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Watchdog Agent—an infotronics-based prognostics approach for product performance degradation assessment and prediction

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Abstract

In today's competitive market, production costs, lead time and optimal machine utilization are crucial values for companies. Since machine or process breakdowns severely limit their effectiveness, methods are needed to predict products' life expectancy. Furthermore, continuous assessment and prediction of product's performance could also enable a collaborative product life-cycle management in which products are followed, assessed and improved throughout their life-cycle. Finally, information about the remaining life of products and their components is crucial for their disassembly and reuse, which in turn leads to a more efficient and environmentally friendly usage of products and resources. Development of the Watchdog Agent™ answers the aforementioned needs through enabling multi-sensor assessment and prediction of performance of products and machines.

Keywords: Watchdog Agent; Performance degradation assessment; Performance degradation prediction; Multi-sensor fusion; Collaborative product life-cycle management; Efficient product reuse

1. Introduction

In today's competitive, customer-oriented market, companies must provide products and services of the highest possible quality in order to attain and retain a favorable market position. The market conditions are so unforgiving that, for example, 1 min of downtime in an automotive manufacturing plant could cost as much as $20,000 [1]. Thus, near-zero downtime function without production or service breakdowns as well as the highest possible products and service quality are fast becoming a necessity for today's enterprises.

In the field of maintenance, most product maintenance today is either purely 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 and result in costly production or service downtimes. 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. It may come as a surprise to many people that most state-of-the-art manufacturing, mining, farming, and service machines (e.g. elevators) are actually quite 'smart' in themselves. Many sophisticated sensors and computerized components 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 the 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 useable form. More often, no infrastructure exists for delivering the data over a network, or

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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 modeled and continually analyzed with sophisticated embedded systems, it is possible to go beyond mere 'predictive maintenance' to intelligent 'prognostics'—the process of pinpointing exactly which components of a machine are likely to fail, and when and autonomously trigger service and order spare parts.

For these reasons, we propose a paradigm shift from the traditional approaches of detecting and quantifying failure toward an approach centered around assessment and prediction the performance degradation of a process, machine, or service [2]. Performance degradation is a harbinger of system failure, so it can be used to predict unacceptable system performance (in a process, machine or service) before it occurs. The traditional fail and fix (FAF) practice can thus be replaced by the new predict and prevent (PAP) paradigm [2].

Mechatronics systems was first introduced by Yaskawa Electric in Japan in late 1960s. It added 'precision' and 'intelligence' to mechanical systems through smart electronics control systems. *Infotronics* technologies transform the paradigm from *precision machine* to *precision information* through the use of intertwined embedded informatics and electronic intelligence in a networked and tether-free environment and enable products and systems to intelligently monitor, predict, and optimize its performance and ultimately perform self-maintenance activities autonomously. Such a paradigm shift towards a continuous assessment and prediction of product's performance will also enable a collaborative product life-cycle management (CPLM) [3] in which products are followed, assessed and improved throughout their life-cycle, starting from product's inception on the design table, and continuing through the entire manufacturing process and product's usage phase. Today, when companies launch a new product, it is often ignored that products are like *living systems*. Their birth—or market launch—is just the starting point in their life-cycle. Not surprisingly, the hug-fest with outsourced development partners ends after the product launch. As more electronics software gets embedded in industrial and office products, predictive tools are needed to *informate* the product life-cycle information for proactive service and sustainable functionality. It can also serves as an infotronics agent to store product usage and end-of-life (EOL) service data and feedback to designers and life-cycle management systems. Through such an integrated life-cycle management, degradation information can be used to make improvements in the product design, as well as in the manufacturing process for that product

Fig. 1 shows the system elements of an *intelligent maintenance systems (IMS)*. Through such an approach, degradation information from the products in the field can be used to predict product performance to enable a near-zero

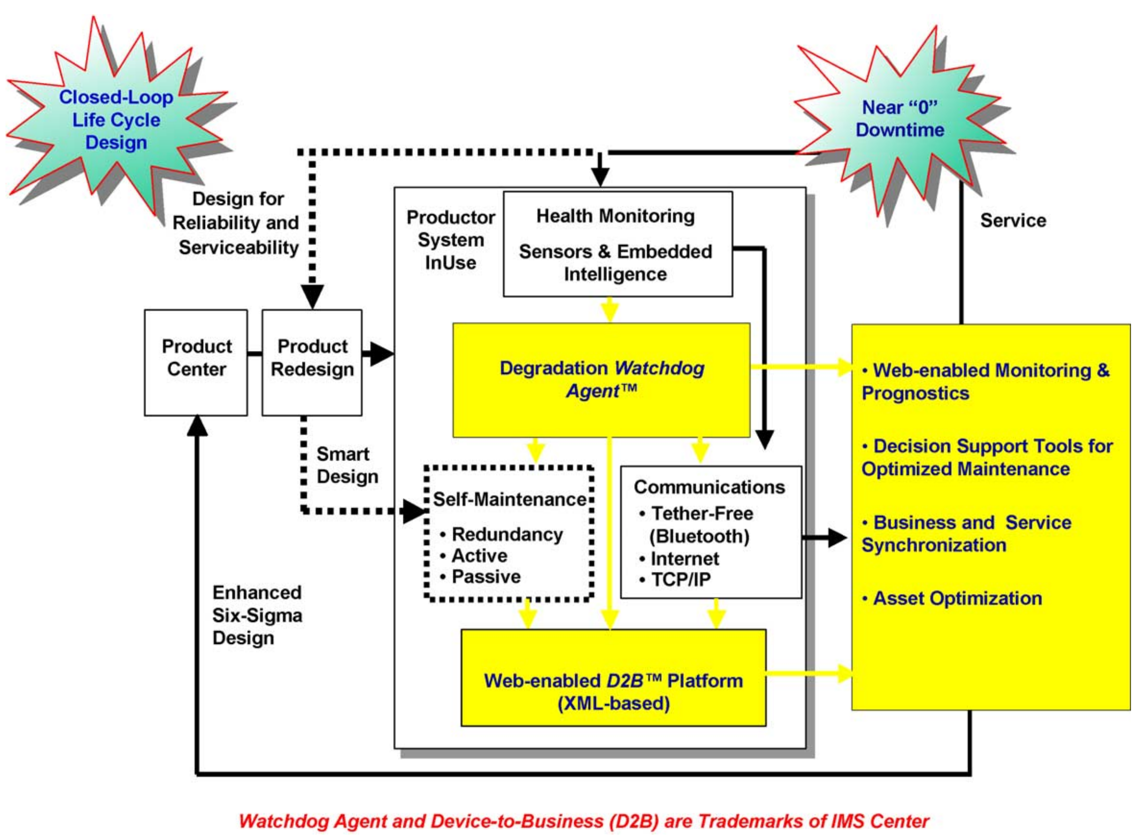

Fig. 1. Intelligent maintenance system and its key elements.

downtime performance. It further can be used to makes improvements in product design as well as for assessing product's 'reusability' and predicting its useful life after disassembly (normally at maintenance stage) and reuse (after the maintenance and repair) [4]. Therefore, an unmet need is to create a device that will store the relevant product information and facilitate its performance assessment and prediction, thus enabling predictive condition-based maintenance (CBM) of the product during its usage and ultimately enable a closed-loop product life-cycle information flow system which can be used to product redesign or validation.

Therefore, a tremendous need exists in the society to create a device that will store the relevant product information and facilitate its performance assessment and prediction, thus enabling predictive CBM of the product and/or its disassembly and reuse in another system. Development of the toolbox of algorithms for assessment and prediction of equipment performance, referred to as the Watchdog Agent™, answers these needs of the society through enabling the infotronic function of converting the multi-sensor data into a meaningful assessment and prediction of systems' performance degradation.

The purpose of this paper is to give an overview of the efforts undertaken in the center for IMS [2] towards developing the Watchdog Agent™ for different applications. The remainder of this paper is organized as follows. Section 2 gives a short outline of the traditional CBM approach, since efforts in the development of the Watchdog infotronics agent can be seen as an extension and enhancement of the traditional CBM approach. Section 3 describes the Watchdog Agent and its main functionalities: health assessment, condition diagnostics and performance forecasting. Section 4 offers several examples of real-life industrial implementation of the Watchdog Agent, while Section 5 summarizes conclusions of the Watchdog Agent development and outlines guidelines for possible future work.

