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Sensor deployment based on fuzzy graph considering heterogeneity and multiple-objectives to diagnose manufacturing system

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ABSTRACT

In this paper, a methodology is presented to generate an optimized sensor deployment deciding sensor types, numbers, and locations to accurately monitor fault signatures in manufacturing systems. Sensor deployment to robustly monitor operation parameters is the corner stone for diagnosing manufacturing systems. However, current literature lacks investigation in methodologies that handle heterogeneity among sensor properties and consider multiple-objective optimization involved in the sensor deployment. We propose a quantitative fuzzy graph based approach to model the cause–effect relationship between system faults and sensor measurements; analytic hierarchy process (AHP) was used to aggregate the heterogeneous properties of the sensor–fault relationship into single edge values in fuzzy graph, thus quantitatively determining the sensor's detectability to fault. Finally sensor–fault matching algorithms were proposed to minimize fault unobservability and cost for the whole system, under the constraints of detectability and limited resources, thus achieving optimum sensor placement. The performance of the proposed strategy was tested and validated on different manufacturing systems (continuous or discrete); various issues discussed in the methodology were demonstrated in the case studies. In the continuous manufacturing case study, the results illustrated that compared with signed directed graph (SDG), the proposed fuzzy graph based methodology can greatly enhance the detectability to faults (from SDG's 0.699 to fuzzy graph's 0.772). In the discrete manufacturing case study, results from different optimization approaches were compared and discussed; the detectability of sensors to faults also increased from SDG's 0.61 to fuzzy graph's 0.65. The two case study results show that the proposed approach overcame the qualitative approach such as signed directed graph's deficiency on handling sensor heterogeneity and multiple objectives; the proposed approach is systematic and robust; it can be integrated into diagnosis architecture to detect faults in other complex systems.

1. Introduction

Fault diagnosis is the action of identifying whether a system is deviating from the desired behavior, and determining potential root causes to abnormal behaviors [1]. To maintain the safety and reliability of a manufacturing system, it is essential to diagnose faults efficiently and accurately upon their occurrence. The underlying reasons of faults can be caused by design errors, manufacturing defects, improper application of parts, or users' programs that do not follow the protocols [1]. In a typical fault diagnosis process, the first step is to use the actual maintenance records to identify components that are critical to system's reliability, safety, repair cost, and their impacts on the system's mission. The second step consists of selecting and locating sensors based on the results of the first step to monitor physical models through sensing signal signatures to faults. Finally, transitional information from the sensor data is processed to identify the root causes of faulty states.

Sensors and sensing technologies constitute the fundamental basis for fault diagnosis in that performance of a diagnosis system critically depends on accuracy and efficiency of sensor measurements on faulty symptoms. Insufficient or inaccurate measurements resulting from improper sensor deployment can significantly deteriorate fault diagnosis performance. Although redundantly sensing every physical parameter of a system can reduce information loss, the redundant sensor network may be cursed with overload on data analysis as well as cost. This is especially critical in remote diagnosis applications [2] or wireless sensor networks [3,4] since it involves transmitting huge amounts of data from remote sites to fusion center for data analysis. Due to limited communication bandwidth,

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transferring large quantities of data to the remote fusion center is a prominent issue. Additionally, as the sensor number increases, the data analysis complexity increases exponentially, leading to tremendous difficulty in data analysis.

Consequently, appropriate sensor deployment is crucial for an effective fault diagnosis system design. It determines the types, numbers and locations of sensors for diagnosis purpose. A good sensor deployment strategy can result in a configuration with the optimal performance while satisfying pre-specified resource constraint criteria. Currently, most sensor deployment strategies for diagnosis are mainly based on ad hoc or heuristic methods. In this sense, the sensor deployment strategy is mostly an artistic procedure, instead of a scientific technique [5]. Although several analytical techniques on sensor deployment optimization have been suggested with qualitative [8–10,24] or quantitative methods [6,16–17,18,19–20,26–34], two typical issues in sensor deployment remain intact: (1) Heterogeneous properties of sensors in the diagnosis process. In a typical fault diagnosis system, it usually deploys sensors which generally have different sensing characteristics including uncertainty, accuracy, resolution and statistical property on physical signal data. Consequently, it is required that different types of control and process variables that are heterogeneous in nature be captured and processed accordingly. Nevertheless, how to systematically select crucial and optimum sensor deployment for heterogeneous sensory system poses a unique problem in the manufacturing system, which has never been reported [7]. (2) Multiple-objective optimization. Sensor deployment for fault diagnosis is a delicate work which tackles multiple objectives including observability, reliability, accuracy and efficiency under the constraints of cost, resources and environment etc. Most of the researchers attack this problem targeting single objective such as either cost or reliability. A comprehensive method that considers the multiple-objective decision making involved in the sensor deployment is yet to be created. As such, these two issues call for a systematical procedure to design a cost-effective and reliable sensor deployment strategy. When being applied in a manufacturing system, it should consider multiple decision attributes and heterogeneous types of sensors thus guaranteeing the performance of monitoring on manufacturing system.

