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Intelligent prognostics tools and e-maintenance

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Abstract

In today's global competitive marketplace, there is intense pressure for manufacturing industries to continuously reduce and eliminate costly, unscheduled downtime and unexpected breakdowns. With the advent of Internet and tether-free technologies, companies necessitate dramatic changes in transforming traditional "*fail and fix* (FAF)" maintenance practices to a "*predict and prevent* (PAP)" e-maintenance methodology. E-maintenance addresses the fundamental needs of predictive intelligence tools to monitor the degradation rather than detecting the faults in a networked environment and, ultimately to optimize asset utilization in the facility.

This paper introduces the emerging field of e-maintenance and its critical elements. Furthermore, performance assessment and prediction tools are introduced for continuous assessment and prediction of a particular product's performance, ultimately enable proactive maintenance to prevent machine from breakdowns. Recent advances on intelligent prognostic technologies and tools are discussed. Several case studies are introduced to validate these developed technologies and tools.

Keywords: E-maintenance; Prognostics; Predictive maintenance; Remote monitoring

1. Introduction

A lot of machine maintenance today is either reactive (fixing or replacing equipment after it fails) or blindly proactive (assuming a certain level of performance degradation, with no input from the machinery itself, and servicing equipment on a routine schedule whether service is actually needed or not). Both scenarios are extremely wasteful. To human beings, it often seems that machines fail suddenly, but in fact machines usually go through a measurable process of degradation before they fail. Today, that degradation is largely invisible to human users, even though a great deal of technology has been developed that could make such information visible. Many sophisticated sensors and computerized components are capable of delivering data about the machine's status and performance. The problem is that little or no practical use is made of most of this data. We have smart devices, but we do not have a continuous and seamless flow of information throughout entire processes. Sometimes this is because the available data are not rendered in a useable form. More often, no infrastructure exists for delivering the data over a network, or for managing and analyzing the data even if the devices were networked. When smart machines are networked and remotely monitored, and when their data is modelled and continually analyzed with sophisticated embedded systems, it is possible to go beyond mere "predictive maintenance" to intelligent "prognostics". *Intelligent prognostics* is defined as a systematic approach that can continuously track health degradation and extrapolating temporal behaviour of health indicators to predict risks of unacceptable behaviour over time as well as pinpointing exactly which components of a machine are likely to fail. Such continuous insight into present and future health of machines and their components, as well as the information flow infrastructure enable the move to *e-maintenance* based on intelligent prognostics, where maintenance actions are *synchronized* with the overall operation of the system as well as with the necessary maintenance resources and spare parts. Such synchronization of maintenance actions and information flow infrastructure should enable autonomously triggering of services and ordering of spare parts, yielding *near-zero*

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downtime system operation through proactive, cost-effective maintenance that is the least intrusive on the normal function of the system [1,2]. The purpose of this paper is to present an overview of the methods that enable the above-described paradigm of intelligent prognostics and e-maintenance.

The rest of this paper is organized as follows. Section 2 offers a brief review of the research in the area of condition-based maintenance. Section 3 outlines more recent achievements in development of predictive condition-monitoring tools and intelligent maintenance decision making based on the use of those tools. Several examples of real-life implementation of predictive monitoring and intelligent maintenance decision-making tools are enclosed in Section 4. Finally, Section 5 summarizes conclusions of this work and outlines guidelines for possible future work.

2. Condition-based maintenance

Traditional reliability prediction is made based on failure time data; meanwhile, maintenance actions are initiated in terms of a reliability index. Usually such preventive maintenance schemes as block-replacement and age-replacement are time-based without considering the current health state of the product, and thus are inefficient and less valuable for a customer whose individual asset is of the utmost concern.

The major role of degradation analysis is to investigate the evolution of the physical characteristics, or performance measures, of a product leading up to its failure. A maintenance scheme, referred to as condition-based maintenance (CBM), is developed by considering current degradation and its evolution. CBM methods and practices have continued to improve over recent decades. For example, a major manufacturer of elevators for high-rise buildings continuously monitors the braking systems, and acceleration and deceleration of elevators globally to meet high safety requirements. The main idea of CBM is to utilize the product degradation information extracted and identified from on-line sensing techniques to minimize the system downtime by balancing the risk of failure and achievable profits. The decision making in CBM focuses on predictive maintenance. To do so, many diagnostic tools and methods have been developed with much success. Sensor fusion techniques are also commonly emploted due to the inherent benefits in taking advantage of mutual information from multiple sensors [3–5]. For example, vibration signature analysis and oil analysis, because of their excellent capacity for describing machine performance, have been successfully employed for prognostics for a long time [6,7]. Alternative approaches in using time/stress, temperature, acoustic emissions [8], and ultrasonic are widely employed as well. However, a major breakthrough has not been made in the development of prognostics since many methods have remained based on traditional signal processing methods [9].

In the recent technical literatures, a large variety of prognostic applications have been reported, and many of these were more application specific rather than generic. For instance, the development of neural networks has added new dimensions to solving existing problems in conducting prognostics of a centrifugal pump case [10]. A comparison of the results using the signal identification technique showed various merits of neural nets including the ability to handle multivariate wear parameters in a much shorter time. A helicopter transmission prognostic application was presented by Parker et al. [11], whereby fault detection, isolation, and estimation were conducted by a polynomial neural network. A fuzzy logic-based neural network and decision tree were applied to the prediction of paper web breakage in a paper mill [12]. Yet another prognostic application presented an integrated prognosis system using a dynamically linked ellipsoidal basis function neural network coupled with an automated rule extractor to develop a tree-structured rule set that closely approximates the classification of the neural network [13]. That method allowed assessment of trending from the nominal class to each of the identified fault classes, which means quantitative prognostics were built into the network functionality. Garga et al. [14] introduced a hybrid reasoning method for prognostics, which integrated explicit domain knowledge and machinery data. In this approach, a feed-forward neural network was trained using explicit domain knowledge to get a parsimonious representation of the explicit domain knowledge.

Some research activities in the infrastructure of prognostics have also been reported. From 1998 to 2000, the U.S. army logistics integration agency funded a project entitled, "Prognostics Framework" [15]. The project aimed at providing an overall architecture to manage the information provided by the individual prognostic techniques. This prognostics framework is generic and scalable, with an open architecture and horizontal technology, which is intended to integrate with embedded diagnostics to provide "total health management" capability.

Generally speaking, current prognostic approaches can be classified into three basic groups: *model-based prognostics*, *data-driven prognostics*, and *hybrid prognostics*. An example of a characteristic *model-based prognostics* application includes data collected from model-based simulations under normal and degraded conditions. Prognostic models are constructed based on different random load conditions, or modes. However, in the absence of a reliable or accurate system model, another approach to determine the remaining useful life is to monitor the trajectory of a developing fault and predict the amount of time until the developing fault reaches a predetermined level requiring action, which is the so called data-driven prognostic method. The alpha–beta–gamma tracking filter and the Kalman filter, two well-known tracking and prediction tools, have been applied to gearbox prognostics [16,17]. Both filters have been investigated for their ability to track and smooth features from gearbox vibration data. The literature presented additional discussions on using Kalman filters to track changes in features like vibration levels, mode frequencies, or other waveform signature features, and how to estimate the future hazard rate, probability of survival, and remaining useful life [18,19]. An example of a hybrid method, which fuses the model-based information and sensor-based information and takes advantage of both model- and data-driven methods, was proposed by Hansen et al. [20], by which a more reliable and accurate prognostic result can be generated.

