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Sensor Selection and Location Scheme for Prognostic and Health Management

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Abstract: The performance of electronic vehicle PHM relies not only on the diagnostic and prognostic algorithms used, but also on the types, location, and number of sensors selected. The paper firstly presents the architecture for PHM. Sensor localization and selection for fault diagnostic purposes is the importance part. It introduces the new sensor approach for PHM, such as smart sensor. Sensor localization and selection for fault diagnosis has been studied. A novel scheme for a diagnostic and prognostic system to integrate the functions of sensor localization and selection, feature extraction, mode identification, fault diagnosis and prognosis is introduced. The detailed process includes modeling, FMECA research, FOM, optimization algorithm and performance assessment .The algorithm combines particle swarm optimization method with a heuristic search algorithm to solve the NP question. *Copyright © 2013 IFSA.*

Keywords: Sensor location, Sensor selection, Particle swarm optimization, Prognostic and Health Management.

1. Introduction

The electronic vehicle will require significantly improved system prognostic health management (PHM) capabilities. The systems that require human intervention or monitoring from critical functions overall are impediments to realization of cost-effective. Because the potential problems with the electron vehicle or habitat must be identified before they cause irreparable harm. They will have to incorporate technologies that will allow sensor system to monitor component conditions, analyze the incoming data, provides caution and warning if necessary or optimize system operations to improved performance and reliability. When some problems do occur, some prognosis, diagnosis, and remediation are necessary, that is, the electronic vehicle will need integrated intelligence PHM systems.

A typical PHM architecture is shown in Fig. 1. The objective of PHM is to diagnose a fault (incipient failure) as early as possible and to prognostics the remaining useful lifetime of the faulty component. It includes sensor/sensing, dada preprocessing, feature extraction, diagnostics, prognostics, and Condition-Based Maintenance. Each module is very critical to performance of the overall system. Diagnostics, or Fault Detection and Identification, attempts to recognize impending or incipient failures in processes and systems and forms a solid basis for the PHM. Fault diagnosis is a relatively mature field with contributions ranging from model-based techniques to data-driven configurations that capitalize on soft computing and other "intelligent" tools. At last, the objective is to predict the advent of failure in terms of a distribution of remaining life, level degradation, or probability of mission survival.

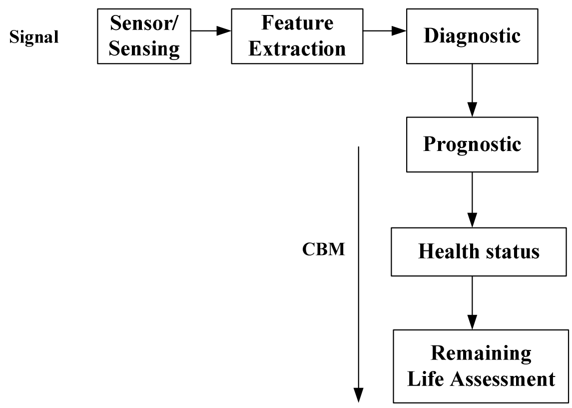

Fig. 1. PHM architecture.

One component of PHM system in particular that will need to be improved is the sensor/sensing, namely, sensors and their associated data acquisition systems, packaging, communication, power, etc. High quality data provided by sensing system is the foundation of PHM.

The paper is intended to give an overview of some of the major issues related to sensor technology and sensor location for PHM applications.

2. Sensor Technology Approaches

A sensor is defined as a device that provides useable output signal in response to a specified measured. A sensor generally translates physical, chemical, or biological phenomena into electrical signals utilizing physical or chemical effects or through conversion of energy from one from into another widely used in both analog and digital instrumentation systems, sensors provide the interface between electronic circuits and the physical world.

A significant change in approach to sensor and instrumentation technology will be the design and inclusion of intelligent into the electronic from the planning stage forward. The ability will be first considered at the same time as the other subsystems. It includes the application of intelligence enabling technology to gather and interpret the relevant information. So sensor technology, as well as PHM, will be integrated into the electronic vehicle from the beginning, not added as an afterthought.

The relevant performance of sensor system includes:

1) Accuracy: the closeness of agreement between the measurement and the true of measured quantity.

2) Sensitivity: the variation of output with respect to a certain variation in input.

3) Precision: the number of significant of digits to which a measured can be reliably measured.

4) Uncertainty: the range of values which contain-ns the true value of the measured quantity.

5) Repeatability: closeness of the agreement between the results of successive measurements of the same measured carried out under the same conditions.

The sensor needs of electronic vehicle are very different than those of other systems. Each application area has different requirements for sensor systems. However, a common thread of technology attributes enables the sensor technology to be useful no matter the stage of implementation. It is the overall combination and balance of these attributes than can enable improved sensor systems.

1) Ease of Application.

