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A Review of Optimal Sensor Deployment to Diagnose Manufacturing Systems

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ABSTRACT Optimal sensor deployment is the foundation of an effective monitoring/diagnosis system design. Unfortunately, owing to the technical complexity, any issues related to optimal sensor deployment can deteriorate the performance of the sensor system, which has consequently received much attention and interest. This paper aimed to review the current literature studying optimal sensor deployment looking at modeling characteristics and strategy implementation. First, the modeling characteristics with four key elements, namely cause-effect model, optimization benchmark, optimization strategies, and performance assessment, are surveyed thoroughly. Second, a wide variety of strategy implementation of sensor deployment is discussed in detail. Finally, the open-ended issues faced by industry and academia are discussed and several principle conclusions drawn.

INDEX TERMS Sensor deployment, monitoring, diagnosis, manufacturing system.

I. INTRODUCTION

Condition monitoring/fault diagnosis are critical and fundamental elements in modern industrial manufacturing systems [1]–[3]. Condition monitoring in manufacturing systems refers to the identification of the functional status of the whole or part of the operation. That is, by analyzing and processing the original equipment status information read by sensors and extracting the characteristic information closely related to it, the system status is judged as to whether it is normal or not, and whether there are any signs of abnormality or deterioration. Then, the deterioration tendency is predicted and the deterioration/wear degree determined [4], [5]. To ensure the safety and reliability of manufacturing systems, it is essential to diagnose the underlying reasons for faults efficiently and accurately upon their occurrence. Fault diagnosis is the action of identifying whether a system is deviating from the benchmark given, and determining the potential root causes for any abnormal behaviors [6], [7]. Normally, a typical fault diagnosis action consists of three steps. First, key components that are crucial to a system's reliability, safety, and repair cost are identified based on actual maintenance records. Second, sensors are selected and deployed to monitor physical models by acquiring signal signatures to faults and, third, the transitional data read by sensors are processed to identify the root causes of the faulty states. Therefore, owing to their apt characteristics, condition monitoring and fault diagnosis are widely applied in the manufacturing industry. Tool condition monitoring has gained considerable attention over the past two decades, as it ensures process efficiency and machined part quality by employing condition monitoring/fault diagnosis [8], [9]. Meanwhile, fault diagnosis of rotary machines with emphasis on their key components, such as bearings [10], gearboxes [4], [11], and rotors [12] has also received extensive and intensive research. In addition, fault diagnosis for chemical processes [13], [14], monitoring/diagnosing discrete component assembly processes [15], [16], and fault detection and identification of the progressive stamping process [17] have also been applied to fabricate an extended range of products to reach a desired quality level. All these are manifested by adequate and efficient sensing data. It is of high priority to ensure that a complex manufacturing system is fully monitored, diagnosed, and predicted by sensors in a cost-effective and timely manner [18].

Condition monitoring/fault diagnosis are primarily focused on the effective measurement and evaluation of several key parameters [19], [20]. Therefore, it is inevitable that multi-sensor systems be involved in the process. Regarded by MIT's technology review as one of the top ten emerging technologies that will change the world [21], sensors and sensing technologies constitute the fundamental basis for condition monitoring/fault diagnosis because the monitoring/diagnosis performance depends on accuracy and efficiency of sensor measurements of the key product characteristics/faulty symptoms [22], [23]. Different types, numbers, and spatial combinations of sensor networks provide dense and sufficient data, which produces a more comprehensive description for the dynamic changes of manufacturing systems. However, in complex manufacturing systems, the ability of the sensor to obtain information is constrained by many aspects, such as the characteristics of the sensor itself, the fault characteristics, the machining process, and, most importantly, the sensor layout in a limited space. By adding a large number of sensors to a manufacturing system, the status information can be comprehensively obtained, which is the basis for monitoring/diagnosing the process status. Sufficient and effective sensor measurement information is helpful to improve the monitoring/diagnosis capacity of the system; however, unplanned sensor placement increases costs and reduces the system monitoring/diagnosis efficiency [24]. Evidence shows that a highly redundant sensor arrangement is not conducive to improving the monitoring/diagnosis capability of a system [25], [26]. In addition, the redundant sensor arrangement can effectively reduce the loss of information. However, massive data transmission not only demands higher transmission bandwidth, but also significantly increases the cost of data analysis and processing, which is particularly prominent in the remote diagnosis/control [27] and wireless sensor networks [28].