2. Condition-based maintenance

Today, machines contain increasingly sophisticated sensors and their computing performance continues to accelerate. Therefore, it is now possible to rapidly and accurately sense performance indicators and thus assess and predict system performance. Under these circumstances, CBM, based on sensing and assessing the current state of the system, emerges an appropriate and efficient tool for achieving near-zero breakdown time through a significant reduction, and, when possible, elimination of downtime due to process or machine failure [2]. With a well implemented CBM system, a company can save up to 20% in smaller production losses, improved quality, decreased stock of spare parts, etc. [5].

Currently, the prevalent CBM approach involves estimating a machine's current condition based upon the *recognition of indications of failure* [6]. Recently, several predictive CBM techniques within this failure-centered paradigm have been proposed. For example, a fuzzy logic neural network has been used to predict failure of a tensioned steel band with seeded crack growth [7]. Ray and Tangirala [8] built a stochastic model of fatigue crack dynamics in mechanical structures to predict remaining service time. Vachtsevanos and Wang [9] gave an overview of different CBM algorithms and suggested a method to compare their performance for a specific application. These approaches notwithstanding, to implement the aforementioned predictive CBM techniques require a significant amount of a priori knowledge about the assessed machine or process because the corresponding failure modes must be known and well-described in order to assess the current machine or process performance.

According to Ref. [6], a different approach to CBM is being developed today. It is based on characterization of the machine or process performance through the overlap of the most recent system signatures and those observed during the healthy process or machine behavior. The Watchdog Agent for multi-sensor performance assessment and prediction is founded on the latter type of CBM in order to facilitate a shift in the maintenance focus from the analysis and quantification of process/machine failure towards detection and description of performance degradation expressed in the drift of the newly arrived system signatures away from those observed during the normal, healthy machine/process operation. As a consequence, neither faulty data nor expert knowledge is needed to set the performance assessment process, enabling a generic approach to a wide range of applications [16–22].

3. Watchdog Agent for multi-sensor performance assessment and prediction

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 of sensor signatures. In addition, a model of the process or piece of equipment that is being considered, available application specific knowledge, or prior historical records of equipment behavior can be used to aid the degradation process description, provided that such a model, expert knowledge or historical records exist. The prognostic function of the Watchdog is realized through trending and modeling of the dynamics of the observed process performance signatures and/or model parameters. This allows one to predict the future behavior of these patterns and thus forecast the behavior 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 observed in the past, or be aware of the situation that was never observed before. Thus, the Watchdog Agent™ has elements of intelligent behavior 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. Thus, in essence, the functionality of the Watchdog Agent can be summarized in the following three tasks:

- Quantitative multi-sensor assessment of performance degradation.
- Forecasting of performance degradation.
- Diagnosis of the reasons of the current or predicted performance degradation.

The prognostic and diagnostic outputs of Watchdogs mounted on all the processes and machinery of interest can then be fed into a 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 the 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 machine fails. Thus, the output of the DST module is an optimal maintenance policy for a number of objects in the system. Those objects are traditionally processes and/or equipment, and the system could be a manufacturing line, or a plant. However, there is no reason why an object could not be a hardware, or software component of a vehicle, and the associated system can be the vehicle itself, or the population of similar vehicles in the field [23,24].

Therefore, the operation of an IMS can be summarized in answering the previously described 'when', 'why' and 'what' questions in order to postulate an optimal maintenance/repair set of decisions that facilitate an optimal set of maintenance/repair actions that enable near zero downtime of the production/service system and maximizes the cost benefits of the predictive machine-level information. Such a system of Watchdogs integrated by a DST thus enables maintenance that is in the same time condition based, as well as predictive and proactive [24].

Furthermore, as indicated in Fig. 2, information about current and predicted performance degradation of components in a product is indispensable in assessing remaining life of those components and possibility of their cost-effective and safe disassembly and reuse in other products. Namely, demands regarding product production, use and disposal continue to increase because of population growth and amplified product expectations, and fulfilling those increasing demands while preserving the natural environment and resources can be realized only through a significant reduction of energy and resource consumption, accompanied by a dramatic increase in efficiency of energy

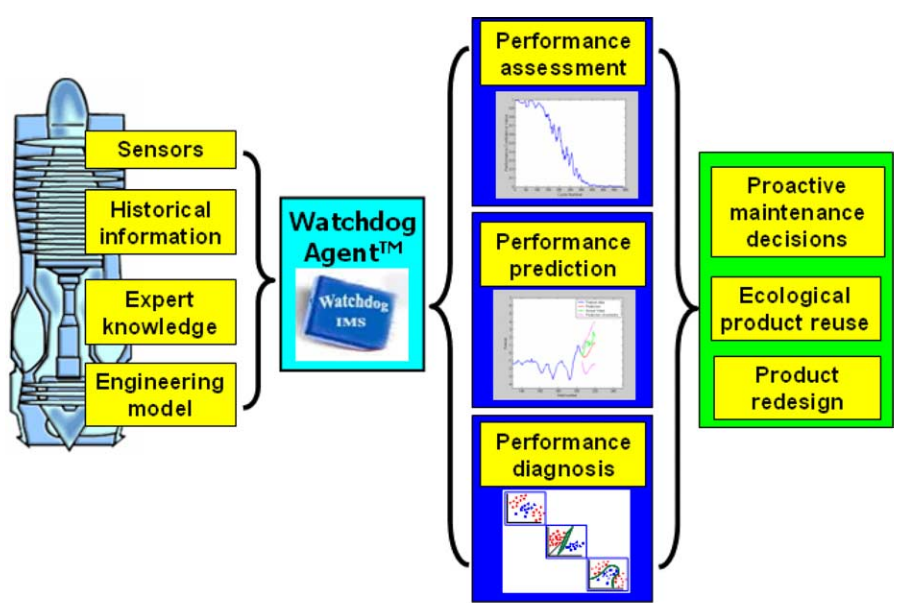

Fig. 2. Schematic representation of an intelligent maintenance system.

and resource usage. Quantitative description and prediction of performance degradation can be utilized to identify those products or components with low-levels of degradation and substantial useful remaining life so that they could be efficiently and cost-effectively disassembled and reused in another system.

Finally, as mentioned in Section 1, systematic creation and collection of performance-related information for products throughout their life-cycle (design, manufacturing and use of the product) in order to close the loop and strategically improve designs of the product, manufacturing process as well as the usage patterns through an integrated life-cycle management of a product [25].

Schematic representation of the structure of IMS operations and the use of predictive performance-related information is illustrated in Fig. 2.

The three main functionalities of the Watchdog Agent are accomplished through several functional modules, as schematically illustrated in Fig. 3. *Assessment of performance degradation* is accomplished through a module performing processing of multiple sensory inputs and extraction of features relevant to description of product's performance, followed by a module executing the multi-sensor performance assessment based on the extracted signal features, with the multi-sensor assessment component being realized through the feature-level, or decision-level sensor fusion, as defined by the Joint Directors of Laboratories (JDL) standard of multi-sensor data fusion ([26], Chapter 2; [27]). *Performance prediction* function is realized through extraction of performance-related features and application of tools capable of capturing dynamic behavior of the extracted performance-related features and extrapolating it over time in order to predict their future behavior and future behavior of the underlying process. Finally, performance diagnosis function of the Watchdog is realized through matching of the currently extracted, or predicted performance-related features with signatures describing different modes (healthy or faulty) of process behavior. Thus, condition diagnosis is a step relevant to both the health assessment functionality (pertaining to the present performance of the monitored process of piece of equipment) and the performance forecasting functionality (pertaining to the predicted performance of the monitored process of piece of equipment).

The multi-sensor performance assessment, diagnosis and prediction functionalities of the Watchdog Agent could be even further enhanced if Watchdog Agents mounted 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.

Furthermore, as mentioned earlier, engineering mode of the monitored process, application specific expert knowledge about the process as well as historical records of process behavior over time can be utilized to improve all functional modules of the Watchdog Agent (sensory signal processing and feature extraction, health assessment, condition diagnosis and performance prediction).

