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Multisensor Process Performance Assessment Through Use of Autoregressive Modeling and Feature Maps

Nicolas Casoetto, Dragan Djurdjanovic, Rhett Mayor, and **Jun Ni,** Dept. of Mechanical Engineering, University of Michigan, Ann Arbor, Michigan, USA
Jay Lee, Industrial and Manufacturing Engineering Dept., University of Wisconsin–Milwaukee, Milwaukee, Wisconsin, USA

Abstract

This paper presents an algorithm for quantitative assessment of process or machine performance. The algorithm is based on the fusion of multiple sensor inputs and matching of the currently observed system signatures against those observed during its normal behavior. In contrast to traditional monitoring techniques, neither faulty data nor historical data are needed for the performance assessment to be made. This quantitative information about process performance can be used to take appropriate maintenance action in a timely manner. Effectiveness of the methods presented in this paper was experimentally demonstrated in multisensor welding process assessment.

Keywords: *Continuous Process Assessment, Condition-Based Assessment, Multisensor Fusion, Autoregressive Modeling, Feature Maps*

Introduction

In today's competitive market, production costs, lead time, and optimal machine utilization are crucial values for companies. It is well known that machine or process breakdowns severely limit a company's effectiveness. Scheduled maintenance is intended to eliminate machine or process breakdowns through scheduled maintenance operations, regardless of the actual machine/process state. Actual time intervals in which maintenance is performed are determined using the reliability theory and machine or process life cycle information. Nevertheless, this practice often results in unnecessary loss of productivity due to maintenance performed when the process or machine is still able to perform at an acceptable level, or due to unpredicted breakdowns before the scheduled maintenance operation is performed.

This paper is an original work and has not been previously published except in the *Transactions of NAMRI/SME*, Vol. 31, 2003.

Nowadays, increasingly sophisticated sensors are installed on machines more and more often, while the speed of computers increases in great leaps. Under these circumstances, condition-based maintenance (CBM) emerges as a more appropriate and efficient tool for achieving near-zero breakdown time through a significant reduction and, when possible, elimination of the downtime due to process/machine failure or any other unacceptable behavior.

According to Engel et al. (2000), two methods exist for condition-based assessment (CBA). One approach involves an estimation of current condition based on the recognition of indications of failure. When implementing this CBA paradigm, expert and a priori knowledge about the assessed machine or process is necessary because one needs to know the corresponding failure modes to assess the current machine or process performance by comparing it against the performance that characterizes those known failure modes; hence, the application-specific nature of this CBA paradigm. For example, Swanson (2001) used a fuzzy logic neural network to predict failure of a tensioned steel band with seeded crack growth. Ray and Tangirala (1996) built a stochastic model of fatigue crack dynamics in mechanical structures to predict remaining service time. Vachtsevanos and Wang (2001) give an overview of different CBA algorithms and suggest a method to compare their performance for a specific application.

The second type of CBA characterizes the machine or process performance through the overlap of the most recent system signatures and those observed during the healthy process or machine behavior. In this paper, the latter type of CBA has been implemented to shift the maintenance focus from the analysis and quantification of process/machine failure toward 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.

Regardless of the adopted approach to CBA, utilization of the information from multiple sensors mounted on the system whose performance is being assessed is highly desirable according to Hall (1992) and Hall and Llinas (2000). Byington (2000) demonstrated several CBM applications based on multisensor fusion. However, this work was in essence application-specific with the need to a priori know of the system failure modes to compare the current system behavior against those failure modes. The merger of multiple sensor readings was accomplished through either feature level, decision level, or model-based sensor fusion (Steinberg, Bowman, White 1998). However, in each case, the sensor fusion was heavily dependent on the prior characterization of the failure modes of the process/machine that was being assessed, and was therefore also strongly application-dependent. In the case of encountering an unforeseen failure mode, the sensor fusion and performance assessment methods presented in that work could easily give spurious and wrong results.