Consequently, appropriate sensor deployment is crucial for an effective condition monitoring/fault diagnosis system design. A good sensor deployment strategy can provide a system configuration with optimal performance under the constraints and limited resources, which determine the types, numbers, and locations of sensors for the condition monitoring/fault diagnosis purpose in a limited space of the complicated manufacturing system. To date, much research effort has been devoted to studying the significant issues surrounding optimal sensor deployment networks in manufacturing systems. However, current literature lacks a comprehensive analysis and discussion of the key issues involved in sensor placement in complex manufacturing systems. The key issues include the cause-effect model, optimization benchmark, optimization approach, performance assessment, and strategy implementation. Significantly, the issues of optimal sensor deployment networks can be selected to achieve better system monitoring/diagnosis capability. The present study reviews in detail the current state of the literature into the issues influencing the efficiency of sensor measurements on faulty symptoms. In addition, the challenges and opportunities associated with optimal sensor deployment in complex manufacturing systems are discussed with some key conclusions.

II. MODELING CHARACTERISTICS

Sensor deployment problems usually involve four sequential phases: (1) modeling the cause-effect relationship for fault variations in sensor measurements, termed the cause-effect model [29]; (2) formulating the functions and constraints to benchmark the effectiveness of a sensor system, called an optimization benchmark; (3) finding a solution approach to solve the sensor deployment strategy, termed optimization strategies; and (4) evaluating the optimized strategy, labeled the performance assessment. These four issues are our focus questions that will be explained and discussed in greater detail in the following sections.

A. CAUSE-EFFECT MODEL

It is the foundation of optimal sensor deployment problems to model the cause-effect relationship between system faults and sensor measurements [25]. The cause-effect model of the sensor-fault issue reveals the variation propagation of the fault information flow during the manufacturing process, the diagnostic relationship between the sensor and the fault, and the coupling relationship among fault information measured by the sensors. Many complex mathematical cause-effect models have been developed by researchers.

Finite element analysis is often employed in sensor optimization arrangements to help build the cause-effect relationship between system faults and sensor measurements. In a complex condition monitoring/ fault diagnosis system, the sensitivity that each sensor has to the fault information differs, and thus the amount of data measured by a sensor also varies in each location [30]. Normally, these sensitive positions can be effectively identified by the finite element method (FEM) and, in this way, more sensitive fault information can be extracted for causality model construction [31]. As shown in Figure 1, assuming S sensors are placed to simultaneously measure the displacement generated by N defect positions, the measured data y can be expressed by a vector as:

$$\begin{aligned} y &= [d^1 d^2 \ldots d^N]q + w \\ &= Dq + w \end{aligned} \tag{1}$$

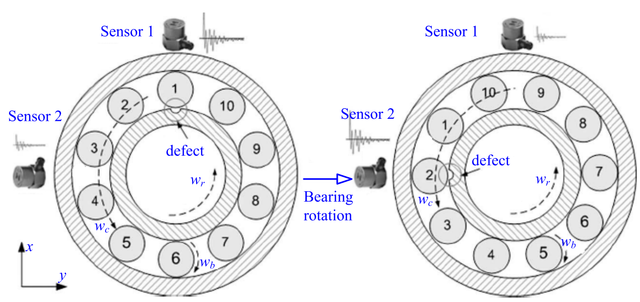

FIGURE 1. Position of an inner raceway defect varying with the bearing rotation [32].