One can now easily observe a parallel between the Watchdog Agent structure illustrated in Fig. 3 with the well-known open system architecture for condition-based maintenance [28] (OSA-CBM) standard, according to which a typical CBM system consists of the following seven layers:

- Sensor module
- Signal processing
- Condition monitoring
- Health assessment
- Prognostics
- Decision-making support
- Presentation

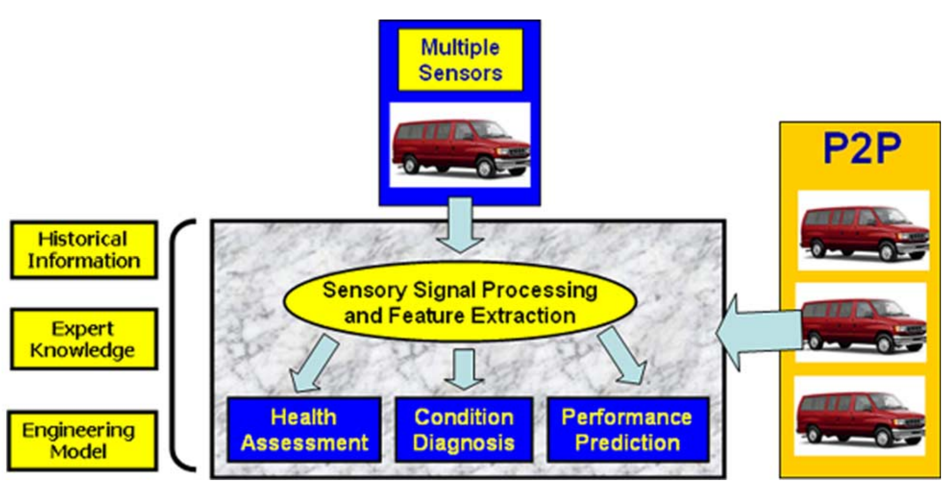

Fig. 3. Functionality of the Watchdog Agent™.

The Watchdog functionality expands this standard topology to a multi-sensor level and realizes sensory processing, condition monitoring, health assessment, health prognostics and presentation (through the current or predicted performance CVs) layers of the CBM scheme. The sensors and decision-making layers within an IMS are realized outside the Watchdog Agent (see Ref. [24] for an example of using predictive information about equipment condition in order to make optimal maintenance decisions, which corresponds to the decision-making layer of the OSA-CBM architecture).

In order to facilitate the use of Watchdog Agents 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 Watchdog Agent has been realized in the form of a modular, open architecture toolbox, with different tools realizing its functional modules (sensory signal processing and feature extraction, health assessment, condition diagnosis and performance prediction functions).

Summary of the tools currently used in this toolbox of algorithms is enclosed in Fig. 4. The open architecture of the toolbox allows one to easily add new solutions to the Watchdog Agent toolbox, as well as to easily interchange different tools, depending on the application needs. More detailed descriptions of the tools summarized in Fig. 4.

3.1. Signal processing and feature extraction tools of the Watchdog Agent

Complex nature of a number of today's products necessitates that in order to describe their performance, the relevant sensor readings first need to be transformed into domains that are most informative of product's performance. Time-series analysis [29] or frequency domain analysis [30] could be used to process stationary signals (signals with time invariant frequency content), while wavelet [31], or joint time–frequency [32] domains could be used to describe non-stationary signals (signals with time-varying frequency content).

Fig. 5 depicts inadequacy of applying a stationary signal processing technique, such as Fourier Transform [30] to non-stationary signals such as simple frequency-hopping signals shown in Fig. 5. Fourier analysis is able to discern three sinusoids present in the signal, but is unable to deduce when each one of those sinusoids occurred. Therefore, when the order of sinusoids is altered, the Fourier analysis is unable to detect this change, as indicated in the figure. On the other hand, a powerful non-stationary signal analysis tool such as the binomial joint time–frequency distribution (TFD) [32,33] readily reveals this change, as indicated in Fig. 6. Most real life signals, such as speech, music, machine tool vibration, acoustic emission, etc. are non-stationary signals, which places strong emphasis on the need for development and utilization of non-stationary signal

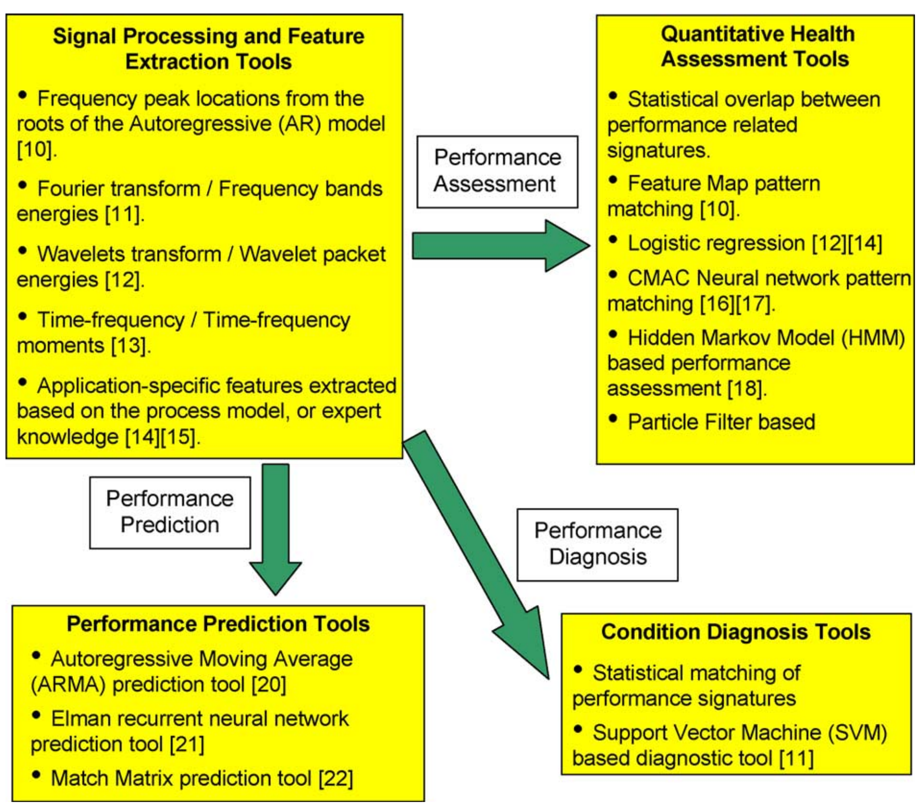

Fig. 4. Toolbox of solutions for the functional modules of the Watchdog Agent™.

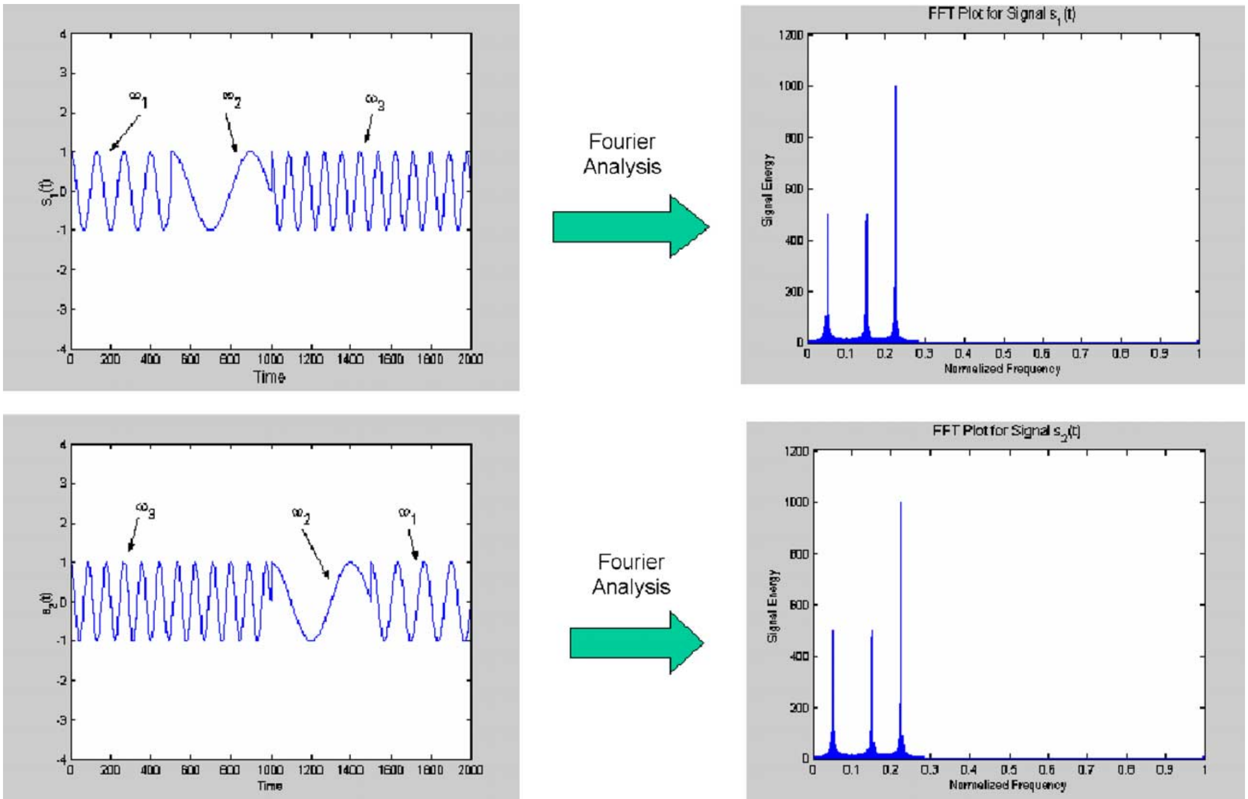

Fig. 5. Application of Fourier analysis on two frequency-hopping signals.

