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ASPECTS OF SENSOR LOCALIZATION AND SELECTION IN CONDITION BASED MAINTENANCE

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Abstract : Life-cycle maintenance has been an important factor in modern industrial companies competitiveness and has lately been attracting more attention in industry. The objective of maintenance is to reduce the number of unexpected breakdowns due to failures, which may be catastrophic and may incur huge loss. Many industrial companies have shifted their maintenance programs to condition-based maintenance (CBM), which, if correctly and effectively implemented, can significantly reduce the maintenance cost by cutting down the number of unnecessary scheduled preventive maintenance operations.

1. INTRODUCTION

The advancement of communication and network technologies has impacted maintenance with multiple technologies. In the case of CBM, preventive actions are taken when symptoms of failures are recognized through monitoring or diagnosis.

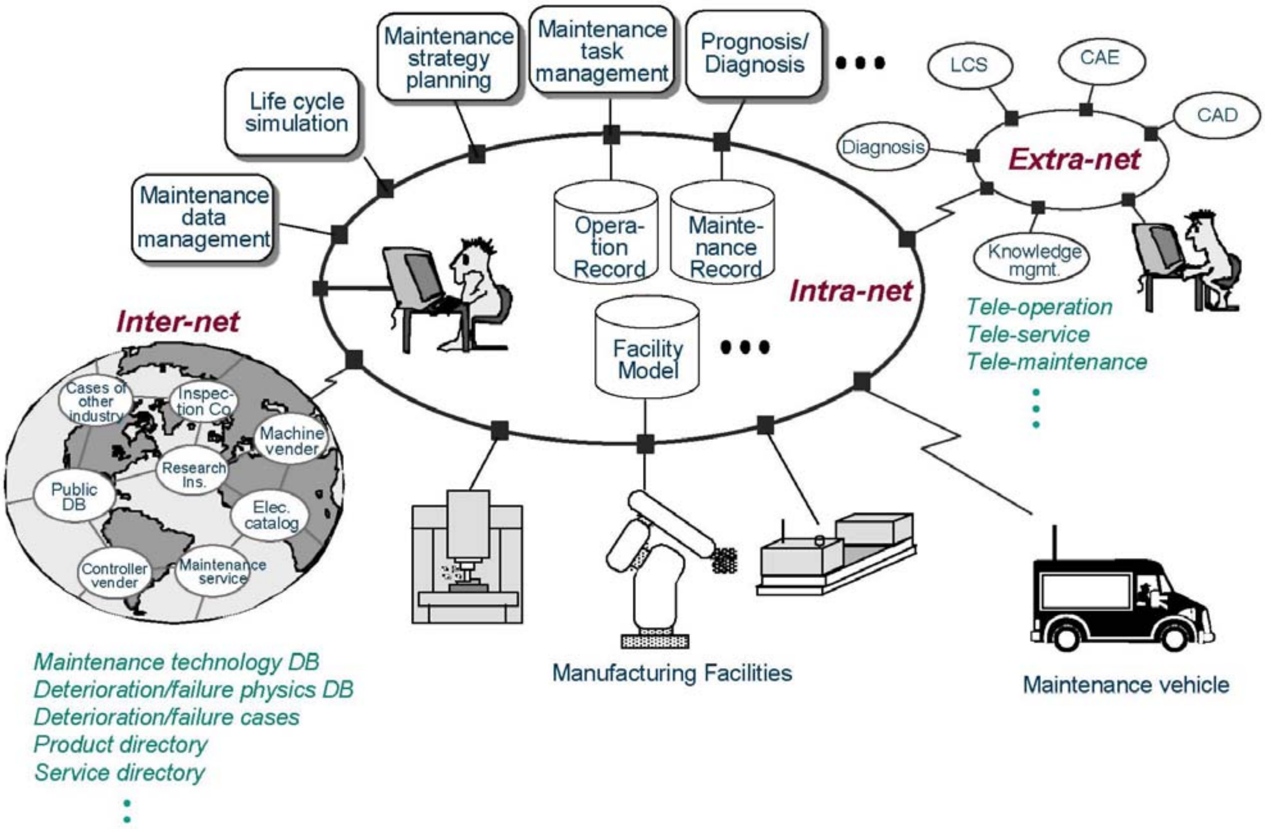

Fig. 1. Concept of a web-based CBM system [2].