Sensor system developed, including the use of nano-fabrication, optical techniques, etc. will enable multipoint inclusion of complete sensor system throughout the vehicle without significantly increasing size, weight, and power consumption. It becomes as easy as "licking and sticking".

2) Reliability.

Senor systems have to be reliable. We must be able to believe the data reported by the systems and have trust in the ability of the sensor systems to respond to changing situations.

Redundancy and cross-correlation

Multi-parameter sensor systems, that is, those which can measure multiple PHM measured at the same times, can be combined together give full field coverage of the system parameters but also allow cross-correlation between the systems to improve reliability and the system information.

3) Orthogonal.

The information provided will be orthogonal. Each provides a different type of information. Because a single measurement is often not enough to give situational awareness, the mixture of techniques to "see, feel, smell, and hear" can combine to give complete information.

A new generation of sensor technology with new capabilities is necessary to incorporate these attributes as a whole. The following discusses smart sensor technology and Wireless Sensor Networks.

Smart sensors are one of the essential components of PHM systems. Smart sensors are defined as basic sensing elements with embedded intelligence, capable of networking among themselves and with higher-level systems to provide both process data and data validity qualifiers to assess measurement health. This novel sensor will possess embedded intelligence to provide the end user with critical data in a more rapid, reliable, and efficient manner. Embedded intelligence, such as self-calibration, self-health assessment, self-healing, and preprocessing or raw data, will provide for a more reliable and robust system. New methods of sensor communication architectures are being investigated, such as arranging sensors in networks.

Smart sensors allow a PHM architecture that relies on acquiring information from smart sensors and actuators, processing this information, comparing the information provided by the sensor's embedded knowledge to its own knowledge information system, and establishing the health of the system. Smart sensor provides several functional layers: signal detection, signal processing, signal validation, and signal transmission.

One approach to smart sensors is to have an embedded "Smart Sensor Agent" (SSA) on each sensor. The SSA module is the heart of the smart sensor architecture. It contains the smart sensor's main processor. The SSA module executes the operation and contains the embedded intelligence that enables the smart sensor to perform sensor and health management function.

This novel generation of smart sensors will form PHM systems capable of predicting the near-term and long-term health issues of the system being monitored.

3. Sensor Selection and Location

System performance of PHM is strongly dependent on available sensor measurements. Inaccurate measurements resulting from improper sensor localization and selection or insufficient measurements can significantly deteriorate system performance.

Sensor localization and selection for fault diagnosis has been studied at two different levels: component level and system level (Fig. 2).

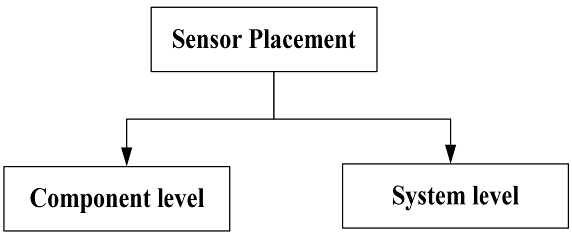

Fig. 2. Two views of Sensor placement.

The sensor placement problems attempted to position sensors in a component's range. Critical systems of interest are characterized as large scale systems consisting of multiple components. For such systems, a fault may propagate through the other components when it happens. So, it is possible that sensors can be located at any of the components to detect the fault. With hundreds or thousands of possible locations of sensors in a system, the selection of a crucial and optimum sensor location, sensor types, and number of sensors poses an critical problem that needs to be solved at the system level before the detailed spatial distribution in a component can be determined.

Although a large body of research work has emerged on, the various approaches vary only in their choices of the three basic components (Fig. 3): model, Figure-of-Merit (FOM), and optimization algorithm. The following discussion of sensor placement is based on these.

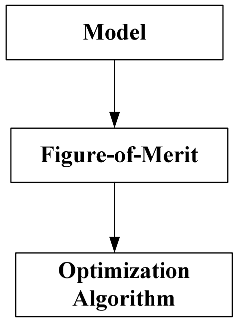

Fig. 3. Basic components of sensor placement.

3.1. Component Level

The models used at this level are usually mathematical models or data-driven models. In a mathematical model, the physical system must be described through the application of scientific or physical principles. A mathematical model is precise without considering disturbances and is suitable for qualitative and quantitative analysis when it is applied. However, building a mathematical or physical model requires a thorough understanding of the physical system, a difficult task for a complex system with highly nonlinear dynamics coupling a variety of physical phenomena in the temporal and spatial domains, especially the modeling for the system of systems.

The data-driven model is a black-box model that requires very large number of useful data. Many intelligent tools can be used as the modeling tools. For example, a neural network is trained when it is fed enough template data and makes a decision based on the knowledge it has learned from the data. Theoretically, if it is given enough useful data, the neural network will be able to simulate a real system very well.

