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Health Indicator Construction For System Health Assessment in Smart Manufacturing

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Abstract—Smart manufacturing is a part of the fourth industry revolution (Industry 4.0), which offers promising perspectives for high reliability, availability, maintainability, and safety production process. Indeed, smart monitoring methods, that are implemented in this kind of manufacturing process, allow efficient tracking of a system degradation in real time through appropriate sensors. Then, the sensor data are analyzed and processed to extract effective health indicators for fault detection, diagnostic and prognostics.

This paper aims to develop a practical methodology for constructing a new health indicator based on heterogeneous sensor measurements to efficiently monitor system states. The proposed methodology is applied to extract the health indicator of a robot cutting tool (i.e. end-flat mill). This indicator is then used to diagnose the different fault types of the tool by an adaptive neuro-fuzzy inference system model.

Index Terms—Smart manufacturing, smart monitoring, industry 4.0, health indicator construction, signal processing, tool condition monitoring.

I. INTRODUCTION

Industry 4.0 is the evolution from automatic systems to cyber-physical systems (CPS) that are fully integrated, automated and optimized [4]. This evolution makes industrial systems more complex and consequently leads to numerous challenges for Prognostics and Health Management (PHM). Indeed, the traditional degradation modeling methods, which are based on the analysis of physical characteristics and system dynamic behaviors, become unfeasible for complex systems. To cope with this complexity, data-driven health monitoring approaches have been developed. They use sensor data to track the system degradation without prior knowledge of the physical nature of the system. The performance of these methods strictly depends on signal processing and health indicator construction techniques.

Considering signal processing methods to construct health indicators, the available studies can be classified into three groups: time, frequency, and time-frequency domain.

In time domain, statistical features (root mean square (RMS), standard deviation (STD), skewness (SKEW), variance (VAR), kurtosis (KUR), crest factor (CF), shape factor (SF),

etc.) are extracted from the raw signals to monitor the asset degradation process [2]. These features are widely used due to their easy implementation and their relation with the system's anomalies [5]. However, these techniques are not viable for noisy signals. They could require preprocessing tasks to enhance the manipulated raw signals before the construction of the health indicators.

The frequency domain analysis allows visualizing the frequency amplitudes by decomposing the signal into a number of discrete frequencies/spectrum of continuous frequencies. For example, the fast Fourier transform (FFT) is used to observe the harmonic frequency amplitudes characterizing faults in planetary gearboxes [9]. This method is easy to implement and detect faults that can be represented by characteristic frequencies (e.g. bearings and gears). However, these frequencies cannot be generalized to all systems.

Finally, the time-frequency domain methods use both time and frequency analysis to construct the health indicator. They are good candidates for non-stationary signals. The most effective techniques used in the literature are the short Fourier transform (SFT), Wigner-Ville distribution (WVD), wavelet transform (WT), and Hilbert Huang transform (HHT) [7] to extract the useful information of the system state. These approaches combine the advantages of the time domain analysis and the spectrum content in the frequency analysis to reduce the uncertainties and false alarms.

Although the traditional features in time, frequency, and time-frequency domain are widely proposed in numerous studies of the literature, the robustness of these indicators was not verified under different operating conditions. In addition, to our humble knowledge, the existing works in the literature do not investigate the health indicator performance with different signal types. This paper aims to fill this literature gap. It proposes a new health indicator that is constructed by a combination of different features in order to efficiently characterize different system states. The robustness and performance of the proposed health indicator are tested on different sensor measurements, and also on various operating

conditions.

The remainder of this paper is structured as follows: Section II presents the global methodology used for the system's health assessment and details the main steps to construct the health indicator. In section III, the performance of the proposed health indicator is highlighted through numerous experimental tests carried out on a robot cutting tool. Finally, the conclusion and perspectives of this work will be presented in section IV.

II. METHODOLOGY FOR SYSTEM HEALTH ASSESSMENT

This section aims to present the main steps to monitor and assess the health state of a given system. The methodology goes from system analysis to fault detection and diagnostics [1, 2] as shown in Fig. 1.