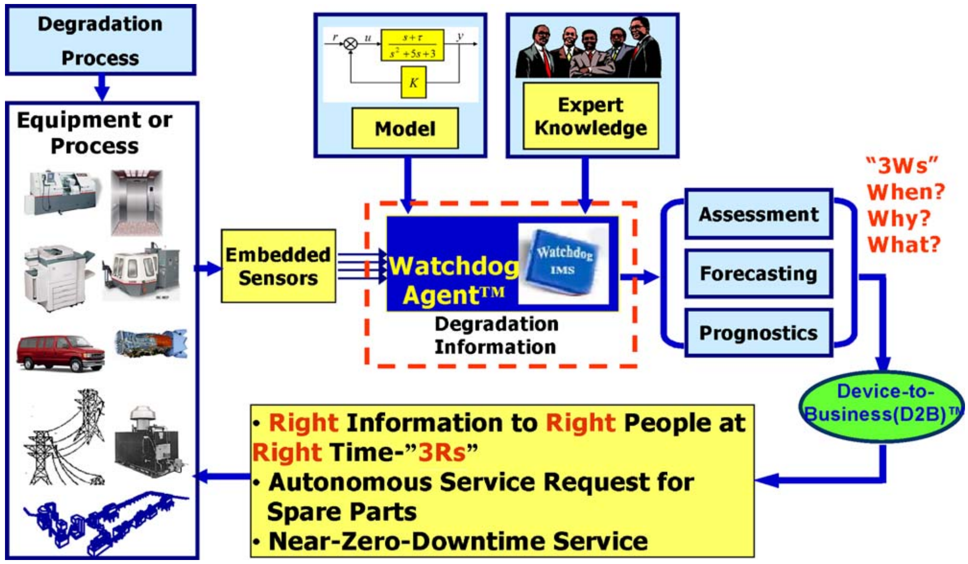

Fig. 1. Infotronics structure of IM systems.

Prognostic information obtained through intelligence embedded into the manufacturing process or equipment can also be used to improve the manufacturing and maintenance operations in order to increase process reliability and improve product quality. For instance, the ability to increase the reliability of manufacturing facilities using awareness of the deterioration levels of manufacturing equipment has been demonstrated through an example of improving robot reliability [21]. Moreover, a life cycle unit (LCU) [22] was proposed to collect usage information about key product components, enabling one to assess product reusability and facilitating reuse of products that have significant remaining useful life.

In spite of the progress made, many fundamental issues still remain:

- Most of the developed prognostics approaches are application or equipment specific. A generic and scalable prognostic methodology or toolbox does not exist;
- Currently, methods are generally focused on solving the failure prediction problem. Tools for system performance assessment and degradation prediction have not been well addressed;
- Features used for prognostics need to be further developed;
- Many developed prediction algorithms have been demonstrated only in a laboratory environment without industrial validations.

To address these issues, a toolbox of algorithms for multi-sensor performance assessment and prediction, named Watchdog Agent™, has been developed at the Center for Intelligent Maintenance Systems (IMS) which is a multi-campus NSF Industry/University Cooperative Research Center between the University of Cincinnati and the University of Michigan. These tools enable one to quantitatively assess and predict performance degradation levels of key product components [23–26], thus offering the possibility of physically realizing closed-loop product life cycle monitoring and management.

3. Development of predictive tools and intelligent maintenance systems

Fig. 1 shows the system elements of ''intelligent maintenance systems (IMS)''. The key research elements of intelligent maintenance systems consist of (1) transforming data to information to knowledge and synchronizing decisions with remote systems; (2) intelligent embedded prognostics algorithms for performance degradation assessment and prediction; (3) infotronics software and hardware platforms that enable a product to think, link, reconfigure and sustain in a networked and tether-free environment; (4) embedded product services and life cycle information for closed-loop product designs.

3.1. Smart prognostics algorithms (Watchdog Agent™)

The Watchdog Agent™ bases its degradation assessment on the readings from multiple sensors that measure critical properties of the process, or machinery, that is being considered. It is expected that the degradation process will alter the sensor readings that are being fed into the Watchdog Agent™, and thus enable it to assess and quantify the degradation through quantitatively describing the corresponding change in sensor signatures. In addition, a model of the process or piece of equipment that is being considered, or specific knowledge available for the application can be used to aid the degradation process description, provided that such a model and/or such knowledge exists. The prognostic function of the watchdog is realized through trending and statistical modelling of the observed process performance signatures and/or model parameters. This allows one to predict the future behaviour of these patterns and thus forecast the behaviour of the process, or piece of machinery that is being considered. Furthermore, the Watchdog Agent™ also has the diagnostic capabilities through memorizing the significant signature patterns in order to recognize situations that have been

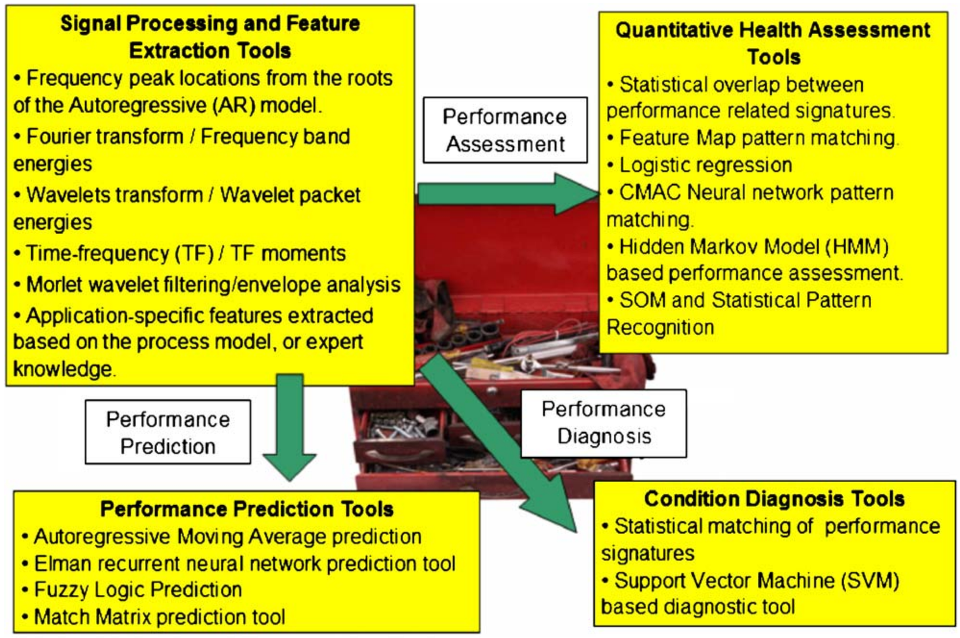

Fig. 2. Tools utilized for feature extraction, performance assessment, condition diagnosis, and performance prediction.

observed in the past, or be aware of the situation that was never observed before. Thus, the Watchdog Agent^{TM} has elements of intelligent behaviour that enable it to answer the questions:

- *When* the observed process, or equipment, is going to fail or degrade to the point when its performance becomes unacceptable?
- *Why* the performance of the observed process, or equipment is degrading, or, in other words, what is the cause of the observed process or machinery degradation?