CBM enables taking the proper actions at the right timing to prevent failures, if there is a proper diagnostic technique. However, CBM is not always the best method of maintenance, especially from the perspective of cost effectiveness. When failures of machines or components are not critical, we can allow breakdown maintenance (BM), in which actions are taken after failures are detected. Figure 1 [2], illustrates a concept of a complex network-based CBM system.

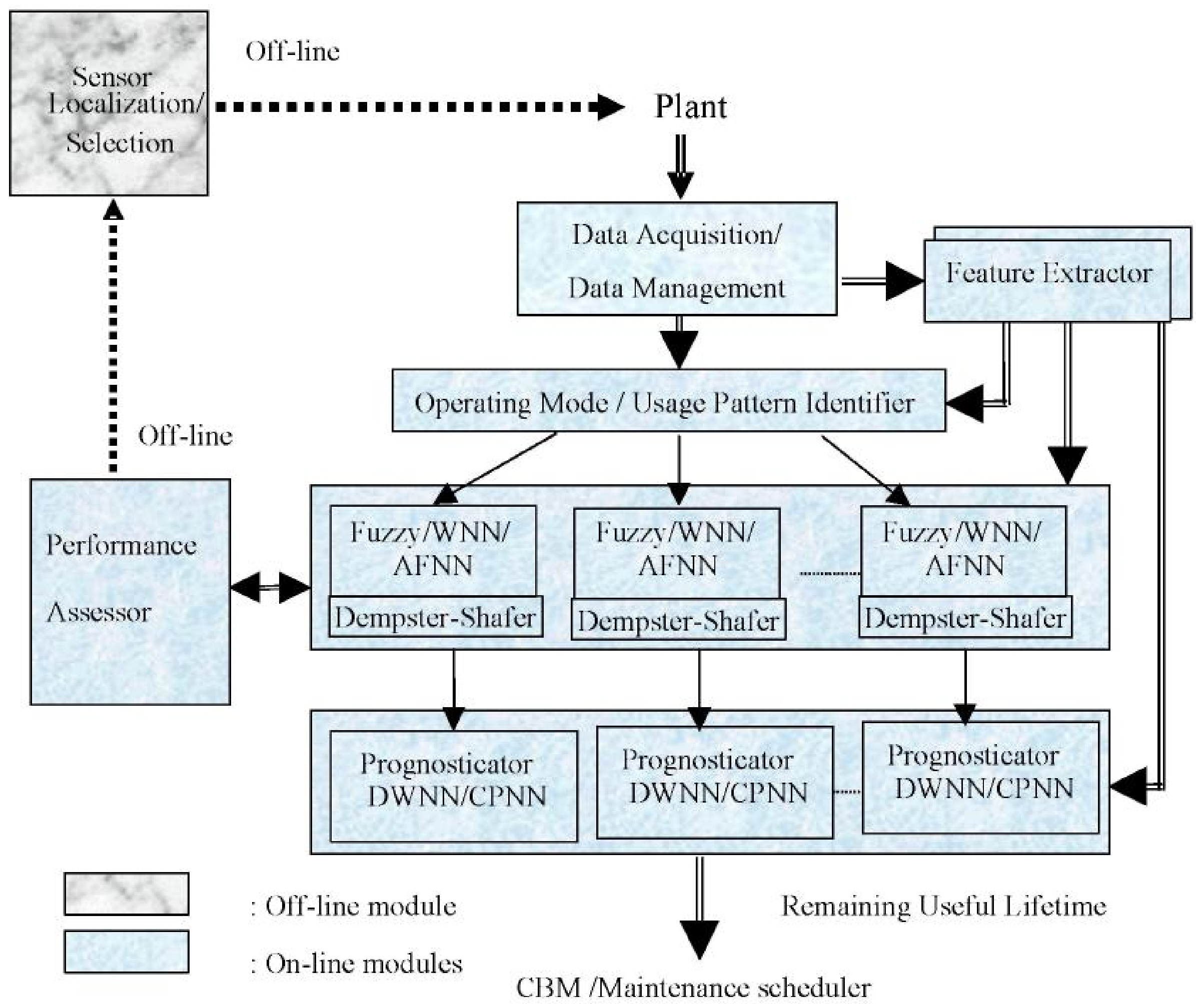

Fig. 2. Integrated CBM system architecture with diagnostics and prognostics [1].

An integrated CBM system architecture with diagnostics and prognostics (figure 2) consists of several on-line modules and an offline module as follows [1] :

- Data Acquisition (DAQ) - Data Management Module: provides an interface for data acquisition from real systems or other software.
- Feature Extractor (FE) : extracts useful information in the form of a feature vector from the raw sensor data according to the requirements imposed by diagnostic and prognostic modules.
- Operating Mode and Usage Pattern Identifier : decides upon a specific operating mode and usage pattern of the system.