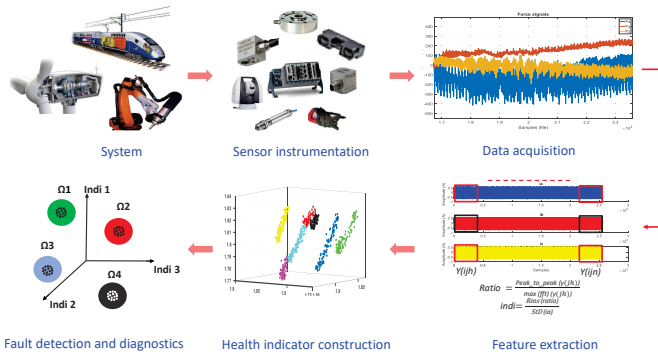


Fig. 1: General overview of the proposed methodology.

First, it is necessary to analyze the system to identify the critical components leading to the system failure [2]. Once the critical components are identified, it is important to define the appropriate physical parameters to be observed and the instrumentation of the sensors to track the component degradation process. The data recorded will then be injected into signal processing algorithms to extract relevant features and build health indicators. Finally, the health indicators will be used to create a model for fault detection and diagnostics (FDD) of the studied system.

Among the system health assessment process, this paper focuses on the health indicator construction step. The developed health indicator is a combination of different features, that are extracted from both time and frequency domains. Its performance is verified on different operating conditions and also on various signal types. In details, the current (i_a, i_b, i_c), the vibration (acc_a, acc_b, acc_c), the force (F_a, F_b, F_c) and the torque signals (T_a, T_b, T_c) are used to illustrate the health indicator effectiveness. The main steps of the proposed methodology are presented hereafter.

- 1) **Load and split every measured signal into Ne observations of length L :** This step, illustrated in Fig. 2, allows reducing the data size for signal processing and takes only the relevant features. It splits the signals into

Ne segments denoted y_{ijh} of length L , where i and j characterize the signal types (current, vibration, force and torque) and the axes ($i_a, i_b, i_c, acc_a, acc_b, acc_c, F_a, F_b, F_c, T_a, T_b, T_c$) respectively with h representing the segmented signal samples ($h \in [1...Ne]$).

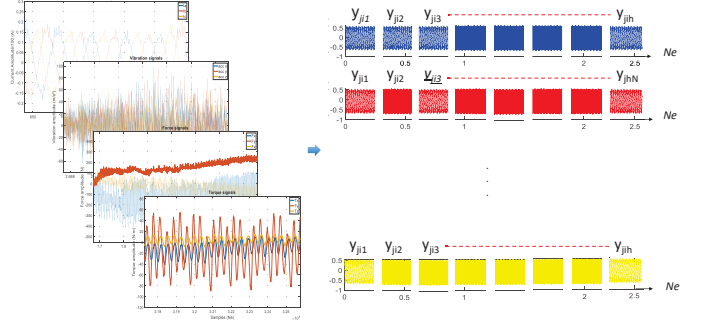


Fig. 2: Sampling signals of different measurements.

- 2) **Signal processing:** Considering Fig. 3, each signal segment is divided by the max value of the segment spectrum, $\max(\text{FFT}(y_{ijh}))$. This step is inspired by the results obtained in [6]. It allows limiting features dispersion caused by load variations and then separating the classes that represent different load levels of the operating mode.

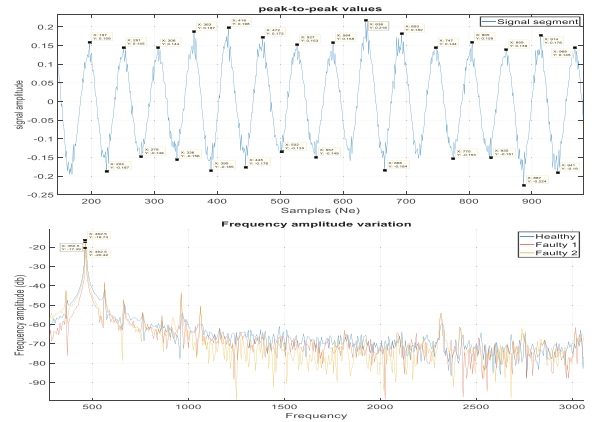


Fig. 3: Time and frequency domain analysis.