In Djurdjanovic, Ni, and Lee (2002), a generic sensor fusion based on statistical reasoning was accomplished through the merger of sensor features, but the work presented in that paper was still focused on the description and detection of process failure. On the other hand, the work by Lee (1995, 1996) follows the other CBA paradigm where the focus is placed on quantifying the performance degradation and no a priori failure knowledge is needed. However, the sensor fusion in this work was accomplished through the direct hashing of sensors in a cerebellar model articulation controller (CMAC) neural network (Albus 1975), which could be unfeasible when highly dimensional sensor readings, such as vibrations, or DC motor current signals are fed into it. Furthermore, the process/product performance was assessed in a rather ad hoc manner and clearly a novel method of assessing the performance degradation was needed.

The goal of the work presented in this paper was to achieve generic process/machine performance assessment based only on the information about the normal system operation. The system performance is described using generic signal features, and multiple sensor readings are merged using an application-independent and algorithmic—rather than application-specific and rule-based—sensor fusion strategy.

Methods

General Description of the Methods

The performance assessment methodology proposed in this paper is based on assessing the overlap between the signatures describing the current machine or process performance and those observed during the normal system operation. Higher overlaps between the two sets of signatures signify a better system performance.

The diagram in *Figure 1* describes the basic steps necessary to assess the system performance by comparing the currently observed system operation with the normal one. Multiple sensor readings are processed into a domain where generic signal features can be extracted to describe the current machine or process performance. First, signatures representing the normal system behavior must be selected to learn the description of the normal system operation. Then the newly arrived signatures can be compared against those learned during the normal system operation, and the performance assessment can be based on the overlap between the normal and current system signatures.

Because this entire approach to performance assessment relies on appropriately describing the normal system operation, it is crucial to correctly select the signatures representing this normal operation state. The problem in accomplishing this task is that the machine degradation cycle is usually composed

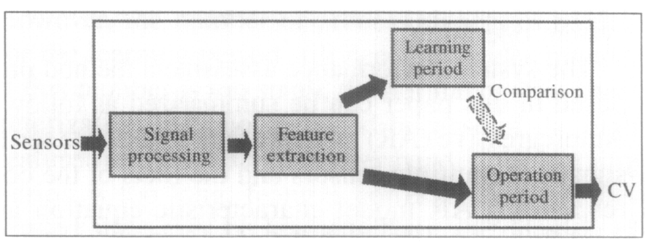

Figure 1
Flowchart of Performance Assessment Algorithm

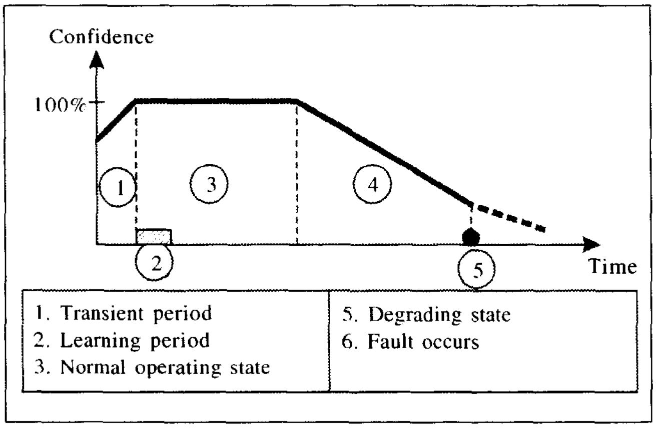

Figure 2
Evolution of Performance Confidence Value (CV) Over Time

of several periods, as shown in *Figure 2*. These periods are:

- transient period
- normal operating period
- degrading period
- fault, machine breakdown, or repair time

The transient period that precedes the normal system behavior represents the warm-up or wear-in period of the system's operation. It can be caused by, for example, the machine temperature that increases up to a steady state or a mechanical wear-in of certain parts and components. Inclusion of the process signatures observed during the wear-in period into characterizing the normal system behavior could result in false characterization of the normal system operation and subsequently adversely affect the performance assessment. Therefore, this wear-in period should be identified and avoided when the normal system behavior is being learned. It is proposed to apply the Schruben's test introduced in Schruben (1982) and Schruben, Singh, and Tierney (1983) to the set of extracted signal features to determine the end of the transient period, after which the system signatures can be used for describing the normal system operation.