To address aforementioned research needs, we developed a systematic methodology based on quantitative fuzzy graph. In our approach, failure mode effect analysis (FMEA) on manufacturing system was firstly conducted to obtain the fault information such as fault effect severity, occurrence rate and detecting rate about the system. Then quantitative fuzzy graph was used to model cause–effect relationship for sensor deployment. The nodes of the graph are constituted of fault nodes and sensor nodes. The fault nodes contain fault information from FMEA, while sensor nodes contain sensor properties such as reliability, sensitivity, and accuracy etc. The edges between sensor nodes and fault nodes represent the sensor detectability to certain faults. To simplify the model it is required to aggregate all factors for edge and node elements into a single value that represents sensors' detectability to certain fault. Here analytic hierarchy process (AHP) was applied to aggregate heterogeneous sensor properties involved in sensor network deployment into single edge values. With node and edge values, mixed integer linear programming and greedy algorithm were respectively conducted to optimally assign the sensors to fault nodes thus optimizing the sensor deployment. Two case studies on (1) a five tank system and (2) a dual robot assembly arm showed that the proposed methodology can be integrated into diagnosis/prognosis system architecture to detect abnormality and faults.

The rest of this paper is organized as follows: Section 2 discusses the state of the art on sensor deployment for diagnosing purpose; it also summarizes the existing gap identified in literature and formulates the problem to be addressed. Section 3 provides details of the proposed sensor deployment method which includes the fuzzy graph model, AHP method and optimization. Section 4 illustrates detailed case studies; the proposed sensor deployment strategy was applied to continuous and discrete manufacturing systems. Section 5 highlights the findings of this research and discusses the future work.

2. Literature review

Sensor deployment problems usually involve four sequential phases: (1) model the cause–effect relationship of fault variations on sensor measurements; (2) set up the objective functions for sensor deployment based on the cause–effect relationship; (3) find approaches to optimize the sensor deployment strategy; and (4) evaluate the optimized strategy. Among them, step (1) and (3) are the most important. Thus we also searched literature on aspects of: (1) modeling cause–effect relationship between system faults and sensor measurements, and (2) optimizing the cause–effect model. The references were summarized in Table 1.

Mandroli et al. [7] presented a comprehensive survey of inspection strategy and sensor distribution in discrete-part manufacturing processes. In his survey, he noted that diagnosis-oriented sensor distribution strategy is a relatively new problem with lots of research opportunities. Especially, no report has been found on how to deploy the heterogeneous sensors.

Graph theory has been applied on optimal sensor deployment strategies from qualitative [8–10,14–15] or quantitative [18–19] perspectives for sensor deployment's effects on assessing complex system status. Ali et al. used the spanning tree to model and optimize the sensor deployment for fault observability and detection reliability [8]. They defined the sensor deployment's process reliability as the smallest reliability among all of the process variables. Mass-flow and energy distribution balances in chemical plants are the basis for generating the spanning tree. Later this spanning tree procedure was extended for optimal design of a redundant sensor network for linear processes [9], as well as a nonredundant sensor network for bilinear processes [10]. Raghuraj and Bhushan et al. had qualitatively investigated the sensor deployment problem with directed graph (DG) and/or signed directed graph (SDG) [14,15] for the chemical plant. The only difference between DG and SDG is that signs are placed on the arcs of DG to get an SDG. However, the structures are exactly the same. The authors assumed that all faults had to be defined clearly along with their tolerances using a priori knowledge; then DG/SDG can be used to

Table 1
Literature summary in sensor deployment.

Modeling	Classification	Reference
Qualitative	Spanning tree	[8,9,10]
	Direct graph	[14,15]
	Signed direct graph	[15]
	Petri net	[23]
	Finite state automaton	[24,25]
Quantitative	Quantitative direct graph	[18,19]
	Mathematic programming	[16,23]
	Fault signature matrix	[12,13]
Optimization	**Classification**	**Reference**
Heuristic search	Simulated annealing	[22,33]
	Tabu search	[34]
	Genetic algorithms	[20,21]
Mathematic programming	Integer programming	[16,23]
	Dynamic programming	[26,27]
	Nonlinear programming	[11]