Based on the objective function or a FOM, it needs to be defined. After a FOM is selected, an algorithm needs to be decided to optimize this FOM. Various optimization algorithms, from random search to heuristic algorithms such as Genetic Algorithms (GAs), have been used for optimizing the sensor location and selection. Random search is suitable for a small and simple sensor placement problem since it is straightforward and easily implemented. But it is time consuming and inefficient when dealing with a large system. Genetic Algorithms, based on the Darwinian principle of natural selection, are widely applied in different domains, among the heuristic methods.

3.2. System Level

Now the interest has been focused on the sensor placement problem for fault diagnosis at the system level.

For the purpose of fault detection and identification recently, Cause-Effect analysis methods, Petri-Net method, and fault tree method, have been widely used as the modeling tools for the sensor location problem for fault diagnosis at the system level because of their simple graphical representations of the process.

Many factors can contribute to a FOM. The optimal location to obtain information for detecting different system component faults was determined based on the criteria of maximal sensitivity with respect to the variations of that component by analyzing sensitivity function. The observed and reliability may be as the FOM for locating sensors.

Particle swarm optimization (PSO) shares lots of similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches by updating generations. But, unlike the GA, PSO has no evolution operators such as cross-over and mutation. In PSO, the potential solutions, called particles, put through the problem space by following the current optimum particles.

4. Sensor Location for Fault Diagnosis and Prognosis

With advancing on computing power, the diagnostic and prognostic techniques are becoming more efficient in detecting the presence of a fault and predicting the remaining useful life time of a faulty component. Meanwhile, optimum type, number, and sensor localization and selection improve the diagnostic and prognostic capabilities of PHM systems.

The sensor localization and selection entails several functional modules: requirements analysis, Failure Mode and Effects Criticality Analysis (FMECA) study, quantitative model, FOM, optimization, and performance assessment. It is shown in Fig. 4. It illustrates how the sensor localization and selection modules are integrated together and interconnect with a diagnostic and prognostic system.

First, in the requirement analysis module, sensor localization and selection requirements are analyzed and basic definitions needed for other modules are provided. Secondly, since the purpose of sensor localization and selection in our research is to achieve maximum fault detection performance with applicable constraints, it is critical to analyze and understand each fault mode/failure mode. A FMECA study is widely employed to identify failure modes and specifies severity of failures and frequency of their occurrence.

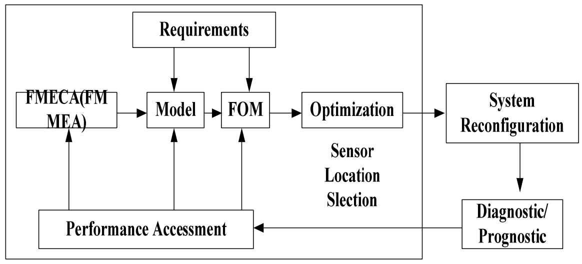

Fig. 4. Sensor localization and selection scheme.

With the information from the FMECA study and the definition given in the requirements analysis module, a quantitative model, Quantified-Directed-Graph (QDG) model is introduced to build the fault propagation model quantitatively in the proposed architecture. The thorough analysis of the sensor localization and selection requirements is also employed to establish a generalized FOM to cover the most important issues in current research. Having selected a generalized FOM, a popular evolution computation technique, particle swarm optimization, is employed considering the rich heuristic information during sensor localization and selection process.

Finally, with selected sensors for fault diagnosis, systems are configured for on-line or off-line diagnostics and prognostics and the diagnostic performance is evaluated through a performance assessment module. Meanwhile, the feedback information from the performance assessment module is utilized by the other sensor localization and selection modules to fine-tune the selected sensors and improve the on-line diagnostic performance.

4.1. FMECA Research

FMECA research identifies failure modes and specifies the severity of failures and time of their occurrence. If the consequence of a fault is more severe, or the occurrence is more frequent, higher detected and fault detection reliability requirements must be imposed on. Based on the FMECA research, failure modes are classified according to their severity and time of occurrence.

The severity index categorizes a failure mode according to its consequence. The severity index is defined on a scale from *a* to *f*, with f being the most severe. The time of occurrence can be defined on a scale from 1 to 8 with 1 being the lowest probability to occur.

Different approaches, such as Petri nets and fault trees are available to model the fault propagation. But Quantified Directed Graph (QDG) model is proposed to simplify it.

Possible type and possible location of sensors can be determined by scanning all the sensors in the fault propagation path. If a propagation path exist from fault j to sensor k, and the propagation gains along the path are then the propagation gain of this path can be calculated by multiplying all the propagation gains along the path. If multiple propagation paths exist from fault j to sensor k, then the overall propagation gain from the fault j to sensor k is defined as the summation of all the propagation gains of each path, and the time-to-detection of sensor k to fault j is defined as the minimum propagation time of all the paths. So, sensor fault detected can be calculated using the QDG model.