- Classifier: employs the Dempster-Shafer theory as a knowledge fusion tool to combine the classification results from a fuzzy inference engine, static Wavelet Neural Networks (WNN), and an Arrangement Fuzzy Neural Network (AFNN). The occurrence of a fault mode is determined and identified on-line based upon the fusion result.
- Prognosticator: capitalizes upon a virtual sensor to provide fault dimensions and a dual approach to prediction — a Dynamic Wavelet Neural Networks (DWNN) (supervised / unsupervised) for fault trending and a Confidence Prediction Neural Network (CPNN) assisted by the Fuzzy Analytic Hierarchy Process (FAHP) aimed primarily at accommodating causal adjustments to the prediction curve and managing uncertainty bounds.
- Performance Assessor: assesses the performance of modules.

2. SENSOR LOCALIZATION AND SELECTION ARCHITECTURE

On of the most important component in CBM implementation is sensor localization and selection (SLS). The purpose of SLS is to specify the types, location, and number of sensors for fault and health diagnosis. Sensor localization and selection entails several functional modules: requirements analysis, Failure Mode and Effects Criticality Analysis (FMECA) study, quantitative model, Figure-of-Merit (FOM), optimization, and performance assessment, as shown in figure 3 [1]. This illustrates how the sensor localization and selection modules are integrated together and interconnect with a diagnostic and prognostic system.