The system performance assessment method proposed in this paper can be summarized as follows. Autoregressive (AR) models are fit to the time series signals of multiple sensors and the roots of the corresponding AR model characteristic equation are used to extract the Power Spectral Density (PSD) peaks of individual sensor readings. These features are first analyzed to determine the signals that shoul be used to represent the normal system behavio The performance signatures observed during no mal operation are stored into a Feature Map (FM during the learning process. The learning process followed by the operation period during which th PSD features are extracted from the newly arrive signals and the overlap between the newly obtaine signal features with those observed during the no mal system behavior is used to assess the curre system performance. Following Lee, this quantit tive measure of system performance will be referre to as the performance Confidence Value (CV).

The following subsections describe: the AR mode ing based spectral content estimation, which correspon to the signal processing block in *Figure 1*, the featu map based process performance assessment.

Spectral Content Estimation

The spectral content of sensor readings was es mated using the autoregressive (AR) modeling tec nique to accurately describe energy peaks and disce nearby modes in the frequency domain. First, autoregressive model of the form

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + \varepsilon_t$$

is fit to the sensor signals to describe the dynami of the signal, where:

- X_t is the sensor reading at time t;
- ϕ_i are the parameters of the AR model;
- ε_t denotes residual noise at time t.

The model parameters, ϕ_i, are calculated usi the modified covariance method, which is based minimizing the forward prediction error (Pandit a Wu 1993).

Frequency domain description of the signal, can now be obtained as follows:

$$X(\omega) = \frac{\sqrt{T\sigma_\varepsilon^2}}{1+\phi_1 e^{-j\omega T} + \phi_2 e^{-2j\omega T} + \ldots + \phi_p e^{-pj\omega T}} =$$

$$= \frac{\sqrt{\sigma_\varepsilon^2}}{(1-r_1 e^{-j\omega T})(1-r_2 e^{-j\omega T})\ldots(1-r_p e^{-j\omega T})}, 0 \le \omega <$$

where T is the sampling interval, σ_ε^2 is the residual noise variance, and

$$r_k = \rho_k e^{j\theta_k}$$

are the roots of the autoregressive characteristic polynomial

$$1 + \sum_{k=1}^{p} \phi_k x^k = 0$$

The power spectral density (PSD) of the signal X_t is the magnitude of the frequency-domain description of the signal X_t, and to extract local PSD peaks, the frequency content of the signal was calculated only at frequencies v such that

$$\omega T = \theta_k,\ k = 1, 2, \ldots, p$$

Thus, for each AR root $r_l = \rho_l e^{j\theta_l}$, the local PSD peak can be obtained, given as

$$|X(\omega_l)| = \frac{\sqrt{\sigma_\varepsilon^2}}{(1 - r_1 e^{-j\theta_l})(1 - r_2 e^{-j\theta_l})\ldots(1 - r_p e^{-j\theta_l})} \qquad (1)$$

The closer the AR root, r_l, is to the unit circle in the complex plane, the more prominent the PSD peak is at the frequency ω_l corresponding to that root. Hence, to extract only the most prominent PSD peaks, the spectral content of all signals was estimated only at roots r_l such that $\rho_l = | r_l | > 0.9$.

The AR-based spectral estimation method is geared toward accurately describing the PSD peaks by determining the roots of the AR model of the signal and evaluating the signal PSD only at the frequencies corresponding to those AR roots. If the speed of the PSD estimation algorithm is critical, then the most prominent PSD peaks can also be estimated using the well-known fast Fourier transform (FFT), where the spectral content of the signal is estimated at predetermined, equidistant frequency samples. (For more information on the methods of spectral estimation, one may refer to Marple 1987 or Kay 1988 and references therein.)

In this method, two parameters need to be set: the order of the autoregressive model and the threshold of the module of the AR roots for which the spectral content will be estimated using Eq. (1). The order of the autoregressive model is set as that of the adequate model for the signals describing the normal machine or process behavior. The order p of the adequate AR model was found using the AIC criterion described in Pandit and Wu (1993), pp. 159–163. From then on, the performance degradation can be assessed using the evolution of the signal features extracted from the AR model of order p of the newly arrived signals. As explained earlier, if the root gets closer to the unit circle, the corresponding PSD peak is more prominent. In this paper, the threshold for the module of the AR roots at which the PSD was calculated was set to 0.9, but application-specific adjustments can be made.