The answer to the first question enables the prognostic Watchdog function and the answer to the second question enables its diagnostic function. The prognostic and diagnostic outputs of Watchdogs mounted on all the processes and machinery of interest are fed into the decision support tool (DST) that addresses the question: *what* is the most critical object, or process in the system with respect to maintenance, or repair?

The answer to this question is obtained through taking into account the risks of taking, or not taking, a maintenance action at a given time, and then optimizing the costs associated with the maintenance operation if the decision to perform maintenance is made, or the cost of downtime and repair, if the maintenance is omitted and the process, or the machine fails.

In order to facilitate the use of the Watchdog Agent^{TM} in a wide variety of applications, with various requirements and limitations regarding the character of signals, available processing power, memory and storage capabilities, limited space, power consumption, personal user's preference, etc., the performance assessment module of the Watchdog Agent^{TM} has been realized in the form of a modular, open architecture toolbox. A toolbox that consists of different prognostics tools has been developed for predicting the degradation or performance loss on devices, processes, and systems. The algorithms include neural network-based, time series-based, wavelet-based and hybrid joint time-frequency methods, etc. Open architecture of the toolbox allows one to easily add new solutions to the performance assessment modules as well as to easily interchange different tools, depending on the application needs. Fig. 2 summarizes the tools used for feature extraction, performance assessment, condition diagnosis, and performance prediction.

- *Sensory processing and feature extraction module* transforms sensor signals into domains that are most the revealing in terms of the product's performance and extracts features most relevant to describing the product's performance. Time series analysis [27] or frequency domain analysis [28] could be used to process stationary signals (signals with time invariant frequency content), while wavelet [29], or joint time-frequency domains [30] could be used to describe non-stationary signals (signals with time-varying frequency content).
- The features are extracted from the domain into which sensory processing module transforms sensory signals, using expert knowledge about the application, or automatic feature selection methods such as roots of the autoregressive time series model, or time-frequency moments and singular value decomposition.
- *Quantitative health assessment module* evaluates the overlap between the most recently observed signatures and those observed during normal product operation. This overlap is expressed through the so-called confidence value (CV), ranging between 0 and 1, with higher CVs signifying a high overlap, and hence performance closer to normal. In case data associated with some failure modes exists, most recent performance signatures obtained through the signal proces-

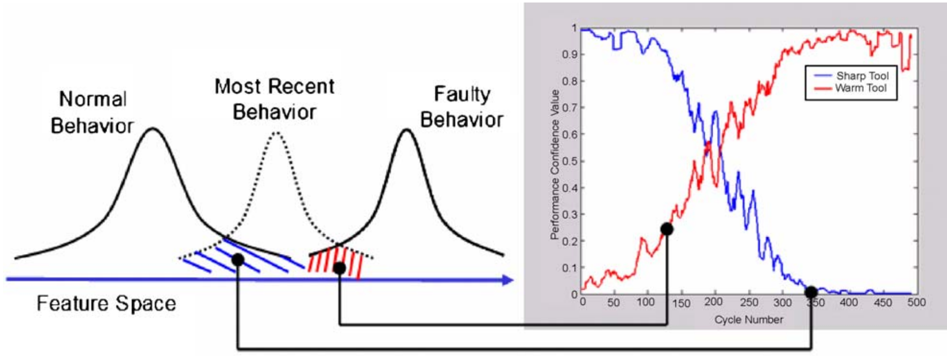

Fig. 3. Performance evaluation using confidence value (CV).

sing, feature extraction and sensor fusion modules can be matched against signatures extracted from faulty behaviour data.

Realization of the performance evaluation module depends on the character of the application and extracted performance signatures. If significant application expert knowledge exists, simple but rapid performance assessment based on the feature-level fused multi-sensor information can be made using the relative number of activated cells in the neural network, or using the logistic regression approach. For open-control architecture products, the match between the current and nominal control inputs and performance criteria can also be utilized to assess the product's performance. For more sophisticated applications with intricate and complicated signals and performance signatures, statistical pattern recognition methods, or feature map-based approach are employed. Over time, as new failure modes occur, performance signatures related to each specific failure can be collected and used to teach the Watchdog Agent™ to recognize and diagnose that failure mode in the future. Thus, the Watchdog Agent™ is can be seen as an intelligent device that utilizes its experience and human supervisory inputs over time to build its own expandable and adjustable world model.

- *Performance prediction module* is aimed at extrapolating the behaviour of process signatures over time and predicts their behaviour in the future. Autoregressive moving average (ARMA) [27] modelling and match matrix [38] methods are used to forecast the performance behaviour. Fig. 4 shows the concept of feature-based prognostics and diagnostics methods explained in more detail in [37].

Performance assessment and prediction can be enhanced through feature-level or decision-level sensor fusion, as defined by the Joint Directors of Laboratories (JDL) standard of multi-sensor data fusion [31], Chapter 2 [32]. Feature-level sensor fusion is accomplished through concatenation of features extracted from different sensors and joint consideration of the concatenated feature vector in the performance assessment and prediction modules. *Decision-level sensor fusion* is based on separately assessing and predicting process performance from individual sensor readings and then merging these individual sensor inferences into a multi-sensor assessment and prediction through some averaging technique.

Condition diagnosis module tells not only the level of behavior degradation (the extent to which the newly arrived signatures belong to the set of signatures describing the normal system behavior), but also how close the system behavior is to any of the previously observed faults (overlap between signatures describing the most recent system behavior with those characterizing each of the previously observed faults).This matching allows the Watchdog Agent(R) to recognize and forecast a specific faulty behavior, once a high match with the failure associated signatures is assessed for the current process signatures, or forecasted based on the current and past product's performance. Fig. 3 illustrates this signature matching process for performance evaluation. Furthermore, this entire infrastructure for multi-sensor performance assessment and prediction could be even further enhanced if Watchdog Agent™ are embedded on identical products operating under similar conditions could exchange information and thus assist each other in building the world model. Furthermore, this communication can be used to benchmark the performance of "brother-products" and thus rapidly and efficiently identify under-performing units before they cause any serious damage and losses. This paradigm of communication and benchmarking between identical products operating in similar conditions is referred to as the "*peer-to-peer*" (P2P) paradigm.

Fig. 5 illustrates the aforementioned Watchdog Agent™ functionalities supported by the P2P communication and benchmarking paradigm. A list of developed prognostics tools

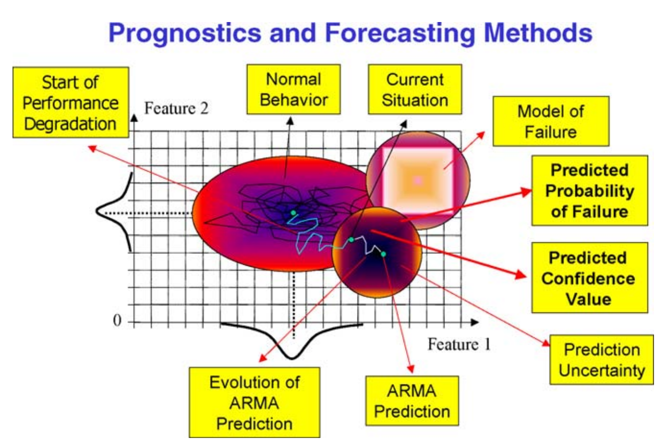

Fig. 4. Prognostics and performance forecasting.