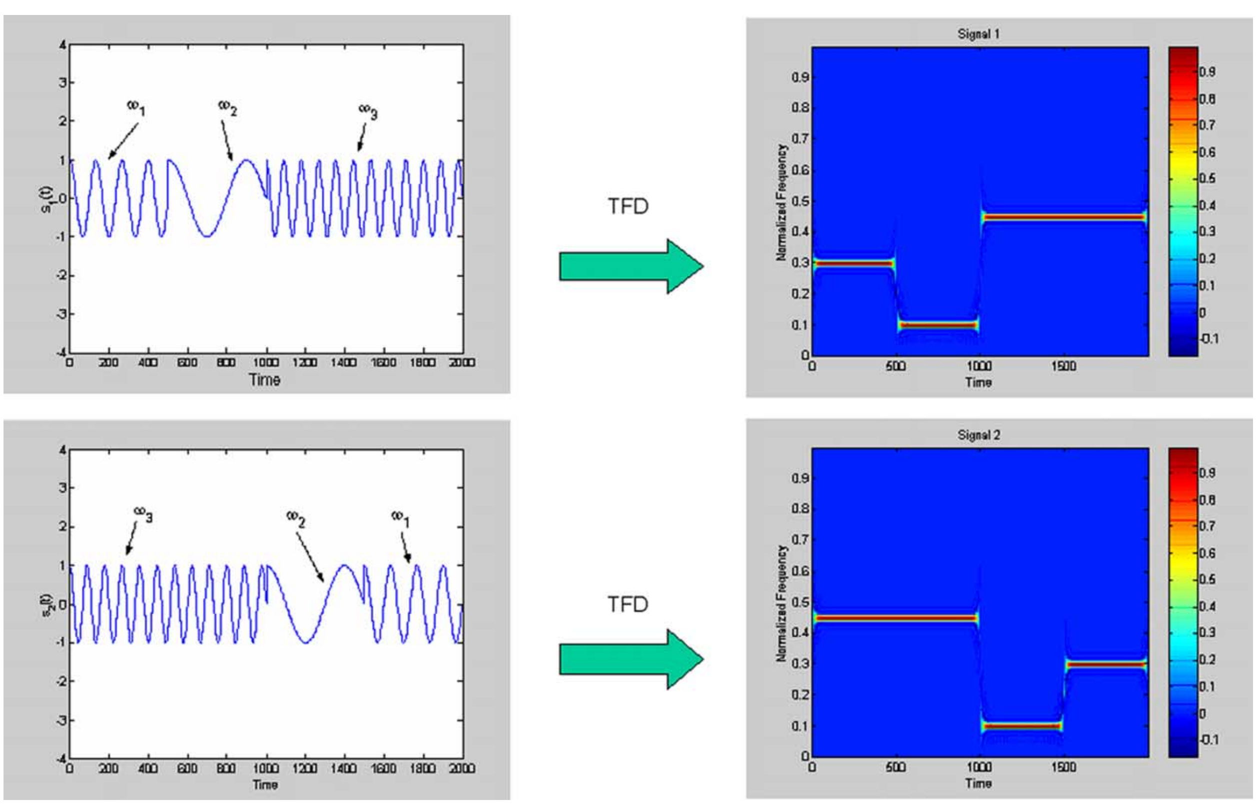

Fig. 6. Binomial joint time–frequency distribution (TFD) of two frequency-hopping signals identical to those analyzed in Fig. 3.

analysis techniques, such as wavelets, or joint time–frequency analysis.

Cohen's class of bilinear joint time–frequency (TF) distributions of signal energy, such as Wigner-Ville [34,35], Born-Jorndan [36], Choi-Williams [37], or binomial-kernel based reduced interference distribution [33,38], possess a number of desirable and intuitively plausible mathematical properties, such as time and frequency shift covariance, scale covariance, time and frequency distribution marginals, instantaneous frequency and group delay properties [32, p. 140–149]. However, bilinear nature of fixed-kernel Cohen's class TF distributions makes them cumbersome to calculate.

On the other hand, recursive nature of wavelet packet decomposition through recursive application of high and low pass wavelet filters enables rapid calculation of non-stationary signal energy distribution, at the expense of loosing some of the desirable properties listed above [31]. Therefore, this essentially time-scale rather than time–frequency signal analysis [32] can be used for rapid processing of non-stationary signals in order to reduce the dimensionality of signal representation or signal de-noising, as was done in Refs. [39,40].

In the case of predominantly stationary signals, the sophisticated non-stationary techniques are not needed and the traditional spectral analysis of signals can be used for processing of sensor readings [10]. Spectral estimation using autoregressive (AR) modeling [26] of the sensor time-series allows one to simultaneously model the dynamic behavior of the signal, eliminate white noise embedded into the signal and accurately identify locations and intensities of frequency peaks (modes) [10], which of utmost importance for describing behavior of mechanical systems. On the other hand, the well known Fast Fourier Transform (FFT) algorithm based estimation enables one to rapidly estimate frequency content in predetermined frequency samples, thus sacrificing spectral resolution and signal de-noising, but offering a greatly increased calculation speed and efficiency.

Once the sensor readings have been processed into a domain indicative of product performance, extraction of features most relevant to describing the product's performance can be accomplished in that domain. Thus, the method of feature extraction is essentially determined by the application and the domain into which sensor signals were processed. In Ref. [14], application specific expert knowledge was used to extract performance-related features directly from the time-domain signatures of the encoder monitoring the performance of an elevator door. In Ref. [10], roots of the AR time-series model fit to the voltage, current and force readings collected during a spot-resistance welding process were used to describe the process, since frequency peak locations were observed to be indicative of the welding process behavior. Similar, frequency domain approach was used in Ref. [11], where energies in selected frequency bands obtained using FFT transforms of vibration signals were used for monitoring of elevator door performance. In Ref. [10], singular value decomposition [41] based principal components of the time–frequency moments extracted from TFDs of vibration, sound and force signals collected in order to monitor the tool wear in a turning process. Such approach was considered adequate, since vibrations, force and sound signals display high levels of non-stationarity during machining operations [42,43]. In Ref. [19], selected wavelet packet energies [44] were used to describe machine tool spindle performance based on wavelet packet decomposition of three vibration signals obtained from the machine tool spindle. Similar concept was used in Ref. [16] to describe metal cutting tool performance throughout lifecycle of one drill-bit.

In summary, the following signal processing and feature extraction tools are currently used in the Watchdog Agent:

- Frequency peak locations and intensities calculated using AR modeling and roots of the AR model, applicable in cases where information about oscillation modes of sensor readings bares significant information about the process [10] (usually, mechanical systems are well described by the modes of oscillations).
- Frequency-bands energies for applications characterized by time-invariant frequency content [11].
- Wavelet packet energies, applicable in cases when non-stationary signals describe a process, but a relatively high speed of processing is required [12].
- Principal components of time–frequency moments, applicable in cases when the process performance is described by highly non-stationary signals and processing time-constraints are not severe [13].
- Application specific features extracted directly from the time-series of sensor readings [14,15], applicable in cases when one can directly extract performance-relevant features out of the time-series of sensor readings).