Feature Maps and Performance Assessment

For each sensor, a two-dimensional feature map (FM) is created. The first dimension of the feature represents the frequency domain, and the second dimension represents the logarithm of the corresponding power spectral density (PSD). The logarithm of the PSD intensity was utilized to better localize the PSD peaks in the FM. Because it is assumed that there is *no* a priori information on the localization of the features, each FM is split into regularly spaced two-dimensional cells (one dimension representing the frequency of the PSD peak, and the other representing the logarithm of the PSD intensity at that frequency).

Though not applied in this paper, methods exist to improve the FM resolution by moving the cells toward the features observed during the period of learning the normal process or machine behavior (Eldracher, Staller, Pompl 1994).

During the learning period, the FM learns to characterize the normal process or machine behavior. The initial wear-in or warm-up period can be identified and disregarded by applying the Schruben's test to the extracted PSD signal features, after which the normal machine or process behavior can be learned. However, the number of process signatures needed for the learning period still needs to be determined. If this number is too small, the normal process characterization may not be good because of the high feature variability. On the other hand, if the learning period is too long, features corresponding to a degraded state may be learned. Thus, the duration of learning period should be carefully chosen and is process dependent. In the experiments presented in this paper, it was observed that the FM is able to learn the nominal process behavior after 20 to 30 signals representing the normal process behavior were presented to it.

During the learning period, the FM cells are updated to model the distribution of the PSD peaks corresponding to the normal process of machine behavior. For each PSD peak i of the jth process signature, the update referred to as activation level (AL) is determined for each FM cell (x,y) as follows:

$$AL_i^j(x, y, freq_i^j, PSD_i^j) = e^{-\frac{(x-freq_i^j)^2}{\sigma^2_{FREQ_i}} - \frac{(y-PSD_i^j)^2}{\sigma^2_{PSD_i}}}$$

where

- $freq_i^j$ and PSD_i^j are the PSD peak frequency and logarithm of its intensity, respectively.
- $\sigma^2_{FREQ_i}$ and $\sigma^2_{PSD_i}$ are the sampled variances of the ith PSD peak frequency and intensity, respectively, estimated from the set of signals chosen to represent the normal process system behavior.
- x and y denote the center of the two-dimensional FM cell.

The final activation level for the ith PSD peak at the FM cell centered at (x, y) is the sum of squares of the activation levels of each sample of that PSD peak, as follows:

$$AL_i^{final}(x, y) = \sum_{j=1}^{n} \left(AL_i^j(x, y)\right)^2$$

Once the learning period is over, the activation levels are fixed. The PSD peak features describing the newly arrived signals are extracted and are fed to the FM to calculate the match value (MV), MV_i^j, corresponding to the ith PSD peak of the jth process signature, as follows:

$$MV_i^j(x, y) = \sum_{x,y} AL_i^{final}(x, y) AL_i^j(x, y)$$

The performance confidence value (CV) based on individual sensor readings is now computed as the average MV of all the PSD peaks extracted for that particular sensor. This method of calculating the CV of an individual sensor reading corresponds to equal weighting assigned to each PSD peak. Another possibility for calculating the performance CV is to utilize dynamic weighting where the weights associated with each PSD peak would be increased for those peaks that migrate away from the normal behavior and thus depict the performance degradation. Dynamic focusing through the weights associated with PSD peaks will be addressed in future work.

The performance CVs calculated from individual sensor readings can now be merged into an overall multisensor CV. This sensor fusion corresponds to the decision-level sensor fusion according to the Joint Directors of Laboratories (JDL) data fusion model (Steinberg, Bowman, White 1998).

In this paper, the final CV is computed as the weighted average of all individual sensor CVs. The weights associated with each individual sensor CV are chosen as the inverse of the variance of that individual sensor CV observed during the learning period. Thus, the smaller the variance of a given sensor CV, the higher the weight associated with it, and any shifts in the features extracted from that sensor reading become more emphasized. The multisensor CV fusion performed this way is also static, with fixed weights. Future research is needed on dynamic focusing on the sensors with migrating PSD peaks as the migration occurs.