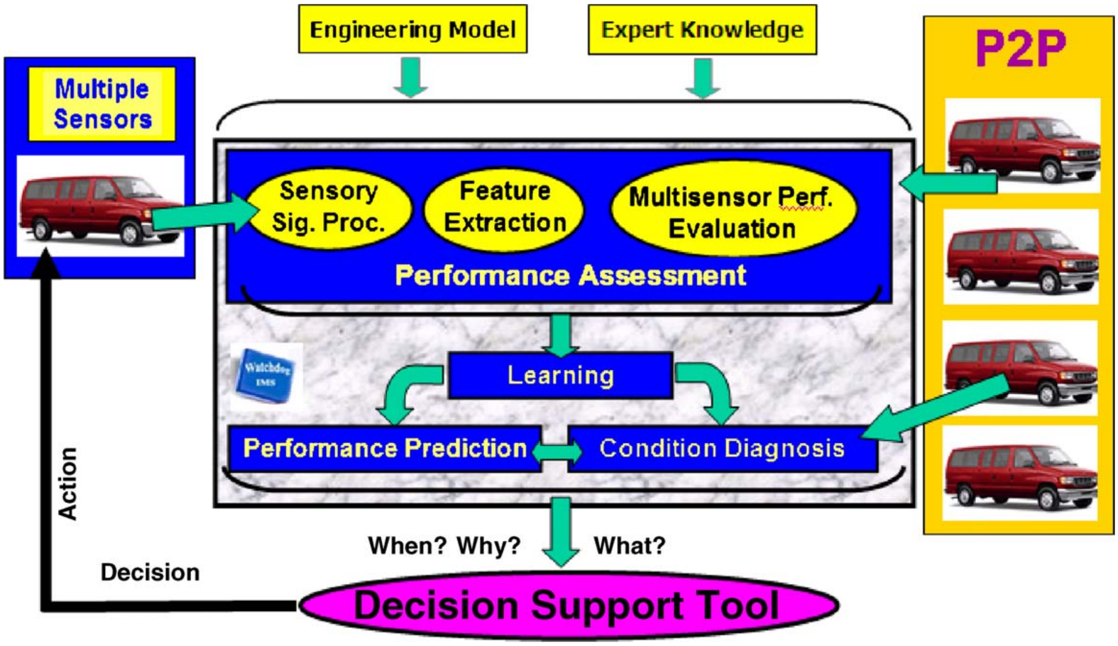

Fig. 5. Peer-to-peer (P2P) functionalities of the intelligent Watchdog Agent™.

and their capabilities are summarized in [37]. Many of these algorithms have been validated on industry testbeds. These works can be seen in the publication list.

Fig. 6 shows the results of predicting the behaviour of machining process spindle load signatures using ARMA modelling techniques. Load sensor readings from a boring machine spindle have been remotely collected and processed into joint time-frequency (TF) distributions. Performance related signatures were extracted from the TF distributions using the TF moments and principal component analysis [26]. ARMA modelling techniques were then utilized to predict the behaviour of the extracted principal components, as indicated in Fig. 6.

4. Implementation examples

Several Watchdog Agents for on-line performance assessment, as well as intelligent maintenance decision-making tools, have already been developed and implemented as standalone applications in a number of industrial and service facilities.

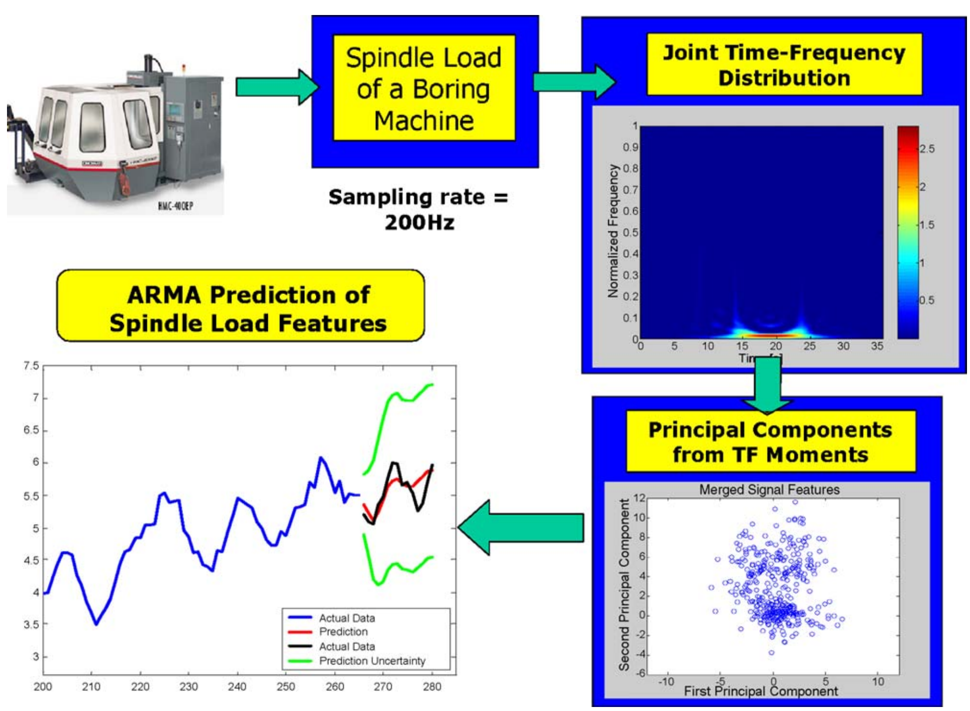

Fig. 6. ARMA prediction of features extracted from the spindle load sensor readings.

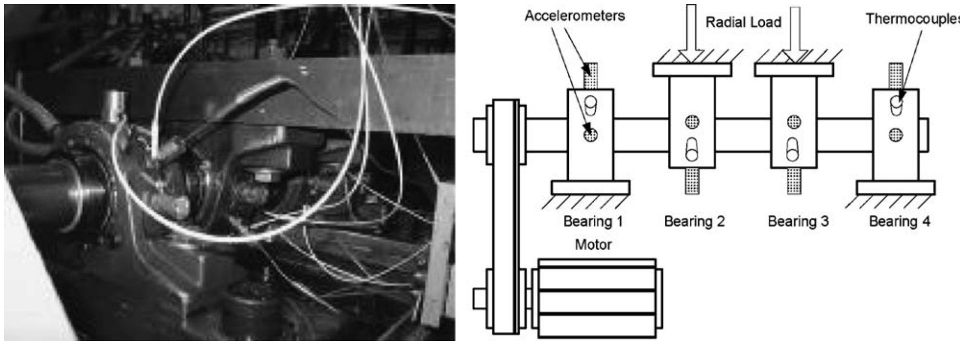

Fig. 7. Bearing test rig.

Below is a list of a few examples to illustrate the developed tools.

4.1. Example 1: roller bearing performance prediction

Most bearing diagnostics research involves studying the defective bearings recovered from the field, where the bearings exhibit mature faults, or from simulated or ‘‘seeded’’ damage. Experiments using defective bearings are less likely to help discover natural defect propagation in the early stages. In order to truly reflect the real defect propagation processes, bearing run-to-failure tests were performed under normal load conditions on a specially designed test rig supported by an industrial partner. More details about this work can be found in [33].