where, $q = \{q_1, q_2, \ldots, q_N\}^{\mathrm{T}}$ with $q_j (j = 1, 2, \cdots, N)$ denoting the contribution of the j^{th} defect position to the measurement data matrix y; w is the noise component related to the sensor measurements, and D is the nodal-displacement matrix [32, 33]. Compared to the FEM, the experimental study is also an effective and direct method to determine the cause-effect relationship between system faults and sensor measurements. It is usually applied when the sensor signal is relatively simple and intuitive. Mendibil et al. [34] developed an experimental study by place pressure and temperature sensors in the runner system and the mould micro-featured cavity on micro-injection moulding. Sensor signals were correlated with quality deviations using confocal microscopy to diagnose the injected micro-parts quality. Oromiehie *et al.* [35] developed an experimental study on glass fiber/high-density polyethylene laminates with embedded fiber Bragg grating (FBG) sensors for manufacturing process monitoring. The FBG sensors are used to monitor reflected wavelengths related to pressure and temperature. Lu *et al.* [36] and Mukhopadhyay *et al.* [37] investigated an acoustic emission sensor location to find the structural crack on an aluminum alloy plate. In Figure 2, the FBG sensor location coordinates are (*x1, y1*), (*x2, y2*), (*x3, y3*) and (*x4, y4*), respectively. The crack coordinate is (*x, y*), and the equation can be obtained as:

$$\begin{aligned} \sqrt{(x-x_2)^2+(y-y_2)^2}-\sqrt{(x-x_1)^2+(y-y_1)^2} &= v\,(t_2-t_1) \\ \sqrt{(x-x_3)^2+(y-y_3)^2}-\sqrt{(x-x_1)^2+(y-y_1)^2} &= v\,(t_3-t_1) \\ \sqrt{(x-x_4)^2+(y-y_4)^2}-\sqrt{(x-x_1)^2+(y-y_1)^2} &= v\,(t_4-t_1) \end{aligned} \tag{2}$$

where, v and t_i $(i = 1, 2, 3, 4)$ is the velocity and the starting time of the crack to FBG sensor, respectively.

For deviation diagnosis in a multi-station assembly process, the cause-effect relationship between system deviation and sensor measurements is usually developed based on a state-space model to integrate sensing information from different measurement stations [24], [38]–[52]. The system given in Figure 3 can be described by the following equation:

$$\begin{aligned} X_k &= A_{k-1}X_{k-1} + B_kP_k + \xi_k \\ Y_k &= C_kX_k + \eta_k, \quad k \in \{1, 2, \ldots, N\} \end{aligned} \tag{3}$$

FIGURE 2. Aluminum alloy plate with FBG sensors stuck on [36].

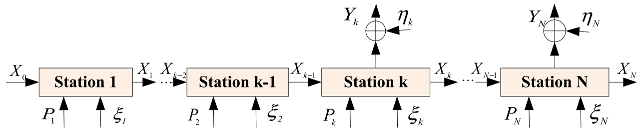

FIGURE 3. Information flow in multi-station manufacturing [24].

where, k is the station index; N is the number of stations; X_k and Y_k are the product dimensional deviation and sensor measurements at station k, respectively; P_k is the random deviations related to fixture locators at station k; A, B, and C are the state matrixes; and ξ and η are un-modeled higher order terms. The analysis method based on the state-space model is always time consuming owing to its complex analysis and calculation processes. Fortunately, Xinmin *et al.* [53] developed the intuitive principles based on the simple state equation transformation to reveal the relationship between the variation transmissibility ratio and the process configuration for the optimal sensor distribution.

Fault diagnostic activity involves identifying the deviation of parts and determining the potential root causes in a manufacturing system [6]. It includes two crucial aspects: a priori knowledge and search strategy. A priori knowledge can be broadly divided into two categories: qualitative and quantitative. The former is usually expressed in terms of mathematical functions as discussed above, whereas the latter is expressed in terms of qualitative functions centered around different units in a manufacturing process [54]. To avoid using cumbersome mathematical terms to model the cause-effect relationship between the system faults and sensor measurements, graph theory has been applied in optimal sensor deployment. Graph theory is more concise and compact [55], [56] compared to the approaches of truth tables, decision tables, or finite-state models [54], [57]. The digraph (DG) or signed digraph (SDG) technique is usually proposed for cause-effect modeling to solve a particular sensor deployment problem to maximize system reliability [58]–[64]. Wu *et al.* [25] proposed a fuzzy graph-based approach to model the cause-effect relationship between system faults and sensor measurements. The sensor-fault relationship properties are aggregated into single edge values in a fuzzy graph by employing the analytic hierarchy process. A fuzzy bipartite graph is illustrated in Figure 4. He *et al.* [26] developed a quantitative cause-effect graph (QCEG) to handle the heterogeneity among the properties of sensors and faults to facilitate the monitoring of a single-station multistep manufacturing process. The virtual fault set Ψ in Figure 5 signifies the detecting characteristic of the sensor to cumulative faults. A QCEG adequately describes the causal behavior of the process.