Experimental Results

Experimental Setup

The experiment has been conducted on the welding machine, shown in *Figure 3* (Continental Acia 781 model no. 601 ES-5). Three sensors used to assess the welding process measured the electrode current and voltage as well as the force that occurs between electrodes during the welding process. The data are collected thru a data acquisition card (NI-6060E), and each of the sensor readings was digitally sampled at the sampling rate of 5 kHz.

A new pair of Ø6mm brass spot welding conical electrodes was set on the machine, and spot-resistance welding was performed until those electrodes wore out. Throughout this process, sensor readings were collected and process performance was assessed according to the methods described in the previous section. A total of 3550 welds were made, and sig-

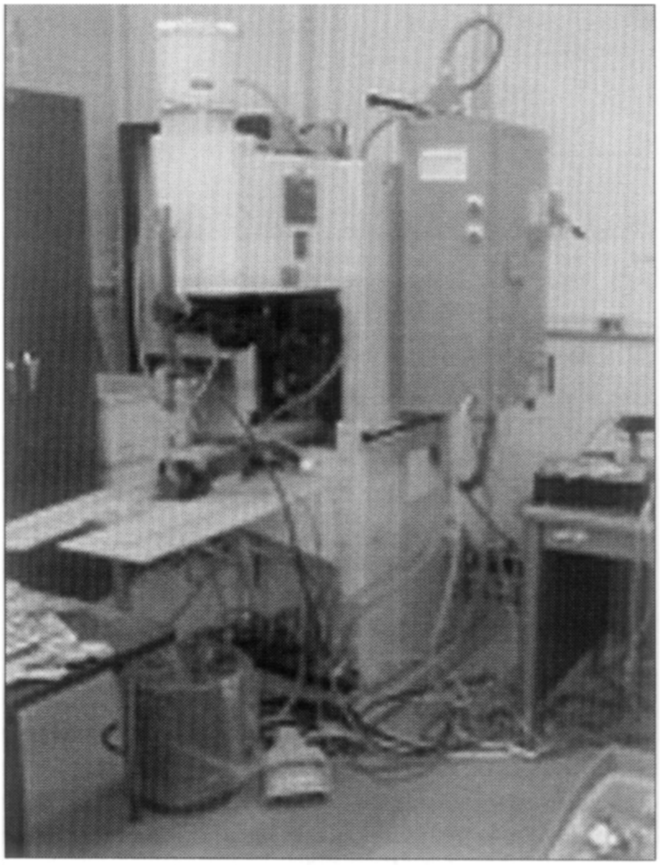

Figure 3
Welding Machine Used for Experiment

natures from every 10th weld were recorded, thus yielding the set of 355 recorded welds.

Results

Autoregressive models of order 50 were fit to all sensor readings and features were extracted as described previously. Schruben's test was individually applied to each extracted feature and yielded that the first 20 recorded welds* represented the wear-in period, and these welds were therefore skipped in the training period. The next 30 recorded welds were used to learn the activation levels of the feature map. *Figure 4* shows the histogram of the power spectral density (PSD) characteristics of one of the AR(50) roots characterizing the current sensor signal. Note that the distribution of these features is cumbersome to parameterize, which renders traditional statistical pattern recognition techniques inappropriate for this application.

* The total of 200 welds was made when those 20 welds were recorded.

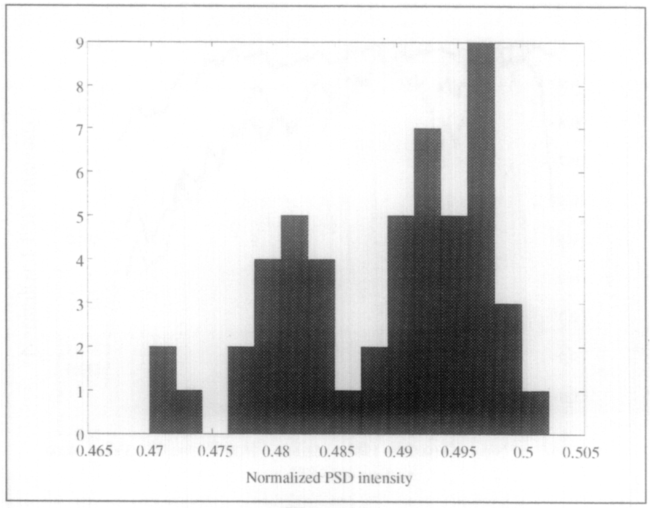

Figure 4
Histogram of PSD Features Extracted from One of the AR(50) Roots Characterizing the Current Signals