3.2. Quantitative health assessment function

Quantitative health assessment function is based on evaluating the overlap between the most recently observed signatures and those observed during normal product operation. In Refs. [16,17], this overlap is expressed through the so-called *performance confidence value* (CV), ranging between zero and one, with higher CVs signifying a high overlap, and hence performance closer to normal. Fig. 7 illustrates this signature matching process for performance evaluation. Plot of confidence values enclosed on the right-hand side of Fig. 7 depicts CVs assessed using the force, current and voltage readings observed over 3550 spot-resistance welds with one set of new ∅6 mm conical brass electrodes that during that time completely wore out. This wear process is depicted in the decreasing trend of the CVs. Fig. 8 shows the brass welding electrodes utilized in this experiment before and after the 3550 welds were performed (taken from Ref. [10]).

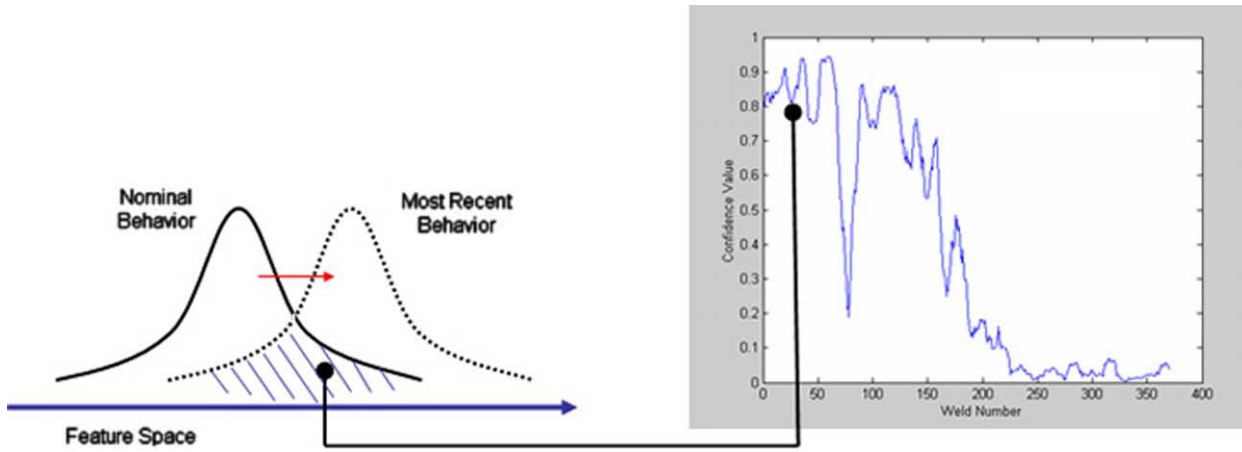

Fig. 7. Performance evaluation through matching of most recent signatures with those observed during normal and faulty product behavior.

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 cerebellar model articulation controller (CMAC) neural network [45,46] that coincide with CMAC cells activated during the normal process behavior, or using the logistic regression approach [12,14,47] where a logistic regression curve is fitted to the features in such a way that its values are close to 1 in the region defined by features observed during normal process behavior and close to 0 for features away from that region. 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 [15]. For more sophisticated applications with intricate and complicated signals and performance signatures, one can use the statistical pattern recognition methods [13], feature map [10], or hidden Markov model (HMM) based approach [18]. Finally, in the case of multi-regime operating equipment, the system function can be described using hybrid continuous/discrete system states and use the recently developed particle-filter performance assessment methods to describe the system performance [19].

In Ref. [10], a feature map was used to track the AR modeling roots obtained from the current, voltage and force signals characterizing resistance spot welding performance throughout the life of the copper electrodes shown in Fig. 3. In Ref. [13], asymptotic Gaussianity of joint TF moments was used to assess the performance of a cutting tool in turning through statistical overlap between Gaussians describing the most recent and normal behavior of the process. In Ref. [18], HMM-based approach was utilized to describe performance of a drill-bit throughout its life, while the concept of particle filters was used in Ref. [19] to describe performance of an elevator door using encoder and vibration sensor readings.

In summary, the following health assessment tools are currently used in the Watchdog Agent:

- Statistical overlap of Gaussians describing the most recent and normal process behavior, applicable when the extracted features are approximately Gaussian, as was the case in Ref. [13].
- A feature map based assessment of the overlap between the normal and most recent process behavior, applicable in cases when Gaussianity of extracted features cannot be guarantied, as was done in Ref. [10].
- A logistic regression curve based assessment, applicable when a good feature domain description of unacceptable behavior is available, as was the case in Refs. [12,14].

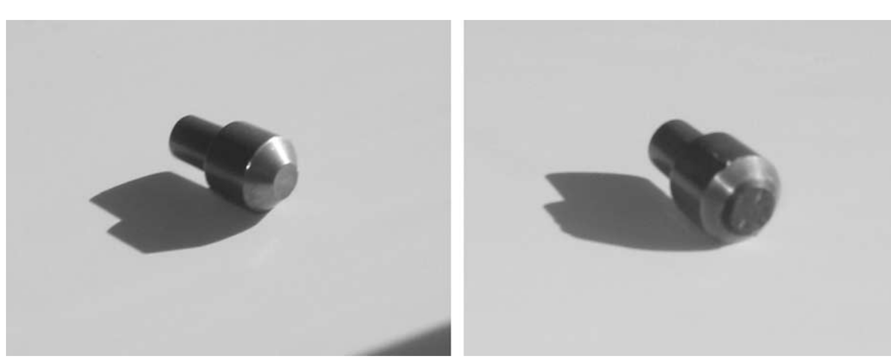

Fig. 8. The 6 mm welding electrode before (picture on the left) and after 3550 welds were made with it (picture on the right).

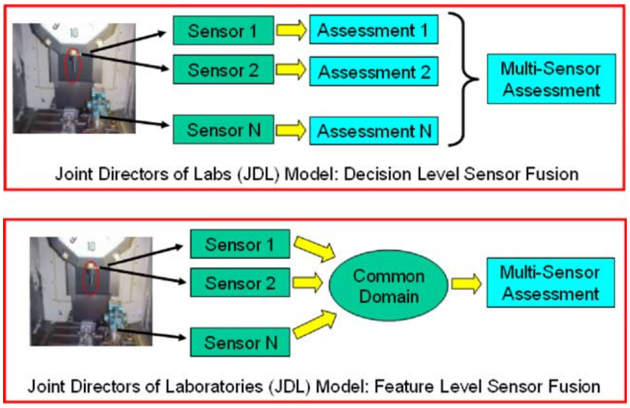

Fig. 9. Decision-level and feature-level sensor fusion.

- CMAC neural network based assessment for applications requiring high speed of performance assessment-related calculations and involving complex, non-linear systems, as was the case in Refs. [16,17].
- In Ref. [18], health assessment based on the HMMs of the normal and most recent behavior of the process signatures, applicable to highly dynamic phenomena when a sequence of process observations rather than a single observation is needed to adequately describe the behavior of process signatures.
- In Ref. [19], a particle filter based overlap between the most recent performance signatures and performance signatures corresponding to the normal behavior modes of the system was used to quantitatively describe the process performance. This method is applicable in cases of complex systems that display multiple regimes of operation (both normal and faulty), in which case a hybrid description of the system is needed, incorporating both discrete and continuous states.

Joint consideration of multiple sensor readings improves observability of the physical phenomenon [26,48,49], and sensor fusion is targeted at mining for that extra information hidden in the combined readings of several sensors. Following nomenclature defined by the JDL standard for sensor and data fusion [27], Watchdog Agents perform sensor fusion at the decision-level [10] or feature-level [12–14,16–19]. 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. Currently, feature-level sensor fusion is accomplished through concatenation of commensurate signal features [10,13], or joint consideration of features within a CMAC neural network [16,17], logistic regression curve [12,14], within an application-specific control criterion [15], or within a particle filter [19]. Fig. 9 illustrates the decision-level and feature-level JDL sensor fusion architectures.

3.3. Performance forecasting

Even though the performance CV described in Section 3.1, already bares significant prognostic information about the remaining product's useful life since it indicates a performance degradation and hence can produce an early warning about the increased possibility of equipment failure, additional prognostic information can be extracted by capturing the dynamics of the product's behavior and utilizing it to extrapolate and predict the product's behavior over time.