The bearing test rig hosts four test bearings on one shaft. Shaft rotation speed was kept constant at 2000 rpm. A radial load of 6000 lbs is added to the shaft and bearing by a spring mechanism. A magnetic plug installed in the oil feedback pipe collects debris from the oil as evidence of bearing degradation. The test stops when the accumulated debris adhered to the magnetic plug exceeds a certain level.

Four double row bearings were installed on one shaft as shown in Fig. 7. A high-sensitivity accelerometer was installed on each bearing housing. Four thermocouples were attached to the outer race of each bearing to record bearing temperature for monitoring the lubrication purposes. Several sets of tests ending with various failure modes were carried out. The time domain feature shows that most of the bearing fatigue time is consumed during the period of material accumulative damage, while the period of crack propagation and development is relatively short.

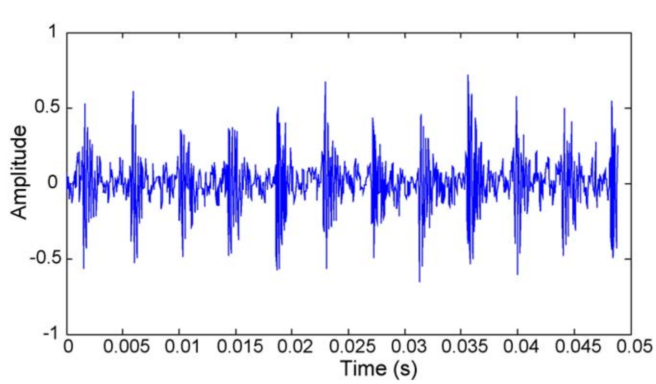

Fig. 8. The vibration signal waveform of a faulty bearing.

This means that if the traditional threshold-based condition-monitoring approach is used, the response time available for the maintenance crew to respond prior to catastrophic failure after a defect is detected in such bearings, is very short. A prognostic approach that can detect the defect at the early stage is demanded so that enough buffer time is available for maintenance and logistical scheduling.

Fig. 8 presents the vibration waveform collected from bearing 4 at the last stage of the bearing test. The signal exhibits strong impulse periodicity because of the impacts generated by a mature outer race defect. However, when examining the historical data and observing the vibration signal 3 days before the bearing failed, there is no sign of periodic impulse as shown in Fig. 9(a). The periodic impulse feature is totally masked by the noise.

An adaptive wavelet filter is designed to de-noise the raw signal and increase the probability of degradation detection.

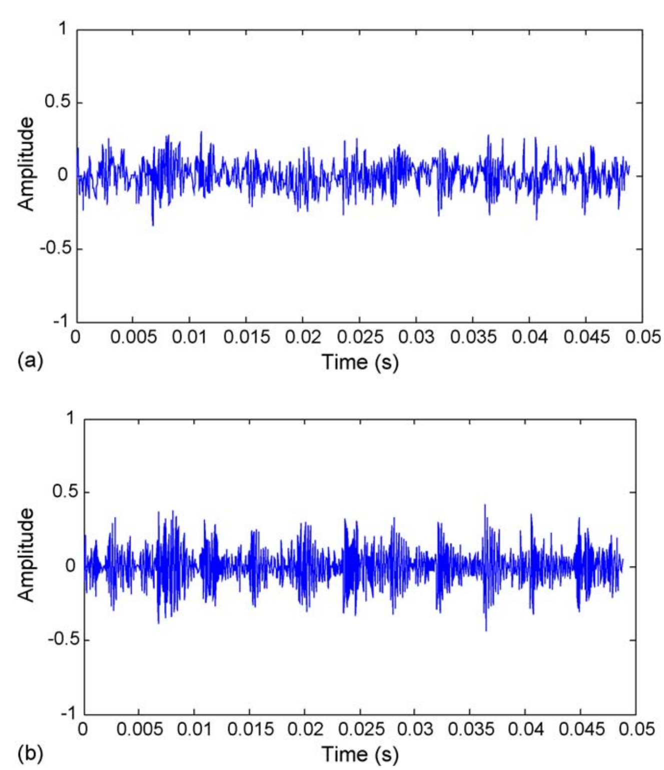

Fig. 9. The vibration waveform with early stage defect: (a) raw signal (b) de-noised signal using the wavelet filter.

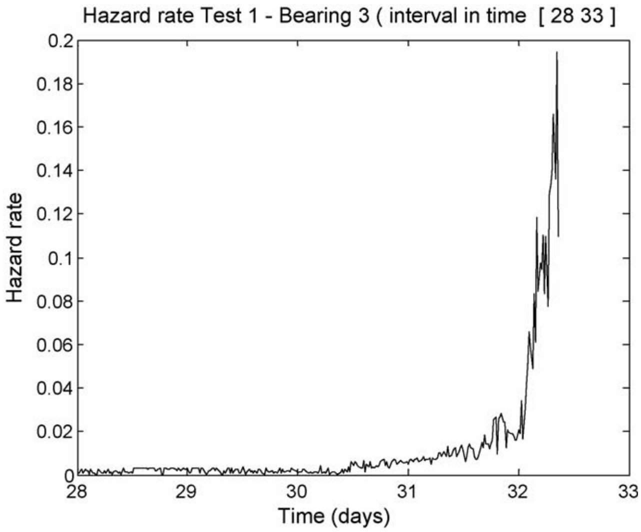

Fig. 10. Hazard rate prediction of bearing 3 in test 1.

The adaptive wavelet filter is yielded in two steps. At first, the optimal wavelet shape factor is found by the minimal entropy method, then the optimal scale is identified by maximizing the signal periodicity. Applying the designed wavelet filter to the noisy raw signal, the de-noised signal can be obtained as shown in Fig. 9(b). The periodic impulse feature is, therefore, revealed, which is strong evidence of bearing outer race degradation. The wavelet filter-based de-noising method successfully enhanced the signal feature and provided potent evidence for prognostic decision-making.

An important issue in prognostic technology is to estimate the risk of failure and the remaining useful life of a component given the component's age and its past and current operating conditions. In numerous cases, failures can be attributed to many correlated degradation processes, which could be reflected by multiple degradation features extracted from sensor signals. These features are the major source of information regarding the health of the component under monitoring; however, the failure boundary is hard to define using these features. In reality, the same feature vector could be attributed to totally different combinations of the underlying degradation processes and their severity levels. In other words, the failure boundary is grey by monitoring the degradation features. There is only a probabilistic relationship between the component failure and certain levels of degradation features. A typical example can be found during bearing operation. Two bearings of the same type could fail at different levels of RMS and Kurtosis of vibration signal. To capture the probabilistic relationship between the multiple degradation features and the component failure, as well as predict the risk of failure and the remaining useful life, IMS has developed a proportional hazards (PH) approach [34] based on the PH model proposed by [39]. The PH model involving multiple degradation features is given by

$$\lambda(t;\underline{Z}) = \lambda_0(t)\exp(\underline{\beta}'\underline{Z}) \tag{1}$$

where $\lambda(t;\underline{Z})$ is the hazard rate of the component given the current age t and degradation feature vector $\underline{Z}$, $\lambda_0(t)$ called the baseline hazard rate function, and $\underline{\beta}$ is the model parameter vector. This formulation relates the working age and multiple degradation feature to the hazard rate of the component. To estimate the parameters, a maximum probability approach could be utilized using offline data, including the degradation features over time of many components and their failure times. Afterwards, the established model can be used for predicting the risk of failure in regards to the component by plugging in the working age and the degradation features extracted from the on-line sensor signals. In addition, the remaining useful life $L(t_{\text{current}})$ given the current working age and the history of degradation features can be estimated by

$$L(t_{\text{current}}) \approx \int_{t_{\text{current}}}^{\infty} \exp\left(-\int_{t_{\text{current}}}^{\tau} \lambda(v;\hat{\underline{z}}(v))\mathrm{d}v \right)\mathrm{d}\tau \tag{2}$$

where $\hat{\underline{z}}(v)$ is the predicted feature vector.