- 3) **Feature extraction from every signal window y_{ijh} :** This step aims to extract the statistical features from the splitting signals to construct the health indicator (HI). Its expression is denoted by the following equation:

$$HI = \left(\text{KUR}(y_{ijh}) \times \text{VAR}(Y_{ij})^2 \right) \quad (1)$$

The KUR and VAR are respectively the kurtosis and the variance values. The kurtosis measures the segmented signal flattening, which indicates the impulsive property of the signal by the centered moment of order 4 of the segmented signal y_{ijh} [8]. It reduces signal's noises due

to the sensor measurement. The variance measures the dispersion of the signal Y_{ij} [8].

$$KUR = \frac{\frac{1}{ne} \sum_{n=1}^{ne} (y_{ijh} - \bar{y}_{ijh})^4}{\left(\frac{1}{ne} \sum_{n=1}^{ne} (y_{ijh} - \bar{y}_{ijh})^2 \right)^2} \quad (2)$$

$$VAR = \frac{1}{Ne} \sum_{n=1}^{Ne} (Y_{ij} - \bar{Y}_{ij})^2 \quad (3)$$

where \bar{y}_{ijh} and \bar{Y}_{ij} are respectively the mean values of the segmented signal and the total signal.

- 4) **Construction of health indicators:** The obtained results by (1) are used to construct the health indicators to detect the system's anomalies and also to classify the different system's states. Note that the use of one sensor measurement, for example only the phase a of the current, is not sufficient to detect different fault types. The combination of several health indicators obtained from sensor measurements, for example, all the three phases of the current, is necessary to clearly separate different system's states. The health indicator presentation is therefore changed from one dimension to three dimension space. In detail, the obtained vector from each signal is used to build the health indicator matrix as illustrated hereafter.

$$indi_{ijh} = \begin{pmatrix} indi_{ij1} & indi_{ij1} & . & . & . & indi_{ij1} \\ indi_{ij2} & indi_{ij2} & . & . & . & indi_{ij2} \\ indi_{ij3} & indi_{ij3} & . & . & . & indi_{ij3} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ indi_{ijNe} & indi_{ijNe} & . & . & . & indi_{ijNe} \end{pmatrix}$$

III. CASE STUDY

This section presents the case study used to highlight the performance of the proposed health indicator. The test bench is a six-axis robot used for machining an aluminum blank, see Fig. 4. This robot is composed of six servo-drive motors to control the robot-arms positions. At the sixth axis of the robot, a tool is placed for machining the workpiece. The machining tool contains the unit (flat-end mill) that is the most critical component in the machining processes. To assess the component's health state, current, vibration, force, and torque measurements are the most suitable parameters to monitor this kind of process. First, the subsection (III-A) describes the experimental process. Then, the subsection (III-B) verifies the performance and robustness of the proposed health indicator on different operating conditions. Finally, the fault diagnostics results are presented in the subsection (III-C).

A. Test bench description

The overall scheme of the test bench is presented in Fig. 4. It is installed at METALLICADOUR, a resource and technology transfer center in the south-west of France.

In detail, a three-phase synchronous motor drives a cutting tool. This latter is used for machining aluminum blanks by 4 level steps of 5 mm as marked in green color in Fig. 4. Note that the cutting tool contains three cutting edges. In the case study, four components are used to achieve the experimental tests. The first one represents a new tool. The second, third and fourth tools represent different degraded states. These states are respectively the first, the second cutting tool defect, and the broken tooth state, see Fig. 5.

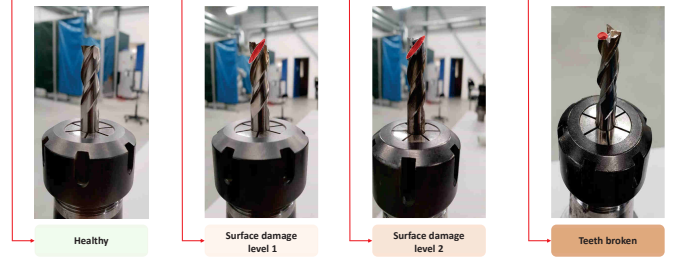


Fig. 5: Illustration of different tool experiences.

Concerning the machining process, the manufacturing of an aluminum blank is investigated. This object is a small part used in aircraft. The machining parameters, which correspond to two different operating conditions (i.e two cutting depth level) of the machining process, are summarized in table I.