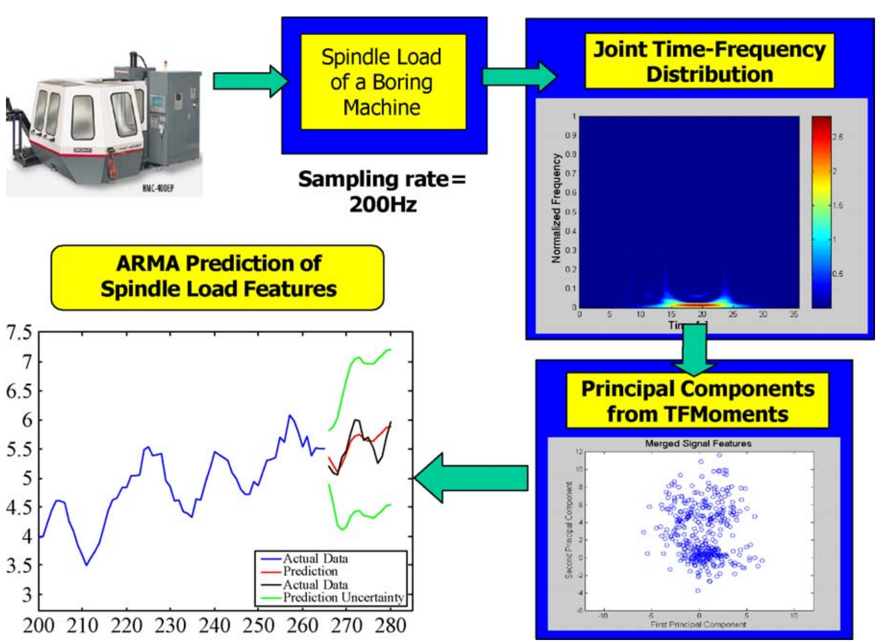

Fig. 10. ARMA prediction of features extracted from the spindle load sensor readings.

Autoregressive moving-average (ARMA) modeling [26] is a standard technique that can be utilized to capture the dynamic behavior of performance CVs [14], or extracted performance signatures. Fig. 10 shows the concept and preliminary results of predicting the behavior of performance-related process signatures using ARMA modeling 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 [13]. ARMA modeling techniques were then utilized to predict the behavior of the extracted principal components, as indicated in Fig. 10.

Nevertheless, ARMA modeling is adequate for prediction of only stationary time-series produced by linear time-invariant systems and may not offer good prediction results in cases of highly dynamic processes, when features extracted from sensor readings display highly irregular, non-stationary behavior. In such cases, the use of recurrent neural network whose delayed outputs serve as inputs for prediction of a time series, may yield more favorable results [21].

Finally, a novel method is recently proposed that is capable of achieving high long-term prediction accuracy by comparing signatures from several degradation processes using measures of similarity that form a match matrix [22]. Through this concept, one can effectively include large amounts of historical information into the prediction of the current degradation process. Similarities with historical records are used to generate possible future distributions of features, which is then used to predict probabilities of failure over time by evaluating overlaps between predicted feature distributions and feature distributions related to unacceptable equipment behavior. Predicted distributions are approximated using mixtures of Gaussian distributions [50] and overlaps were assessed based on the cosine between two distributions in L_2 space [51], expressed as

$$\frac{|f_1(\bar{x})\cdot f_2(\bar{x})|_{L_2}}{||f_1(\bar{x})||_{L_2}\cdot ||f_2(\bar{x})||_{L_2}}$$

where $f_1(\bar{x})$ and $f_2(\bar{x})$ are mixtures of multivariate Gaussians. Experimental results based on signatures extracted from 25 full boring tool wearout cycles collected over 8 working days of operation in the automotive E-manufacturing testbed indicated significant improvements in the prediction accuracy over the ARMA-based prediction, especially in the case of long term accuracy, as is depicted in Fig. 11. The reason for this increased prediction accuracy is the fact that ARMA prediction is utilizing only dynamics embedded in the signatures of the current maintenance cycle (in the signatures observed after the last tool change in the experiment shown in Ref. [22]), while the match matrix based prediction looks for similarities in the entire dataset of

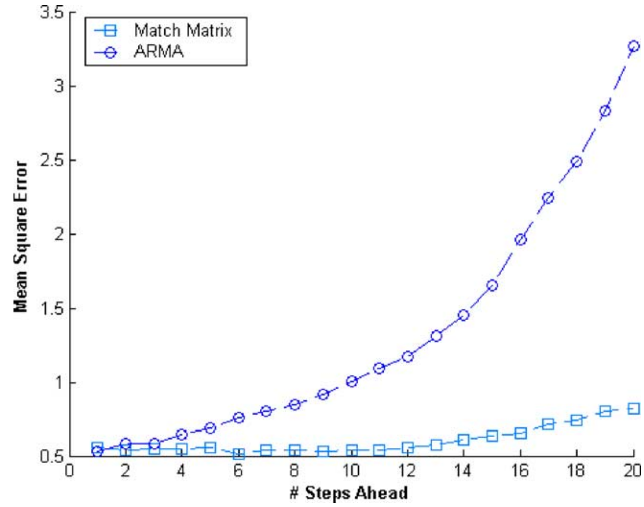

Fig. 11. Comparison of prediction errors for ARMA modeling and match matrix based prediction.

25 previous maintenance cycles and exploits them for prediction within the current maintenance cycle.

In summary, the following performance forecasting tools are currently used in the Watchdog Agent:

- ARMA based prediction tool, applicable to linear time-invariant systems whose performance features display a stationary behavior [20].
- Elman neural network based prediction tool, applicable to non-linear systems whose performance features display non-stationary behavior [21].
- A match matrix based prediction method applicable to cases when abundant records of multiple maintenance cycles exist and can be used to extract and exploit similarities of the current maintenance cycle with those observed in the past in order to achieve a greatly increased accuracy of prediction, as was done in Ref. [22].

Nevertheless, in spite of the encouraging results presented in this section, further work is needed to better understand and further test the aforementioned prediction tools. Furthermore, it is necessary to better correlate the behavior of the predicted process features with the actual breakdowns of the process or system that is being monitored, which could be accomplished through correlation of the database of performance signatures and historical records of the corresponding behavior of the process or system.

3.4. Condition diagnosis

Condition diagnosis is a more traditional condition-based technique based on recognizing indications of failure in the behavior of the system. Namely, if signatures describing system behavior in the presence of a given fault are available from the past system operation, it is possible to evaluate the overlap between the newly arrived signatures with not only those describing the normal system behavior, but also with those characterizing the previously observed fault behavior. This way, one knows 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). Hence, such matching allows the Watchdog Agent 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 forecast based on the current and past product's performance.

Fig. 12 illustrates this diagnostic concept. The plot on the lower part of Fig. 12 is obtained based on signatures extracted from the spindle load sensor during the boring meal-cutting process and collected throughout a lifecycle of one boring tool, from the moment it was placed into the machine, to the moment it was replaced due to excessive wearout. The signatures were extracted from the joint TF distributions of the spindle load sensor readings, using the TF moments and principal component analysis [13]. The decreasing trend of the solid line denoting the cutting process performance confidence value indicates the degradation of the cutting process. On the other hand, the increasing trend of the overlap between the newly arrived signatures with those describing cutting process performance with a warn tool indicates that the cutting process degradation develops due to the wear of the cutting tool. Overlaps were assessed based on the asymptotic Gaussianity of the time–frequency moments, which is applicable when behavior of the process is not changing too rapidly because if the process changes rapidly, asymptotic Gaussianity cannot take effect and results based on approximate Gaussian descriptions of the normal, faulty and most recent process behavior are not adequate). In cases when Gaussianity of the performance-related features cannot be guarantied and when process may display multiple normal and faulty modes of behavior (multiple regimes of operation and/or multiple possible faults in the process), utilization of a support vector machine [52] and directed acyclic graphs for classification and fault detection, as was done in Ref. [11] for diagnosing different failure modes of an elevator door using encoder readings and frequency band energies extracted from vibration sensors readings.

In summary, the following condition diagnosis tools are currently used in the Watchdog Agent:

- Condition diagnosis based on analytically calculated overlaps of Gaussians describing the signatures corresponding to the current process behavior and to the signatures corresponding to various modes of normal or faulty equipment behavior, applicable to the cases when performance-related features approximately behave as Gaussians, as was the case in Ref. [13].
- Support vector machine (SVM) based diagnostic tool applicable when Gaussianity of the performance-related features cannot be guarantied and when process may display multiple normal and faulty modes of behavior (multiple regimes of operation and/or multiple possible faults in the process) [11].