Figure 5 shows the CVs computed for each sensor reading individually, and *Figure 6* gives the result of sensor fusion where the performance CV was calculated as the weighted average of the individual sensor CVs, with weights equal to the inverse of the individual sensors' CV variance observed during the learning period.

Discussion

During the 3550 welding operations performed in this experiment, the features extracted from the current, voltage, and force sensor readings migrate. This migration is illustrated in *Figures 7a* and *7b* for feature 16 of the current sensor. This migration is caused by the degrading characteristics of the welding process, which in this case can be attributed to the wear process of the welding electrode. *Figure 8* shows the electrode used in this experiment before any welds were done with it, as well as how it looked after it was used to perform 3550 welds.

The welding process degradation mirrored in the migration of the extracted signal features incurs ever smaller and smaller overlaps between the newly arrived process signatures and the learned signatures. As this overlap decreases, the CVs show a decreasing trend, as shown in *Figures 5* and *6*. CVs shown in *Figures 5* and *6* indicate a clear degradation in the welding process performance after some 1500–2000 welds. One should note that this degradation process precedes the actual process failure when the

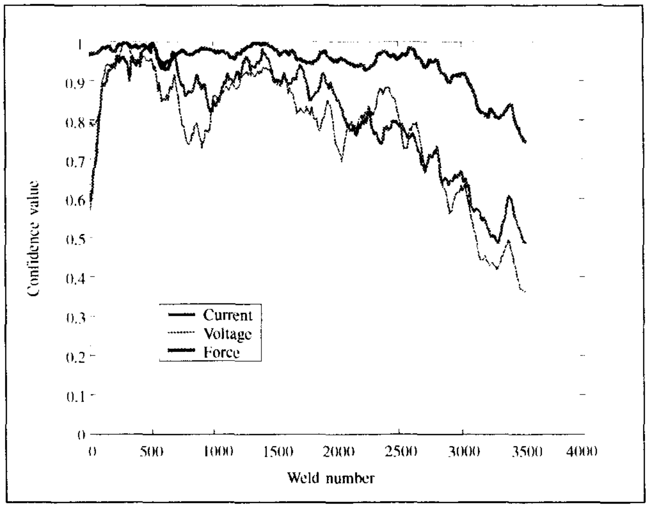

Figure 5
Confidence Values (CVs) of Welding Process Performance Calculated Using Individual Sensor Readings

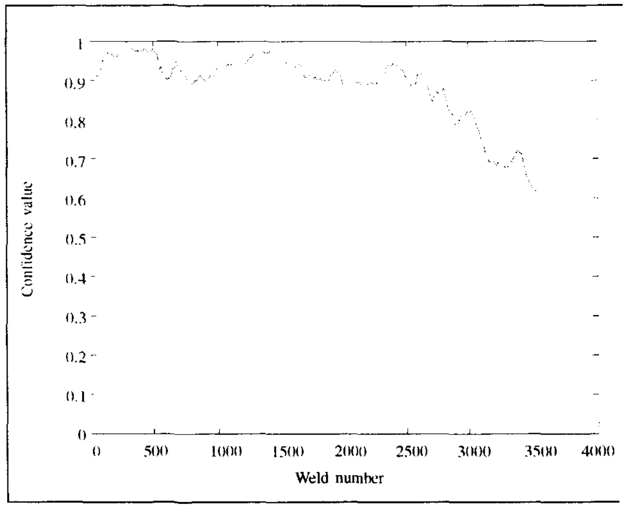

Figure 6
Overall Confidence Values (CVs) of Welding Process Performance

welding performance becomes unacceptable due to excessive electrode wear. The degradation process can be used to change the "almost-worn" pair of electrodes before the process performance becomes unacceptable, thus always ensuring the high quality of the welds.