Table 1
Estimates of expected remaining useful life — Test 1, bearing 3

Time[a]	26	29	31
Estimated expected remaining useful life[a]	3.5549	3.3965	1.5295
True remaining useful life[a]	6.5278	3.5278	1.5278
Error[a]	2.9729	0.1313	0.0017

[a] In days.

Consider the vibration data obtained from the signal enhanced using the Morlet-wavelet filtering described above. To facilitate on-line implementation, root-mean-square (RMS) and Kurtosis are calculated and used as degradation features. Fig. 10 shows the predicted hazard rate over time based on these degradation features. This value can be utilized to trigger maintenance when the risk level crosses a predetermined threshold level. Table 1 provides the remaining useful life predictions given the current bearing age and the feature observations. The predictions are in accordance with the actual life of the studied bearing (32.5278 days) with minor prediction errors when the degradation progresses.

4.2. Example 2: industrial network fault detection

A large number of industrial network failures are attributed to loose or degrading terminating resistors. This data set is from an experiment done at the University of Michigan using a controller area network (CAN) test set-up from an industrial sponsor. Normal signals were acquired using a properly functioning terminating resistor and then faulty signals were created by removing one terminating resistor from the network. The CAN signal is a logical differential signal, with a high and low voltage component (Fig. 11). One way to detect a faulty resistor in a network that emits this kind of signal is to measure the overshoot and the signal-to-noise ratio of the logical 0's and 1's in the signal. Since the changes happen very quickly, the signal must be sampled at a very high sampling rate. Here we used a sampling rate of 20 MHz.

The overshoot is the percentage at which the signal goes beyond the steady state value. The signal-to-noise ratio (SNR)

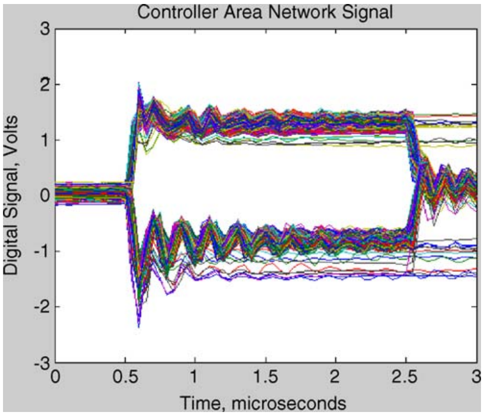

Fig. 11. Time series data for CAN Network.

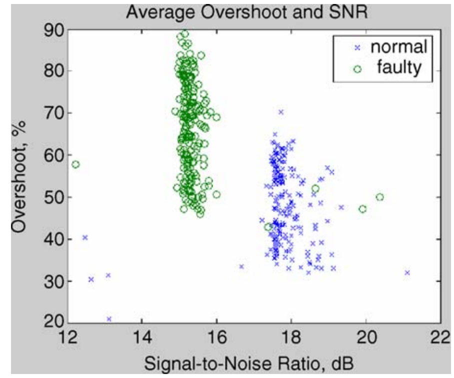

Fig. 12. Categorized normal and faulty signals.

is a measure of signal strength to background noise, usually given in decibels. It was found that the overshoot value tended to increase while the SNR decreased whenever system resistance increased; for example, a terminating resistor is removed. Fig. 12 shows how normal and faulty data can be categorized by taking an average of the overshoot and signal-to-noise ratio between the CAN high and CAN low signals.

For manipulation of the network data, we do not use the frequency-based methods for feature extraction, instead the overshoot and signal-to-noise ratio are used as expert extracted features. These expert extracted features are taken from 10 normal and 10 faulty signals for training. Using these signals, it is possible to use logistic regression to classify the 200 measured signals as normal or faulty. The data cannot be successfully classified using statistical pattern recognition.

4.3. Example 3: maintenance scheduling using predictive information about equipment condition

Discrete-event simulation and heuristic optimization can be utilized for strategic scheduling of maintenance operations that are the least intrusive on the normal production operation in a manufacturing system, as suggested in [35]. In this paper, the cost effectiveness of many maintenance schedules were evaluated based on predicted probabilities of equipment failures over time, obtained from predictive condition-based algorithms, such as those described in [37]. The impact of equipment failures and maintenance operations was assessed through discrete-event simulations and a GA-based search algorithm was suggested to search for maintenance schedules with highest corresponding average cost-benefits. The following is a short description of an example given in [35] where advantages of the newly proposed maintenance scheduling method over more traditional methods are demonstrated. This method is also being used for maintenance decision-evaluation and -making by a major automotive manufacturer.

Three types of maintenance strategies have been simulated and compared with the maintenance schedule obtained using the method from [35], where the predictive information about equipment condition-based is used to maximize average cost-benefits of the maintenance using discrete-event simulations and a GA-based search. The four maintenance strategies considered in this example were:

- *Corrective maintenance strategy*, which uses the simple first-come–first-serve scheme in which the maintenance is performed whenever there is a machine failure and there is a maintenance person available. If any of the two conditions is not satisfied, the machine will remain in a failed mode, not producing anything. This maintenance strategy will be referred to as ‘Strategy A’;
- *Scheduled maintenance strategy*, in which maintenance is performed in regular time intervals. This strategy will be referred to as ‘Strategy B’;
- *Condition-based maintenance*, in which maintenance crews possess information about the current condition of the equipment. Thus, instead of waiting for machine failure, it is assumed that user-defined thresholds are set on the degradation level of any given machine to trigger maintenance operations. It is different from purely reactive maintenance in the sense that condition-based information enables a portion of the maintenance action to be done as scheduled maintenance-before equipment failure actually happens. This strategy will be referred to as ‘Strategy C’;

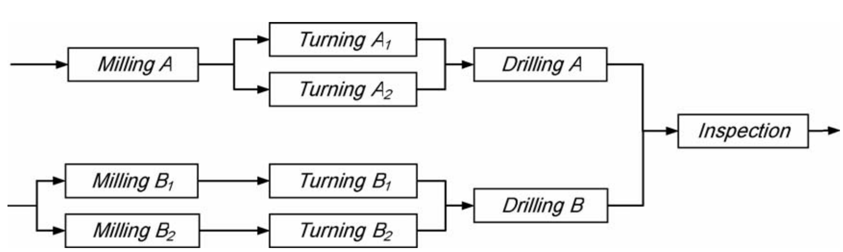

Fig. 13. Manufacturing system used for evaluation and benchmarking of strategies A–D.