In addition to the DG, the Bayesian network (BN) has been employed to represent the causal relationships among the physical variables in distributed sensor networks to detect system abnormality [13], [65]–[68]. The BN is utilized for modeling, updating, and reasoning causal relationships and

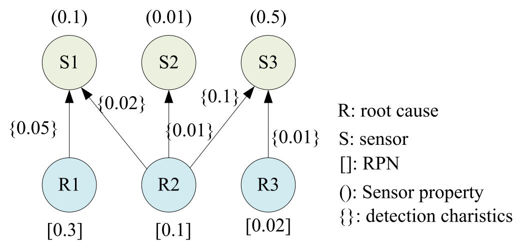

FIGURE 4. Fuzzy bipartite graph for sensor deployment [25].

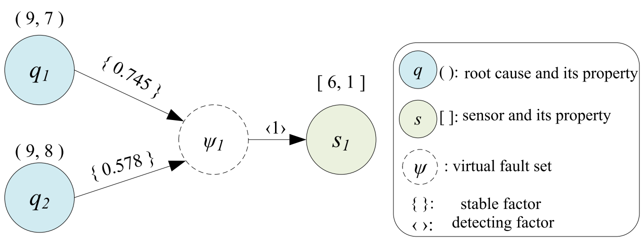

FIGURE 5. QCEG for sensor deployment [26].

uncertainties. It usually involves three steps [67]: identifying the relevant variables and their possible values, defining the network's edges, and defining the conditional probability tables. Compared to the cause-effect model based on the DG, the methodologies for causality representation based on BN usually utilize qualitative techniques and involve complex conditional probability calculations [13], [65]–[68], which need to be further studied. In summary, different causality model building techniques have different characteristics in different industrial application systems, as shown in Table 1.

B. OPTIMIZATION BENCHMARK

In a manufacturing process, the focus of consideration is different when conducting a monitoring/diagnostic activity [69].

TABLE 1. Typical strategy for cause-effect model constructed for sensor deployment.

Techniques	Complexity	Practicality	Application	References
Finite element analysis	★★	★★	Fault diagnosis/ structural states monitoring	[32, 33], [30].
Experiment al study	★	★★	Manufacturing process monitoring	[34-37].
Bayesian approach	★★★	★	Process monitoring/dia gnosis	[13],[16],[6 5-68] , [72].
State-space model	★★★	★★★	Multi-station assembly process	[24, 38-52], [53].
linear diagnostic model	★★	★★★	Automated coordinate checking fixture (CCF) design.	[31].
Graph theory	★	★★★	Manufacturing process monitoring	[55, 56], [58-64], [25], [26].

Therefore, the sensor optimization benchmark also shows diversity. Owing to the complexity of the manufacturing system itself as well as the signal transmission, initial sensor distribution research is mainly aimed at a single optimization target. A general bilevel formulation takes the following form:

$$\begin{aligned} &\min_x \; F(x, y) \\ &s.t \; H(x, y) = 0 \\ &\quad\;\; G(x, y) \leq 0 \end{aligned} \tag{4}$$

where, x, $F(x,y)$, and y denote decision variables, outer objective function, and inner decision variables, respectively. This is usually called a leader-follower problem, where x is decided by the leader while y is decided by the follower [70]. In the current research on sensor placement, the outer objective usually refers to the sensing cost, the system diagnosability, the system reliability, and the fault unobservability.