It is also apparent that the CVs associated with the earliest few welds are lower, which is a reflection of the electrode wear-in period. Inclusion of the wear-in period could hamper the performance assessment, and this is why the Schruben's test is used to eliminate these signatures from the learning period. *Figure 9* shows the evolution of one of the PSD features extracted from the current sensor readings. The wear-in period is obvious as the features grate toward some steady state (normal behav within the first 15–20 recorded welds (correspo to the first 150–200 performed welds). It is this ste state apparent after the first 15–20 recorded w that characterizes the normal welding process] formance against which the newly arrived pro signatures need to be compared to assess the] cess performance.

Conclusions and Future Work

Quantitative methods for multisensor-based] cess assessment are presented in this paper.]

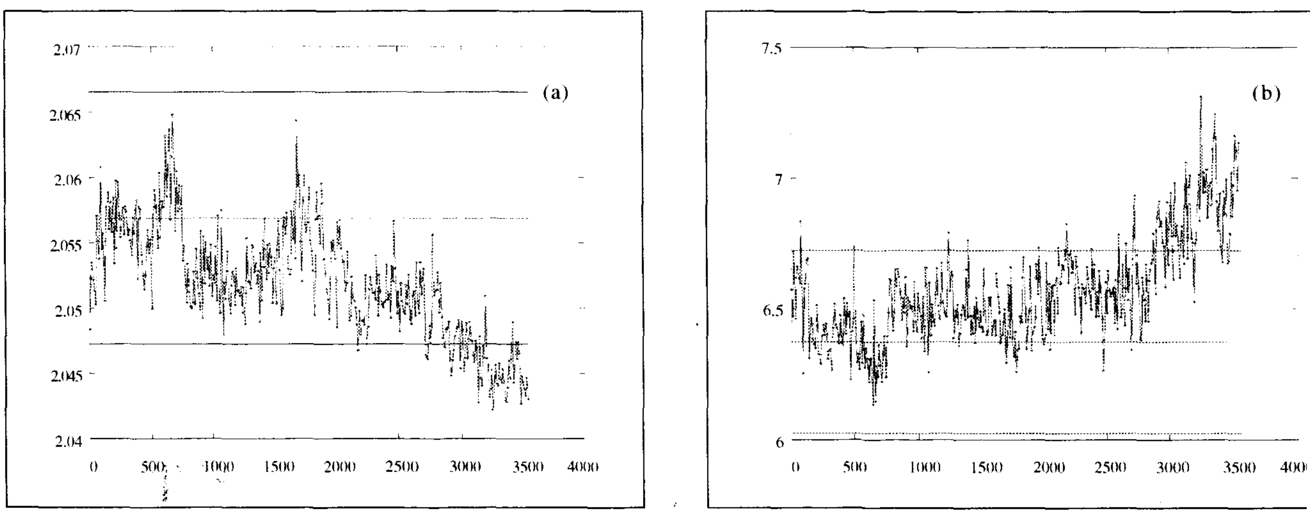

Figure 7
(a) Evolution of Frequency for Feature 16, (b) Evolution of PSD for Feature 16

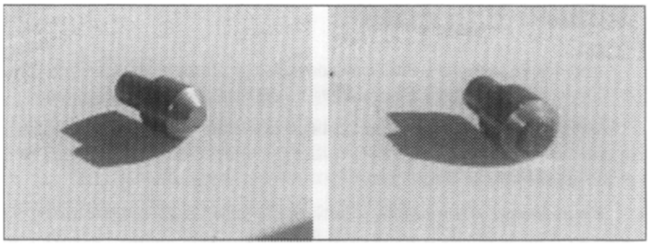

Figure 8
Ø6mm Welding Electrode Before (left) and After (right) 3550 Welds

quency content of multiple sensory inputs is extracted through the use of autoregressive modeling, and matching of the currently observed process signatures against those observed during the normal process behavior is accomplished through the use of feature maps. High overlap of the currently observed and normal process signatures results in a high performance confidence value (CV), while drift of the currently observed system signatures away from those observed during the normal system behavior causes a drop in the performance CV. This quantitative information about process performance can be used to take appropriate maintenance action in a timely manner.