It should be noted that over time, as new failure modes occur, performance signatures related to each specific

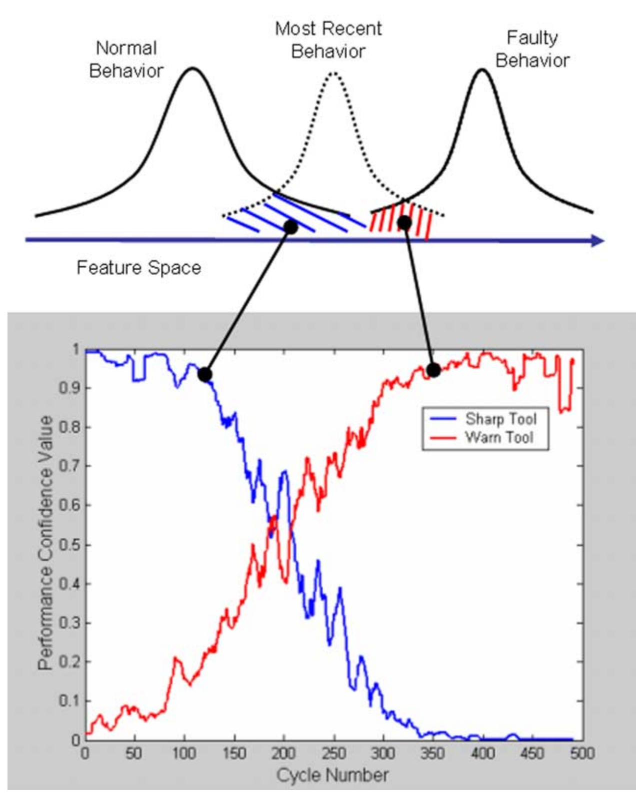

Fig. 12. Diagnostic information obtained from the Watchdog Agent for the performance of a cutting tool in the boring metal-cutting process.

Fig. 13. Elevator door equipped with a logistic regression based Watchdog Agent.

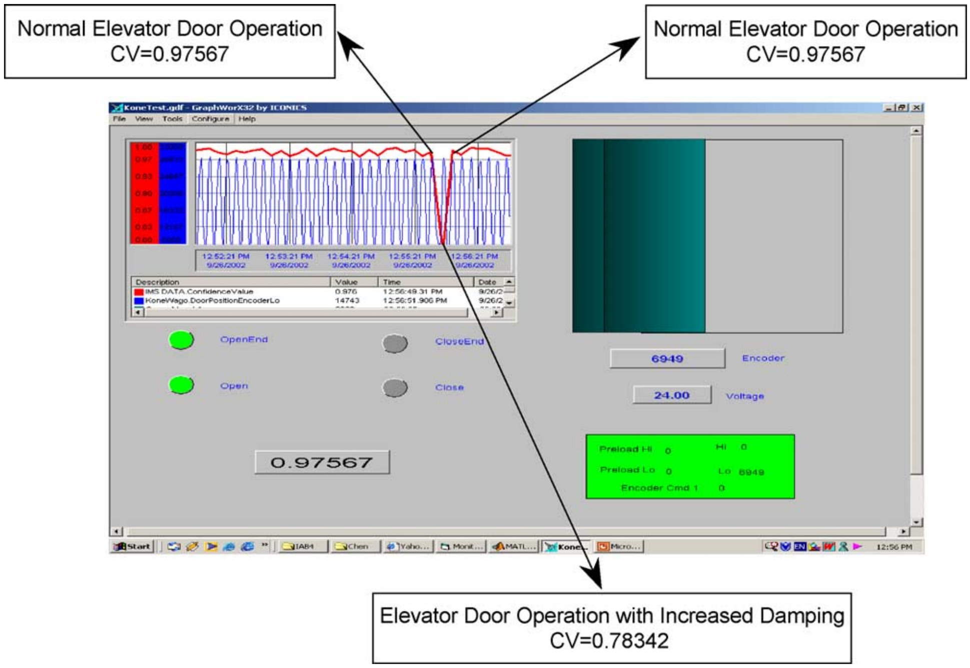

Fig. 14. Screenshots of the logistic regression based Watchdog Agent assessing performance of the elevator door shown in Fig. 7.

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 envisioned as an intelligent device that utilizes its experience and human supervisory inputs over time to builds its own expandable and adjustable world model [53].

4. Implementation examples

Several Watchdog Agents for on-line performance assessment have already been implemented as standalone applications in a number of industrial and service facilities.

A Watchdog Agent based on the logistic regression [47] and expert extracted features has been implemented on a commercial elevator door [14] shown in Fig. 13. Following recommendations from the elevator door manufacturer's maintenance experts, cycle time for door opening and closing as well as the maximum speed of the door are utilized to evaluate the performance confidence value (CV) of the elevator door using the logistic regression function of the form

$$\mathrm{CV}(x_1, x_2) = \frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2}}{1+e^{\beta_0+\beta_1 x_1+\beta_2 x_2}}$$

where x_1 and x_2 are the maximal speed of the elevator door motion and the door cycle time, respectively. Firstly, parameters β_0, β_1 and β_2 of the logistic regression curve were estimated by finding the nearest (in the least square sense) logistic regression function to the function that is equal to 1 in the training set representing the acceptable elevator door behavior, and equal to 0 in the training set representing the unacceptable elevator behavior. Then, performance degradation was assessed by evaluating the logistic regression function for the newly arrived elevator door performance features x_1 and x_2. The loser those features are to the normal elevator door behavior, the closer the performance CV calculated using the logistic regression will be to 1.

Fig. 14 shows a screenshot of the software application housing this logistic regression based Watchdog Agent. Firstly, normal door operation was observed and the performance CV was estimated to be 0.976. Then, a person leaned against the door and thus effectively increased the damping of the system and altered the door performance. The resulting performance CV then dropped to 0.783.

Fig. 15. Material handling device for staging.

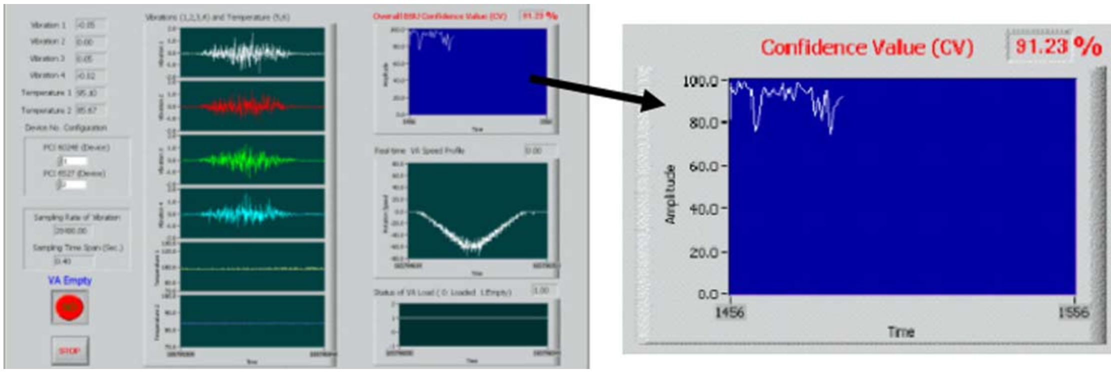

Fig. 16. Screenshot of the time–frequency based Watchdog Agent assessing performance of the material handling deice shown in Fig. 15.

Finally, the door was released and nominal conditions of door operations were re-established. The resulting performance CV was then again estimated at 0.976.

In Ref. [12], the same elevator door was equipped with vibration sensors and more advanced performance assessment could be achieved based on the encoder readings and the wavelet packet energies extracted from the vibration sensors, which allowed a more sophisticated performance assessment and diagnosis of different elevator door faults.

A time–frequency signal analysis based Watchdog Agent [13] has been implemented for performance assessment of a gearbox in a material handling device shown in Fig. 15. Four vibration sensor readings have been fused to autonomously and on-line evaluate its performance. The vibration signals were processed into joint time–frequency energy distributions [32] and a set of time-shift invariant time–frequency moments [13,54,55], was extracted. Since those moments asymptotically follow a Gaussian distribution [56], statistical reasoning was utilized to evaluate the overlap between signatures describing the normal process behavior (used for training) and those describing the most recent process behavior. Fig. 16 shows a screenshot of the software application housing this time–frequency based Watchdog Agent used for performance assessment of a material handling device.