Table 2
Parameters used in the testing system

Station name	Cycle time (s)	Life (part)	Variation of life (part)	MTTR (h)	Variation of MTTR (h)
Milling A	36	10000	100	1.0	0.2
Turning A_1	72	7000	50	1.0	0.2
Turning A_2	72	7000	50	1.0	0.2
Drilling A	36	15000	150	2.0	0.2
Milling B_1	48	15000	70	1.2	0.2
Milling B_2	48	15000	70	1.2	0.2
Turning B_1	48	10000	20	2.0	0.2
Turning B_2	48	10000	20	2.0	0.2
Drilling B	24	15000	100	1.0	0.2
Inspection	14.4	20000	200	0.5	0.2

- *Predictive maintenance strategy* based on the maintenance scheduling methods described in Sections 2 and 3 of this paper, using the current and predicted equipment conditions and taking into account both production benefits and maintenance expenses. This strategy will be referred to as 'Strategy D'.

For all four strategies, it was assumed that any unscheduled equipment failure in the manufacturing systems will be addressed as soon as a maintenance team is available.

A simple production line consisting of 10 machines, as shown in Fig. 13, is used for simulation and benchmarking of the four maintenance policies described above. For each machine a distribution describing failure events on that machine over time, and a distribution describing the corresponding repair events, is used. Parameters of these distributions are listed in Table 2. Moreover, it is assumed that information about risks of unacceptable behaviour of each machine over time is available, which can be for example obtained using performance prediction methods reported in [37]. It is also assumed that only one maintenance person is available.

The cost-effects of any maintenance schedule were assessed as

$$P \times \sum_i [\mathrm{IPR}_{\mathrm{system},i} \times (t_{i+1} - t_i)] - (C_\mathrm{s} \times M_\mathrm{s} + C_\mathrm{u} \times M_\mathrm{u}) \quad (3)$$

where the following notation is used: P is the profit per product, $\mathrm{IPR}_{\mathrm{system},i}$ the system IPR for system state i, t_i the starting moment of system state, M_s the total scheduled maintenance time spent on maintaining machines, C_s the corresponding unit cost for M_s, M_u the total unscheduled maintenance time, and C_u is the corresponding unit penalty cost for M_u.

Simulations have been conducted for four different cases, which were designed to evaluate the effects of different components in the cost function (1).

In Case 1, the basic system is analyzed with cost factors set as P = \$ 10 for each product made, C_s = \$ 100 for each man-hour spent on scheduled maintenance, C_u = \$ 1000 for each man-hour spent on unscheduled maintenance. Hence, the cost factors used in the simulation were: P = \$ 10, C_s = \$ 100 and C_u = \$ 1000.

In Case 2, the following set of cost factors was used: P = \$ 10, C_s = \$ 1000 and C_u = \$ 1000. The cost factors are chosen in such way that the cost of scheduled and unscheduled maintenance is the same, which means that the penalty for unscheduled maintenance is essentially removed. Under such circumstances, the benefits of predicting equipment failures will not exist any more since cost effects of performing maintenance before or after equipment will be the same. Thus, this case indicates how the ratio between the cost factors C_s and C_u would influence the cost-benefits of utilizing the predictive information about equipment condition.

In Case 3, the same set of parameters as in Case 1 is used, except that one pair of machines in the basic system is merged into a single machine, thus forming a new bottleneck in the system, as shown in Fig. 14. In normal operating conditions, the line performs exactly the same as the original line. However, the robustness of the system considered in Case 3 is reduced because now the failure of the merged machine will cause a larger portion of the system to stop. As the criticality of one of the machines in the production system is increased, it is expected that the prediction of equipment behaviour will become more beneficial in a case where the failure of the merged station could cause downtime of the entire system. In essence, this case will point out how the structure of the system

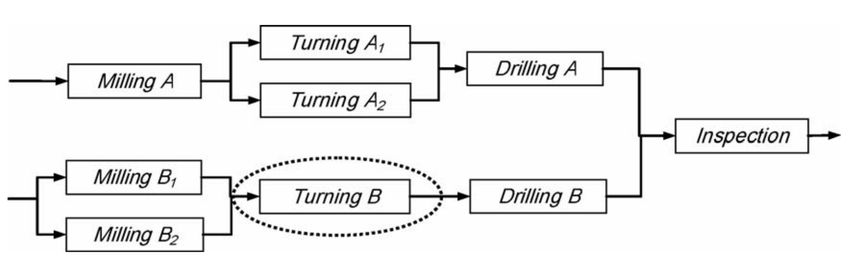

Fig. 14. Case 3 test system with one pair of machines merged into the "Turning B" machine.

Table 3
Comparison of maintenance strategies A–D in Case 1

Type	Scheduled maint. (H)		Unscheduled maint. (H)		Produced part		Effective gain		Improvement (%)
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean ($)	S.D. ($)	
Strategy A	0.00	0.00	7.33	1.00	3016.16	267.56	22833	3429	
Strategy B	2.68	1.12	6.01	1.34	2848.88	165.25	22214	2280	−2.71
Strategy C	6.76	2.35	2.78	1.63	2880.58	240.07	25346	3069	11.01
Strategy D	5.58	1.04	2.81	1.24	3315.39	144.30	29787	2285	30.46

affects the cost-benefits of utilizing the predictive information about the equipment's condition.

In Case 4, the same set of parameters as in Case 1 are used, except that unscheduled maintenance takes 50% more time to finish than the same maintenance performed according to the schedule, meaning that more maintenance time is needed for unscheduled events. This Case is constructed in order to demonstrate the effects of downtime on the system-level benefits of various maintenance schedules. It is expected that prediction of equipment performance and elimination of unscheduled maintenance events through maintenance schedules provided by the newly proposed Strategy D will yield more prominent system-level benefits in this case.

From the results of the first test case given in Table 3, it is noticeable that an improvement in the overall cost-benefits can be achieved using the GA optimized maintenance scheduling 'Strategy D'. With 'Strategy B', some maintenance is done as scheduled work to prevent machine failures. However, the fixed length of the time interval between two successive maintenance tasks on one machine does not always match the actual machine life. Thus, maintenance is either done too early, when there is still remaining useful life in the equipment, or too late, after failure already occurs and maintenance is performed as an unscheduled task. Thus, the corresponding cost effects of maintenance are characterized by high-cost maintenance and reduced overall gain expressed by Eq. (1). In 'Strategy C', more scheduled maintenance occurs, due to the direct use of machine conditions as indicators of imminent machine failure. Shorter and more flexible maintenance intervals on each machine increase the overall maintenance time, but results in fewer unscheduled maintenance events. Thus, it achieves a higher profit than the purely reactive 'Strategy A' or 'Strategy B' characterized by fixed schedules. As for 'Strategy D', the corresponding increase of productivity is even bigger. Even though the overall maintenance time and unscheduled maintenance time both increased, the schedule of the maintenance is arranged in such a way that the system productivity grew, which proved to be more than enough to compensate for the increased maintenance cost.