Regarding the data acquisition part, firstly, three-axis force and torque sensors are placed at the sixth axis of the robot. Secondly, the three axes vibration sensors are placed as near as possible to the cutting tool. Finally, the three-phase current sensors are placed at the output of the inverter of the machining tool. The sensor data are then recorded by a National Instrument software (Labview) with a sampling frequency of 25.6 kHz and a duration of 40 seconds. These data are saved in *csv* files of 5 seconds of data in each file.

TABLE I: Machining parameters for experimental tests.

Cutting depth (mm)	Feed rate (mm/mn)	Speed (rpm)	Health state HS
5	1890	14000	Healthy
5	1890	14000	Faulty 1
5	1890	14000	Faulty 2
5	1890	14000	Faulty 3
10	1890	14000	Healthy
10	1890	14000	Faulty 1
10	1890	14000	Faulty 2
10	1890	14000	Faulty 3

B. Investigation of the proposed methodology performance

In this subsection, the performance of the proposed health indicator is highlighted when compared with the classical ones proposed in the literature, such as (STD and KUR). The results are shown in Fig. 6.

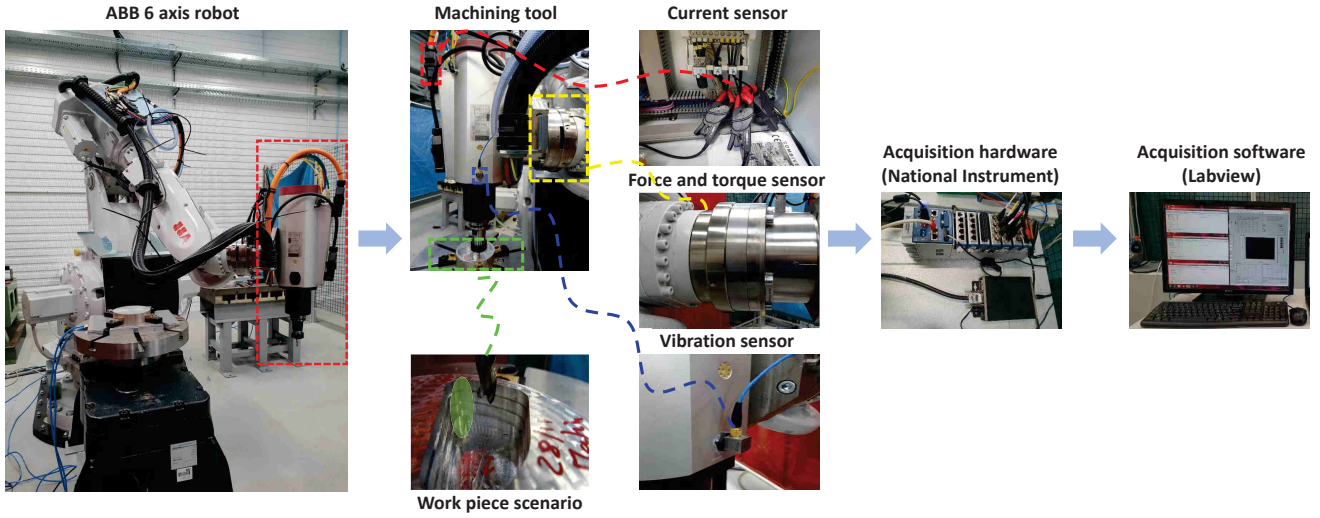
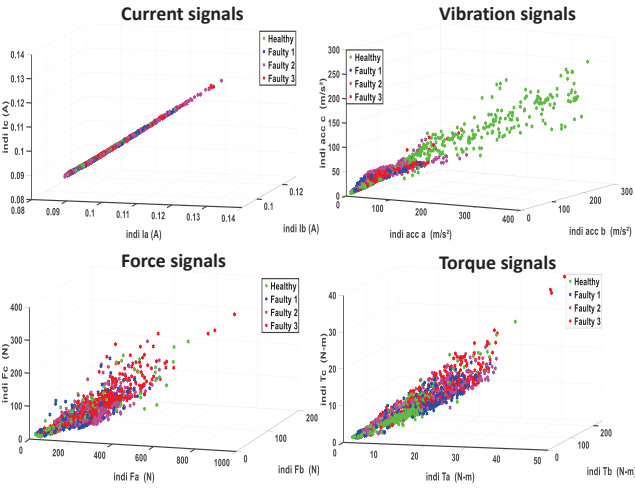
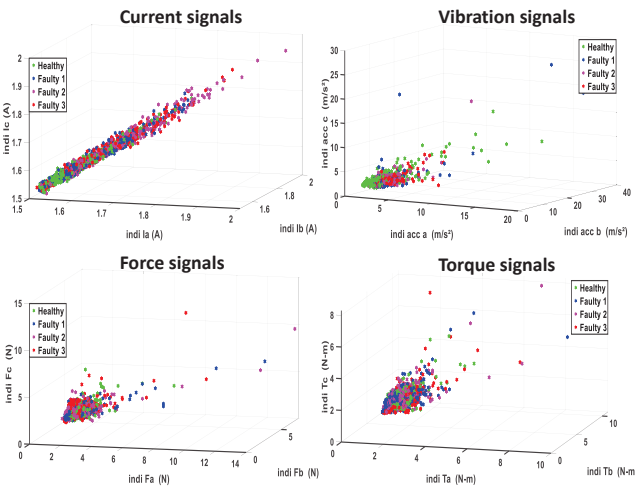