The same time–frequency based Watchdog Agent has also been implemented for performance assessment of manufacturing equipment within a web-enabled E-manufacturing testbed realized by one of the leading US car manufacturers. A Labview™ based application [57] has been developed to systematically capture and record sensor readings from machine tools across the factory floor. A web-enabled tool allows the user to remotely search the recordings by plant, machine, sensor, date and time, facilitating unique DNA-like identification of each product that exits the factory floor. Desired data could then be collected and downloaded for rapid performance analysis. Algorithms for performance assessment have been developed by the center for IMS. Organization and functionality of this E-manufacturing testbed is indicated in Fig. 17. Fig. 18 shows performance CVs of a boring process based on the spindle load sensor readings collected over one day of operation. As can be seen from Fig. 18, performance CVs repeatedly drift away from 1 (which indicates ideal performance), indicating performance degradation, which is attributed to inevitable tool wear. Abrupt jumps of performance signatures and associated CVs, after which they return to normal levels, coincide with tool changes, when worn tools have been replaced by sharp ones

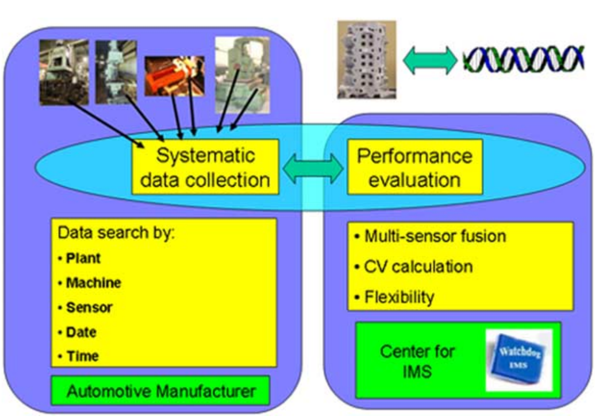

Fig. 17. Organization and function of the E-manufacturing testbed.

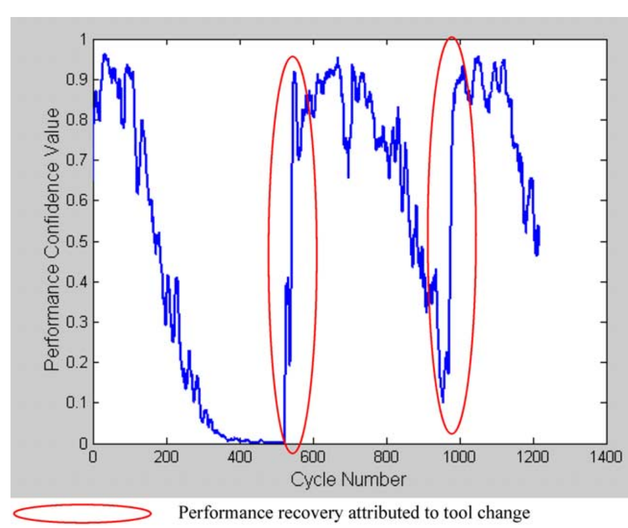

Fig. 18. Confidence values extracted from load sensor readings on a boring machine spindle in the E-manufacturing testbed.

(tools were changed at each shift change and 3 day shifts are clearly visible in Fig. 18).

5. Conclusions and future work

Watchdog Agent is a tool for multi-sensor assessment and prediction of machine or process performance. This tool can be utilized to realize predictive CBM, CPLM as well as identification of components with significant remaining useful life that could be efficiently and cost-effectively disassembled and reused.

A wide variety of Watchdog Agent realizations have been devised to address applications of different nature and different levels of complexity and criticality. Innovative sensory processing and autonomous feature extraction methods are developed to facilitate the plug-and-play approach in which Watchdog Agent can be set and ran without any need for expert knowledge or intervention. Watchdog Agents have been successfully implemented in laboratory and industrial testbeds that include Watchdogs for performance assessment of an elevator door, gearbox of a material handling device for staging and web-enabled E-manufacturing testbed of a leading US automotive manufacturer.

Future work includes deeper understanding and improvements of the performance forecasting methods (knowing '*when* something is going to happen'). Incorporation of historical data on the process performance and expert application-specific knowledge will be crucial in improving the prognostic results and facilitating viable and reliable maintenance decision-making based on those results. In addition, similarly how historical records of past process performance were used in Ref. [22] to greatly increase long-term prediction of process performance signatures, the performance of similar systems in operation (brother-systems) can be used to further improve the diagnostic and prognostic features through the P2P paradigm [2].

Also, a link should be established with a decision-making module that will enable optimal maintenance action in a timely manner [16,24]. This link will complete the Watchdog Agent functionalities and facilitate the OSA-CBM standard topology in which an IMS can operate as a near-zero down-time, self-sustainable and self-aware artificially intelligent system that learns from its own operation and experience [2].

In the area of collaborative product life-cycle design and management, Watchdog can serve as an infotronics agent to store product usage and EOL service data and feedback to designers and life-cycle management systems. Currently, an international intelligent manufacturing systems (IMS) consortium on product embedded information systems for service and EOL (PROMISE) has been proposed. The goal is to integrate Watchdog capabilities into product and systems for closed-looped design and life-cycle management (see Fig. 19).

Finally, an embedded infotronics agent is needed to *assess* and *predict* product performance, and based on that prediction enable assessment of product's reusability, as well as its proactive maintenance. Embedding is crucial for creating an enabling technology that can facilitate proactive maintenance and life-cycle assessment for mobile systems, transportation devices and other products for which cost-effective realization of predictive performance assessment capabilities is not implementable on general purpose personal computers (PCs). The main research challenge

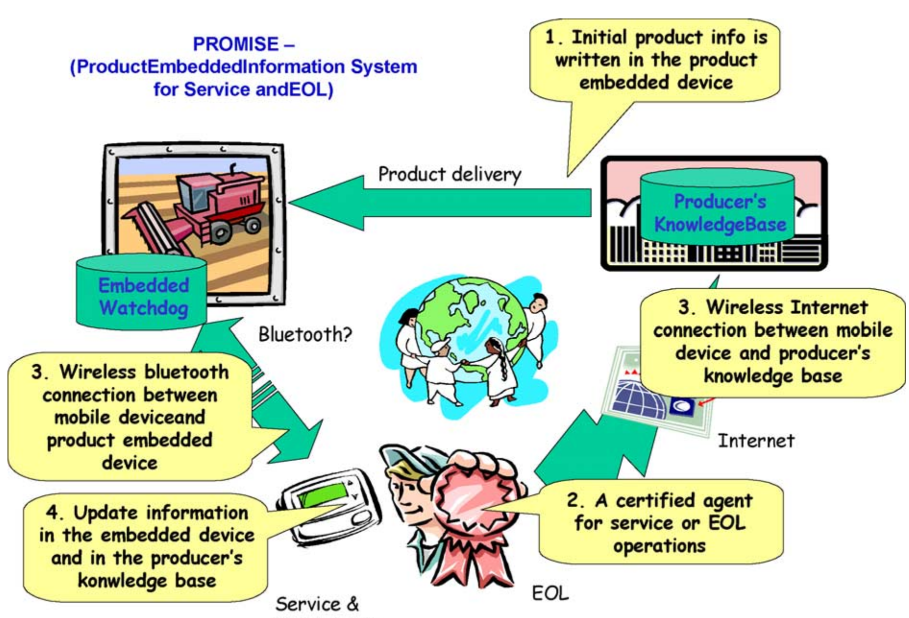

Fig. 19. Product embedded information systems for service and EOL (PROMISE).

will be to accomplish sophisticated performance evaluation and prediction capabilities under severe power consumption, processing power and data storage limitations imposed by embedding. Successful realization of the embedded infotronics agent will have a profound effect on the society and could fundamentally improve both state-of-the-art technology and quality of life. For example, embedding this technology into manufacturing equipment will facilitate near-zero downtime operation, even when the general-purpose, PC-based Watchdog Agent™ is deemed not cost effective. Similarly, this embedded technology could be well suited to application in the transportation industry where it could reduce the logistical footprint associated with fleet maintenance. Finally, minimal additional research effort would be required to adapt the embedded infotronics agent based technology to perform continuous, advanced tele-care and tele-health functions for the early detection and prevention of diseases and disorders. This advance could thus improve the overall quality of living for the general public, and particularly for those whose abilities are changing due to aging.

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