A hybrid sensor optimization problem has been investigated by Costiner *et al.* [71] to determine the locations of n sensors X^* that maximize the probability POD(X, C) of detecting a set of cracks C. This can be expressed by:

$$X^* = \arg\max_x \mathrm{POD(X,C)} \tag{5}$$

Simultaneously, several constraints must be met. For example, (1) sensors cannot be closer to each other than a minimal distance, and (2) sensors cannot be positioned where strain fields might exceed given safety thresholds. The advantage of this optimization benchmark is that it can directly determine the sensing position, even the number of sensors, without the need for the calculation of other metrics. Similar optimization benchmarks are the quadrilateral array location equations for an acoustic emission location [36] and the optimal assignment of the locating pin wear rates [41]. Apart from that, other optimization benchmarks involve some indirect optimization indicators, which are optimized to obtain the optimal sensor placement. In general, these optimization benchmarks have some restrictions. For example, an optimal sensor allocation has been investigated previously [24], [39], [46], [72] to achieve the desired diagnosability with minimum cost in a multi-station manufacturing system. The optimization problem of the sensing cost is formulated as follows:

$$\begin{aligned} &\min \left\{ \frac{c_1 \cdot \theta + c_2 \cdot \zeta}{n} \right\} \\ &s.t \; \mu = 1 \end{aligned} \tag{6}$$

where, c_1 and c_2 are the average costs of an individual sensor and a single sensing station, respectively; θ denotes the total number of newly installed sensors; ζ stands for the number of newly added sensing stations or stations with sensors for measurement upgrade; n is the total number of operating stations; and μ denotes the diagnosability. Here, the system diagnosability is the constraint. In addition, the constraints are subject to the optimal objective of the minimum cost of the system including the geometrical constraint on the principal locating points [44], [47] and the union of the duty sets, which are feasible solutions [65], [73]. A number of previous studies [74]–[76] have proposed a fault isolation index $\mathrm{J_{opt}}$ to quantify the diagnosibility of the system. The objective function $\mathrm{J_{opt}}$ is maximized subject to inequality constraints:

$$\mathrm{J}_{opt} = \forall_{i=j} \max \left[\min \sum_{\mathrm{i}=1,2,\cdots,6} \sum_{\mathrm{j}=1,2,\cdots,6} \mathbf{W_{ij}} \|\mathbf{d(i)} - \mathbf{d(j)}\| \right]$$
$$\mathbf{s.t\ G(x, y, z)} \leq 0 \tag{7}$$

where, the $\{\mathbf{d(i),\ d(j)}\}$ pair is the Euclidean distance between pairs of diagnostic vectors, which varies during the iterative search procedure, and $\mathbf{G(x,\ y,\ z)}$ denotes the constraint set on sensor locations.

In summary, the single target-based sensor optimization layout, owing to its flexible form in the manufacturing system, has been extensively studied. However, with the advent of distributed sensing networks and the diversity of monitoring/diagnostic needs, a single optimization target sometimes does not meet these monitoring/diagnostic requirements. Therefore, it is necessary to further study the multitarget-based sensor layout strategy.

While satisfying the minimum sensor cost constraints, an optimization formulation aimed at maximizing the reliability of the fault monitoring system has been proposed [58]–[60], [62], [64]. A combined optimization of minimizing the maximum unobservability of the system has been developed, which may be formulated as:

$$\underset{x_j}{min} \left[\underset{\forall i}{max} \{ln(U_i)\} - \alpha x_s \right]$$
$$s.t. \sum_{j=1}^{n} c_j x_j + x_s = C^* \tag{8}$$

where, U_i is referred to as the unobservability value of fault, x_s is the slack in the cost constraint, x_j is the number of sensors placed on variable j, c_j is the cost of placing a sensor on variable j, and C^* is a positive constant. Similarly, a sensor-fault matching algorithm to minimize fault unobservability and cost for the whole system, under the constraints of detectability and limited resources, has been proposed to achieve optimum sensor placement [25], [26]:

$$\min : \max\,(\log(U_i)) = \max \left(\log(f_i) + \sum_{j=1}^{n} d_{ij} \times \log(\mathrm{Pr}_j) \times x_j \right)$$
$$\min : \sum_j \left(C_j \times \sum_i d_{ij} \right)$$
$$\sum_j p_{ij} x_i \geq M_i^* \tag{9}$$