Fig. 4: Overall scheme of the test bench.



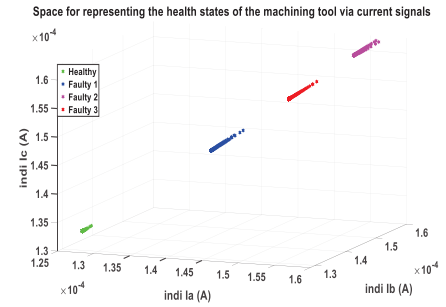
a) Health indicator construction using STD value.



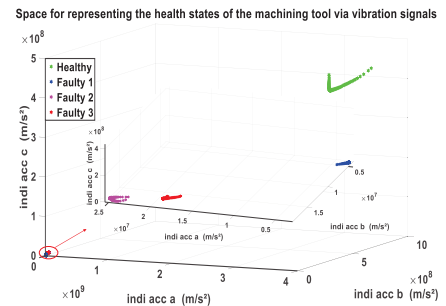
b) Health indicator construction using KUR value.

Fig. 6: Health indicators construction with traditional features.

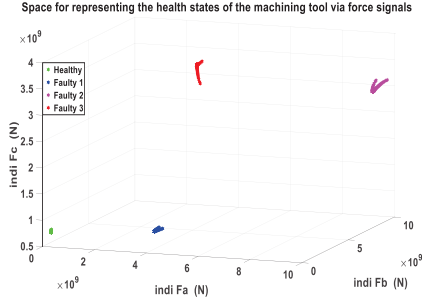
Fig. 6 shows clearly that the traditional features (STD and KUR) proposed in the literature presents a large dispersion of the observations in the same group. Thus, one can conclude that when using these traditional features, different system health states cannot be detected. Next, the performance of the proposed health indicator is then proved when considering all signal types: the current, the vibration, the force, and the torque signals. First, the proposed HI is used to diagnose different states of the cutting tool that works in the first operating mode (5 mm , $1890\text{ mm}/\text{mn}$, $14000\text{ tr}/\text{mn}$).



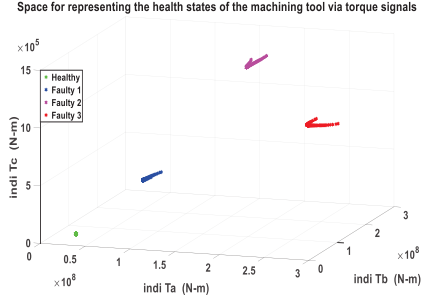
a) Three-phase current indicators.



b) Three-axes vibration indicators.



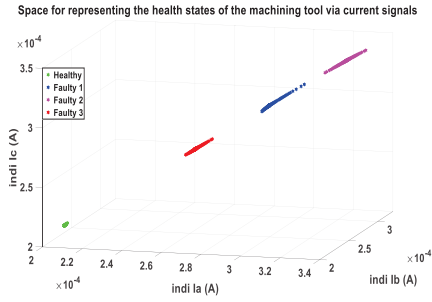
c) Three-axes force indicators.