In Case 2, the cost factors are changed so that the costs for scheduled maintenance and unscheduled maintenance are the same. As can be seen in Table 4, both 'Strategy B' and 'Strategy C' achieved lower system gain than the purely reactive 'Strategy A'. Removing the cost penalty on unscheduled maintenance resulted in no benefits in performing any maintenance action before machine breakdowns actually happen. Then, the cost-benefits associated with any maintenance schedule are determined only by the system productivity and overall maintenance time. The increased maintenance activities in both 'Strategy B' and 'Strategy C' reduce the system productivity relative to the one corresponding to 'Strategy A', thus causing the corresponding profits to be decreased. In this extreme case, the benefits of using 'Strategy D' are non-existent since there is no benefit in performing scheduled rather than unscheduled maintenance.

In Case 3, two identical machines working in parallel in the original configuration (identified as Turnings B_1 and B_2 in Fig. 8), are merged into one machine (identified as Turning B in Fig. 9). Obviously, the Turning B machine from Case 3 is more critical in the new system than the original two machines were in the original system from Case 1 because when it fails, a larger portion of the production system is down, and the production losses are higher (essentially, machine Turning B is a local bottleneck in the system considered in Case 3). The maintenance schedule offered by the newly proposed 'Strategy D' calls for timely maintenance based on the predicted equipment conditions, while avoiding excessive usage of maintenance resources by eliminating schedules that call for excessive maintenance, and thus resulting in low system-level cost-benefits as defined by Eq. (1) that do not propagate through the GA-based optimization procedure. Thus, the overall profit it

Table 4
Comparison of maintenance strategies A–D in Case 2

Type	Scheduled maint. (H)		Unscheduled maint. (H)		Produced part		Effective gain		Improvement (%)
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean (%)	S.D. (%)	
Strategy A	0.00	0.00	7.28	0.78	3135.24	185.35	24067	2255	
Strategy B	2.75	1.25	5.50	1.31	2885.03	164.26	20595	1861	−14.43
Strategy C	6.99	2.67	2.85	1.97	2896.69	226.90	19125	3671	−20.53
Strategy D	1.27	1.10	6.19	1.26	3221.34	216.13	24745	3018	2.82

P = $ 10, cm = $ 1000, Ci = $ 1000.

Table 5
Comparison of maintenance strategies A–D in Case 3

Type	Scheduled maint. (H)		Unscheduled maint. (H)		Produced part		Effective gain		Improvement (%)
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean ($)	S.D. ($)	
Strategy A	0.00	0.00	6.42	1.20	1670.95	171.26	10288	2582	
Strategy B	0.85	0.85	5.40	1.04	1684.30	99.00	11361	1500	10.43
Strategy C	5.53	2.27	2.11	1.66	1607.05	163.96	13407	2439	30.32
Strategy D	6.68	0.77	2.43	1.11	1751.04	92.53	14410	1923	40.07

Table 6
Comparison of maintenance strategies A–D in Case 1

Type	Scheduled maint. (H)		Unscheduled maint. (H)		Produced part		Effective gain		Improvement (%)
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean ($)	S.D. ($)	
Strategy A	0.00	0.00	10.90	1.07	2634.86	350.01	15451	4006	
Strategy B	1.86	1.11	9.05	1.87	2644.84	216.68	17212	3416	11.39
Strategy C	6.44	2.42	4.21	1.83	2797.37	311.63	23118	3579	49.61
Strategy D	5.52	1.32	4.31	2.18	3099.46	248.77	26135	4278	69.14

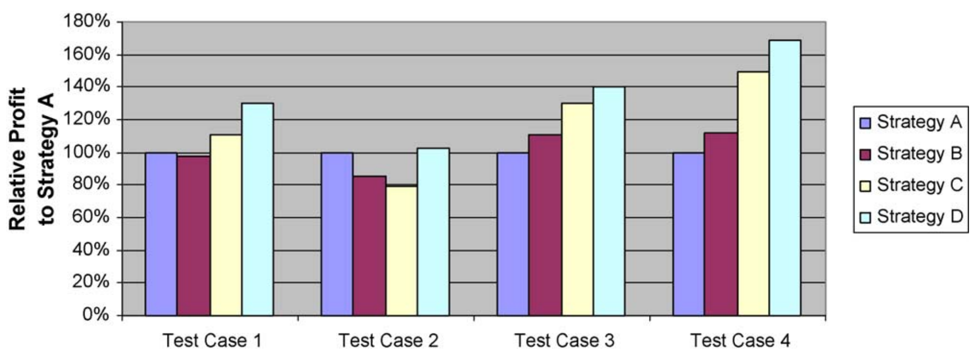

Fig. 15. Relative profit chart between maintenance strategies for the four test cases.

made exceeded all other strategies, as illustrated in Table 5. Furthermore, due to the existence of the more critical Turning B machine, the benefits of avoiding the costly downtime increased even more, which resulted in an increase in system-level cost-benefits associated with the maintenance 'Strategy D', as compared to the corresponding benefits observed in Case 1.

In Case 4, the increased time needed for unscheduled tasks implied that unscheduled maintenance tasks would involve more machine downtime and thus effectively increases the detrimental costs associated with unscheduled maintenance that takes place after equipment failures occur. The maintenance schedule offered by 'Strategy D' showed the ability of the newly proposed maintenance scheduling method to avoid unscheduled downtime and thus achieve high system-level cost-benefits, as defined by Eq. (1). Furthermore, since the impact of unscheduled downtime was increased in this case, the cost-benefits of utilizing the maintenance schedule offered by the newly proposed scheduling 'Strategy D' improved even more dramatically compared to the improvement observed in Case 1, as can be seen in Table 6 (the cost-benefits increased by as much as 69% over the corrective 'Strategy A', while in Case 1 the corresponding improvement was 30.5%).

Relative effects of the four maintenance strategies for the four test cases are shown in Fig. 15. In each Case, the cost-benefits for corrective 'Strategy A' are set to 100%. One can conclude from these results that overall production profits, due to lower maintenance costs, can be increased through the implementation of this proposed method. Furthermore, the more critical the unscheduled system downtime and maintenance are, the higher the benefits associated with utilizing this newly proposed method will be.

5. Conclusions and future work

The Watchdog Agent™ is a tool for multi-sensor assessment and prediction of a machine's or process's performance. This tool can be utilized to realize predictive condition-based maintenance as well as to identify the components that possess significant remaining useful life that could be efficiently and cost-effectively disassembled and reused. A wide variety uses for the Watchdog Agent™ have been devised to address many applications of a different nature, with different levels of complexity and criticality. Even though preliminary results for autoregressive moving average (ARMA) modelling-based behaviour prognostics have already been obtained, performance forecasting will be more thoroughly investigated in future work (knowing "when something is going to happen"). Also, a link should be established with a decision-making module which will enable optimal maintenance actions to be carried out in an even timelier manner. This link will compliment the Watchdog Agent's™ many functions and facilitate the OSA-CBM [36] standard topology for scalable applications. Finally, an embedded infotronics agent is needed to assess and predict product performance and, based on that prediction, enable the assessment of the product's reusability, as well as its need for proactive maintenance. The research challenge will be accomplishing this level of sophisticated performance evaluation and prediction capabilities under the severe power consumption, processing power and data storage limitations imposed by embedding. Successful realization of the embedded agent will have a profound impact on near-zero downtime performance of machines and manufacturing systems.

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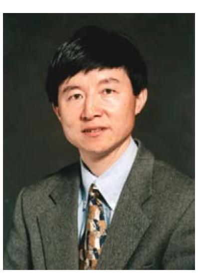

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