A major advantage of the newly proposed methods for performance assessment is their generality achieved through extraction of generic signal features and generic methods of signature matching. Thus, the methods described in this paper can be applied in a wide range of applications. Furthermore, to facilitate the "plug-and-play" implementation of the proposed process assessment methods, special attention was dedicated to reducing and eliminating the need for expert human involvement in setting up the parameters of the feature extraction methods and feature map based pattern matching.

Research work is currently under way to facilitate generic process performance assessment in the presence of nonstationary sensory signals with time-varying spectral content (Djurdjanovic, Ni, Lee 2002). Also, methods for autonomous selection of the order of the AR model and of the FM resolution are being investigated to fully enable the "plug-and-play" implementation of the newly introduced methods. Furthermore, performing additional experimental tests with the methods presented in this paper in applications other than welding needs to be done. Future work in the development of the AR/

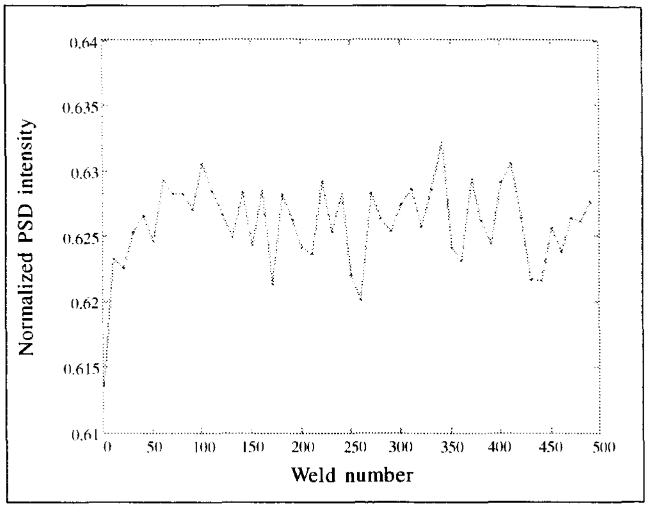

Figure 9
Power Spectral Density Features Extracted from Current Sensor Readings During First 500 Welds

FM-based approach to process performance assessment also includes tests of the FM in recognizing faulty states once those states are presented to it, which would enrich the diagnostic information in the process assessment (knowing not only that "something is happening," but also "*what* is happening"). In addition, forecasting of the process behavior and performance is essential for predictive condition based maintenance, and this problem will be thoroughly investigated in the future work (knowing "*when* something is going to happen"). Historical data on the process performance, as well as the performance of similar systems in operation ("brother-systems"), will be used to facilitate both the diagnostic and prognostic features through this "peer-to-peer" paradigm. Finally, a link must be established with a decision-making module that will enable optimal maintenance action in a timely manner (Chen et al. 2002).

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Authors' Biographies

Nicolas Casoetto is a PhD candidate and graduate research a: the Dept. of Mechanical Engineering at the University of Mich

Dragan Djurdjanovic is an adjunct assistant professor of operations and a research fellow in the Dept. of Mechanical En at the University of Michigan.

Rhett Mayor is a research fellow in the S.M. Wu Manufact search Center at the University of Michigan. He received his PhD BS degrees from the University of Natal, Durban.

Jun Ni is director of the S.M. Wu Manufacturing Research Ce University of Michigan; deputy director of the NSF Engineering Center for Reconfigurable Manufacturing Systems; and co-direc NSF Industry/University Cooperative Research Center for Inte Maintenance Systems. He received his MS and PhD degrees fron versity of Wisconsin-Madison. Dr Ni's research interests manufacturing science and engineering, with special focuses on machining, manufacturing process modeling and control, statist ity design and improvement, micro/meso systems and manufactı cesses, and web-enabled intelligent monitoring, maintenance, ar systems.

Jay Lee is the Wisconsin Distinguished Professor in the Dept. trial and Manufacturing Engineering at the University of Wisco waukee. He is also director of the NSF Industry/University Co Research Center for Intelligent e-Maintenance Systems. Dr. Lee his PhD in mechanical engineering from George Washington U His research interests include innovative design methods for sel nance products, Internet-based machine degradation assessment maintenance, e-factory and e-manufacturing, and business ir strategies.