "Machine condition monitoring using vibration analysis", BA 7095-14, Bruel and Kjaer, Denmark.
33. J. E. Berry, "How to specify machinery vibration spectral alarm bands", Journal of Sound and Vibration, pp. 16–26, September 1990.
34. E. Downham and R. Woods, "It is dangerous to associate a single vibration level with machine performance", Proceedings of ASME Conference, Vibration 96, Toronto, Paper no. 71, 1971.
35. J. J. Hopfield, "Neural networks and physical systems with emergent collective abilities", Proceedings of National Academy of Science, 79, pp. 2554–2558, 1982.
36. J. J. Hopfield, "Neurons with graded response have collective computational properties like those of two-state neurons", Proceedings of National Academy of Science, 81, pp. 3088–3092, 1984.
37. J. T. Luxhj, "An artificial neural network for nonlinear estimation of the turbine flow-meter coefficient", Engineering Application of Artificial Intelligence, 11, pp. 723–734, 1998.
38. J. Shao, "Application of an artificial neural network to improve short-term road ice forecasts", Expert System, 14, pp. 471–482, 1998.

39. L. Fausett, Fundamentals of Neural Networks, Prentice-Hall, New York, 1994.
40. W. Weigend and N. Gershenfeld, “Results of the time series prediction competition at the Sante Fe Institute”, Proceedings of the IEEE ICNN’93, San Francisco, USA, pp. 1786–1793, 1993.
41. J. T. Connor, R.D. Martine and L. E. Atlas, “Recurrent neural networks and robust time series prediction”, IEEE Transactions on Neural Networks, 5(2), pp. 240–254, 1994.
42. Robert J. Schalkoff, Artificial Neural Networks, McGraw-Hill, New York, 1997.