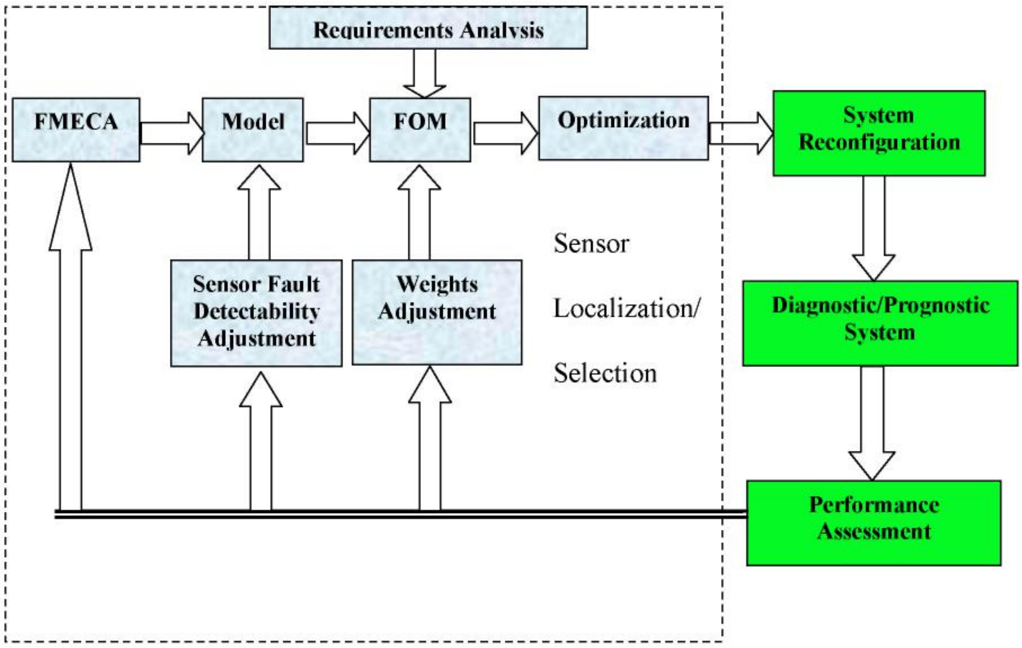

Fig. 3. Sensor localization and selection architecture [4].

In the requirement analysis module, SLS requirements are analyzed and basic definitions needed for other modules are provided. Since the purpose of SLS is to achieve maximum fault detection performance and health accuracy with applicable constraints, it is critical to analyze and understand each fault mode and failure mode. A FMECA study is widely employed to identify failure modes and specifies severity of failures and frequency of their occurrence. The SLS is focused on qualitative analysis that usually leads to a qualitative fault propagation model. 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 SLS requirements is also employed to establish a generalized Figure-of-Merit (FOM) to cover the most important issues. Having selected a generalized FOM, a popular evolution computation technique, particle swarm optimization, is employed considering the rich heuristic information during sensor localization/selection process. With selected sensors for fault diagnosis, systems are configured for on-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 SLS modules to fine-tune the selected sensors and improve the on-line diagnostic performance.

Four main requirements need to be met to optimally place sensors for fault diagnostic purposes: detectability, identifiability, fault detection reliability, and a requirement associated with limited resources. Meanwhile, sensor uncertainty needs to be addressed since uncertainty is always related to the sensor measurement capability [3].

A FMECA study identifies failure modes and specifies the severity of failures and frequency of their occurrence. When the consequence of a fault is more severe, or the occurrence is more frequent, higher detectability and fault detection reliability requirements must be imposed. In other words, detectability, identifiability, and fault detection reliability requirements are determined by the criticality and frequency of an occurrence of a fault based on the FMECA study.

Fault propagation information is necessary and important for sensor localization and selection at the system level. Different approaches, such as Petri nets, fault trees and digraph-based methods are available to model the fault propagation. Among them, the Directed Graph (DG) and Signed Directed Graph (SDG) methods, with simple graphical representations of a system that represent the cause-effect analysis of fault propagation, are widely used.

FOM maximizes the fault detectability and minimizes the required number of sensors while achieving optimum SLS. The FOM is in the form of the weighted sum of the fault detectability and the number of sensors. The weights are adjustable and are mainly determined by the severity of failure effects and the probability of failure occurrence.

The optimization step includes two main tasks: optimize sensor locations and optimize selected sensors. The selected FOM is an Integer Nonlinear Programming (INLP) model. Current commercial INLP solvers, such as SBB and DICOPT, can be used to find the optimal number of sensors. In the optimization module, not long the number of sensors at each location needs to be optimized, but also the sensors selected for each fault needs to be determined [5].

The performance of the sensor localization and selection strategy is validated and verified in the integrated diagnostic and prognostic architecture. The goal of the performance module is to estimate the fault detection error rate with selected sensor suite. For a fault that is concerned, it may not be detected by selected sensors, or the selected sensors may claim other faults happening by mistake.

3. CONCLUSIONS

The performance of CBM systems relies on the diagnostic and prognostic techniques used and the sensor suite selected. Although many sensor localization and selection, diagnostic and prognostic techniques exist, most of them were studied independently without an integrated architecture. The most important is to use an open and flexible architecture to integrate the functions of sensor localization and selection, feature extraction, mode identification, diagnostics, and prognostics, with a focus on sensor localization and selection methodology for fault diagnosis. The integrated diagnostic and prognostic architecture is able to tackle the basic issues rising from sensors, features, and faults.

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