where, f_i is fault occurrence probability, Pr_j is sensor failure probability, x_j is the number forsensor j, $d_{ij} \in \boldsymbol{D}$, $\boldsymbol{D}$ is a binary bipartite matrix, p_{ij} is the connection strength between sensor j and fault I, and $\boldsymbol{M}_i^*$ is the detectability. Compared to Eq. (8), this equation adds the detectability constraint Mi^*. In several other applications, the limited resource is regarded as the constraint. For example, Bruant et al. [49] studied the bi-objective sensor optimization to ensure good observability, which minimize the number of sensors x_s and J_s:

$$J_s(x_s) = \min_{i=1,\ldots,N} \frac{(W_0(x_s))_{ii}}{\max_{x_s}(W_0(x_s))_{ii}}$$
$$\max_{x_s} \ \min_i O_i(x_s) \geq \eta$$
$$s.t.\ C = \{x_s \ such\ that\ \forall i \in 1, \ldots, N, O_i(x_s) \geq \eta\} \tag{10}$$

where, $O_i(x_s)$ is an observability index on the i^{th} mode. Compared to single-target optimization benchmarks, the multi-objective optimization benchmarks can meet the diversity of fault diagnosis requirements in the actual industrial application. Usually, single-objective optimization benchmarks rarely take into account the characteristics of sensors and faults, whereas multi-objective optimization benchmarks can effectively integrate sensor and fault characteristics into sensor optimization placement strategies; therefore, they can achieve more objective optimization results.

In recent years, with the introduction of communicating mobile devices, industrial wireless sensor placement has drawn increasing attention. Most of the factors considered are real time, reliability, resource constraints [78], coverage, cost, and connectivity [77]. However, the current applications of industrial wireless sensors are still on a small scale and need to be further studied because of technical obstacles in the industrial wireless sensor placement [78]. In summary, the optimization objectives and constraints are different in the different applications of complex manufacturing systems. Characteristic descriptions of optimization benchmarks for sensor deployment in a manufacturing system are shown in Table 2.

C. OPTIMIZATION APPROACH

After establishing the optimization benchmark, the sensor arrangement model needs to be optimized. A variety of optimization algorithms, from mathematical programming to heuristic searches [44], [79] have been employed to optimize sensor deployment. Nearly all the literature for sensor deployment, particularly in a manufacturing system, ultimately derives a nonlinear function for the optimization benchmark in which some of the decision variables must only be integer values. Therefore, almost all of the problems can be attributed to nonlinear programming or integer programming (IP) problems [25], [64].

To solve nonlinear programming or IP problems effectively, a number of researchers [80]–[82] have proposed a FEM simulation methodology for the optimum sensor location. Other researchers [43], [83], [84] have developed exchange algorithms for the optimal layout of the sensors or fixture layout design for the diagnosis of dimensional variation sources in assembly processes. Ding et al. [24] developed a backward-propagation strategy for the optimal allocation of sensors to determine the locations of measurement stations and the minimum number of sensors required

TABLE 2. Descriptions of optimization benchmark applied for sensor deployment.

Single target	Multi-target	Reference	Objective function: Detectionability	Fault observability	Cost	Coverage	System reliability	Constraints: Diagnosability index	Geometric constraint
◆		[71], [74-76].	◆						
◆		[73],[65].			◆				
◆		[24, 46, 72].			◆			◆	
◆		[41].					◆		
◆		[44, 47]	◆						◆
◆		[58-60, 62, 64]		◆					
	◆	[25], [26]		◆	◆			◆	
	◆	[49]		◆	◆				
	◆	[77],[78]			◆	◆	◆		

to achieve full diagnosability in a multi-station assembly process. Previous studies [74]–[76] have proposed a gradient-based search to achieve an optimal sensor distribution for the diagnosability in a multi-fixture assembly of sheet metal parts. Wu *et al.* [25], [64] investigated a multiple-objective optimization involved in the sensor deployment (Eq. (9)), and developed a lexicographical mixed integer linear programming and greedy search for sensor deployment optimization.

Compared to FEM, exchange algorithms, gradient-based search, and IP mentioned above, which have greater computational complexity and sometimes cannot be implemented easily for sensor deployment in an actual manufacturing system, a heuristic algorithm can produce a better solution and is employed to describe the sensor deployment optimization. For the maximum-reliability optimization problem expressed as Eq. (8), a greedy search heuristic shown in Figure 6 has been developed [58]–[61], [71]. As a heuristic algorithm, greedy searches tend to be more effective in discovering good feasible solutions as a new approach for a posteriori articulation of preferences [85]. Li and Jin [65] developed an integrated algorithm by combining a pre-processing algorithm and the greedy algorithm (Figure 7) to optimize sensor layout with the objective of the abnormalities detection on a hot forming process, in which X is the physical variables, L_G is a feasible solution, and $C^{\{X_K\}}$ is the duty set of X_k.