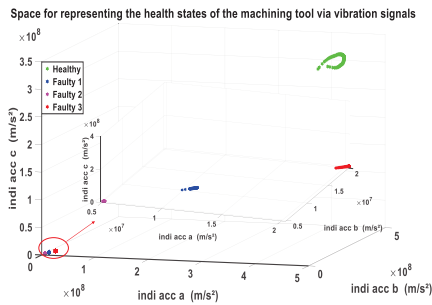
d) Three-axes torque indicators.

Fig. 7: Health indicators construction for TCM in first operating condition: 5 mm, 1890 mm/mn, 14000 tr/mn.

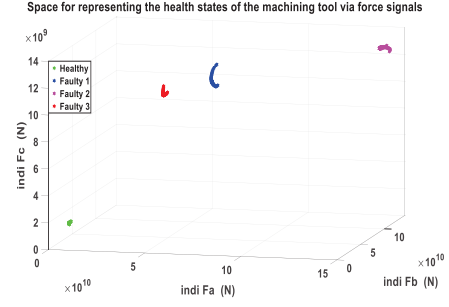
From Fig. 7, it can be seen that the proposed methodology allows clearly separating different health states of the cutting tool, regardless of the signal type. In addition, another operating mode (10 mm, 1890 mm/mn, 14000 tr/mn) is investigated to highlight the HI performance.



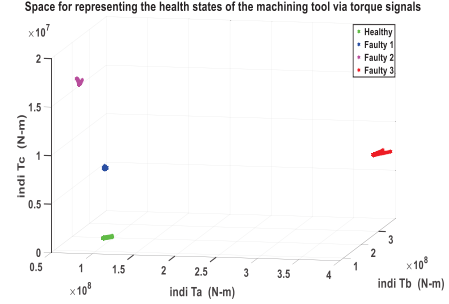
a) Three-phase current indicators.



b) Three-axes vibration indicators.



c) Three-axes force indicators.



d) Three-axes torque signals

Fig. 8: Health indicators construction for TCM in first operating condition: 10 mm, 1890 mm/mn, 14000 tr/mn.

Fig. 8 shows also a negligible dispersion of health indicator observations within a group and a large distance separation between different groups representing the tools health states. This proposed methodology offers a promising way for assessing the system's health, e.g. when using the current sensors, which are not expensive and are easy to mount on the machine without perturbing the machining process.

C. Fault classification

In this section, to verify the fault detection and diagnostics performance, the constructed health indicators matrix is divided into two sets: training (50%) and testing sets (50%). In this application, the number of considered system's states is equal to 4 denoted by s , where $s = 1$ represents the healthy state and the rest of the values correspond to three fault types. The training set is used to train an ANFIS model [3] to classify tool's states.

The classification results obtained by ANFIS are verified by considering two operating conditions, see table I. It can be seen that, in all cases, the accuracy score given by the ANFIS classifier is 100%.

TABLE II: Accuracy score (%) using ANFIS at different operating modes. 2 operating modes: C1 (5 mm, 1890 mm/mn, 14000 tr/mn), C2 (10 mm, 1890 mm/mn, 14000 tr/mn).

Case	C1	C2
ANFIS	100	100

IV. CONCLUSION

In this paper, a new health indicator has been presented for a system's health assessment. This HI is a combination of statistical features extracted from the time and the frequency domains. Then, the proposed HI is fed into the ANFIS model to classify the different health states of the monitored system. The methodology performance was highlighted when investigating a machining robot test bench, where the studied system was a cutting tool (end flat mill), that is used for milling an aluminum workpiece. The experiment tests were performed in different operating conditions and monitored by different parameters (current, vibration, force, and torque signals) in three-dimensional space. The obtained results highlighted the robustness of the proposed health indicator regardless of the system operating modes and of the signal types.

As a perspective of this work, the proposed health indicator will be applied in different complex systems with various operating conditions to investigate its robustness and effectiveness.

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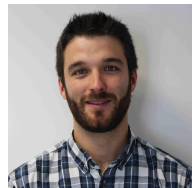
Since September 2006, Prof. Medjaher leads research works in the field of prognostics and the health management of industrial systems.



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