4.2. FOM

The proposed FOM maximizes the fault detected and minimizes the required number of sensors while achieving sensor localization and selection. The FOM is in the form of the weighted sum of the fault detected and the numbers of sensors. The weights may be adjustable and are mainly determined by the severity of failure effects and the probability of failure occurrence.

Optimize sensor locations and optimize selected sensors may be the two main tasks. Because the model of FOM is a NP question, to reduce the optimization scale, an optimization algorithm is proposed in this research to optimize the formularized FOM. This algorithm combines PSO method with a heuristic search algorithm. The possible number of sensor locations is optimized based on particle swarm optimization method and the sensors selected for each fault is selected based on a heuristic search algorithm.

In the optimization module, the number of sensors is not long, but also the sensors selected for each fault needs to be determined. In the worst case, the maximum optimization variables will be large. In order to reduce the optimization number, an algorithm is proposed in this research to optimize the formularized. This algorithm combines PSO method with a heuristic algorithm. We need to convert the NP problem to a standard PSO problem. Because the number of sensors at each location is a discrete variable, the real number variables need to be rounded to integer numbers.

An important issue is how to select sensors for each fault to achieve maximum FOM based on the sensors selected. The step is the following.

Check every possible sensor for our requirements, and find the sensor with maximum detected that meets all the constraints. If several sensors have the same detected, select the one with maximum reliability; if no such sensor exists, the constraints cannot be met and penalty will apply, go to step b.

Try to find another sensor in the set with detected greater than the current fault detected and the probability. And calculate current FOM on the basis of the selected sensors.

So, the proposed sensor localization and selection approach based on the QDG model is able to detect faults with high detected and have a small number of sensors.

4.3. Performance Assessment and Reexamined

The performance of the sensor localization and selection strategy is validated and verified in the diagnostic and prognostic scheme for PHM system.

The core of the performance module is to estimate the fault detection error rate with selected sensor. For every fault, Single False Positive Rate (SFPR) and Single False Negative Rate (SFNR) are defined as the performance metrics [5].

$$SFPR = \frac{\text{Number of misfired faults}}{\text{Number of faults interested}} \tag{1}$$

$$SFNR = \begin{cases} 1 \text{ if the fault is detected} \\ 0 \text{ if the fault is not detected} \end{cases} \tag{2}$$

The Average False Positive Rate (AFPR) and the Average False Negative Rate (AFNR) may define in the flowing equations.

$$\text{AFPR} = \frac{\sum SFPR}{\text{Number of faults interested}} \tag{3}$$

$$\text{AFNR} = \frac{\sum SFNR}{\text{Number of faults interested}} \tag{4}$$

If the performance is not satisfactory, i.e., the SFPR, SFNR, AFPR, or AFNR does not meet predefined specifications, the sensor may not be well selected for fault diagnosis. Sensors need to be reselected, and the following steps can be taken, which is also shown in Fig. 5.

The detected weights can be adjusted in the FOM accordingly. The detected and the reliability definitions can be adjusted according to the diagnostic performance information. Finally by going back to the FMECA study level, the fault propagation and fault cause effect relationships can be re-examined.

5. Conclusions

The paper presents the common architecture for PHM. It is importance that sensor localization and selection for fault diagnostic purposes. And it introduces the new sensor technology for PHM, such as smart sensor. Sensor localization and selection for fault diagnosis has been studied. By improved a novel scheme for a diagnostic and prognostic system to integrate the functions of sensor localization and selection, feature extraction, mode identification, fault diagnosis and prognosis is introduced. The detailed process includes modeling, FMECA research, FOM, optimization algorithm and performance assessment. Because the algorithm combines particle swarm optimization method with a heuristic search algorithm to solve the NP question. This scheme will have practical application.

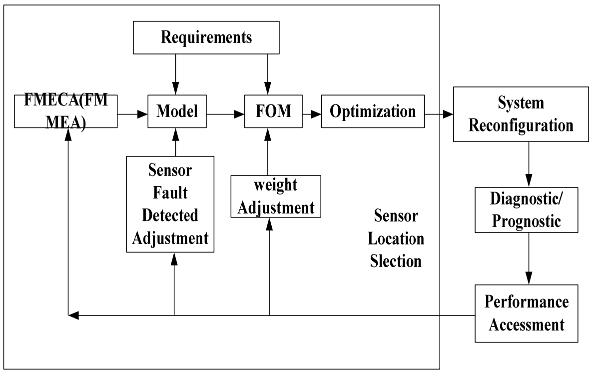

Fig. 5. Sensor reselection with Performance Assessment Feedback.

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