For sensor deployment optimization in an actual manufacturing system, the computations will escalate as the number of sensor nodes increase. The capability of the greedy algorithm in solving a large-scale problem is limited. Therefore, many types of evolutionary algorithms are often developed to reach a better solution. Although these might not always obtain the global optimal solution, they have strong high-dimensional data optimization ability, and thus are widely applied in sensor optimization layout for diagnosing manufacturing systems. By employing the principles of genetic algorithms (GAs), many optimal sensor placements have been developed in a complex system to optimize several competing evaluation

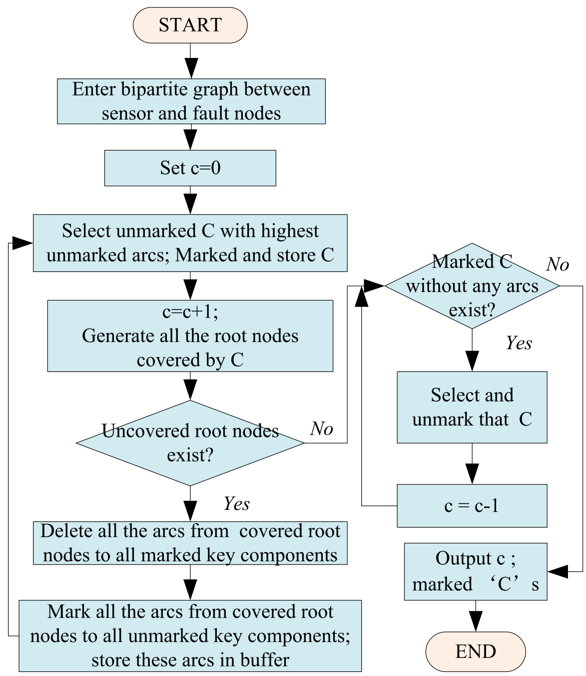

FIGURE 6. Flow chart for sensor layout using greedy search algorithm [58].

criteria [42], [49], [77], [86]–[91]. Some GA-based combinatorial algorithms, such as data-mining guided GA, have also been developed to solve the sensor distribution problem to achieve a maximal variance detection capability in a multi-station assembly process [47]. Similarly, an improved particle swarm optimization (PSO) algorithm has been proposed to achieve the acoustic emission optimal location [36]. By using the information fusion of multiple standards PSO [92], the process of an improved PSO is realized, as shown in Figure 8, where PSO $i, i = 1, 2, 3, \ldots, 10$ denotes the i^{th} standard PSO, ZY i, $i = 1, 2, 3, \ldots, 10$ represents the optimal value of the i^{th} standard PSO. In addition, a heuristic

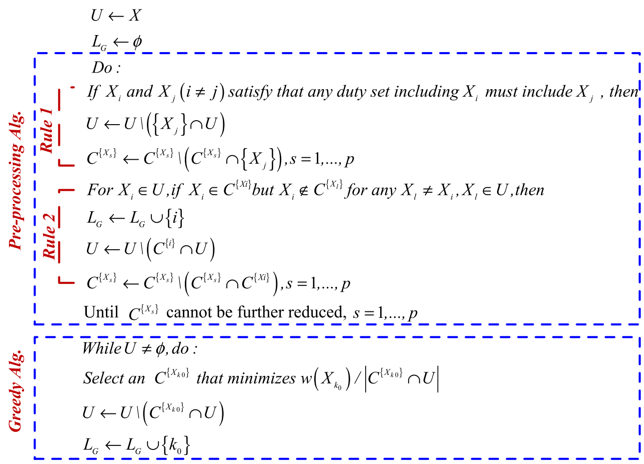

FIGURE 7. An integrated algorithm by combining a pre-processing algorithm and the greedy algorithm [65].

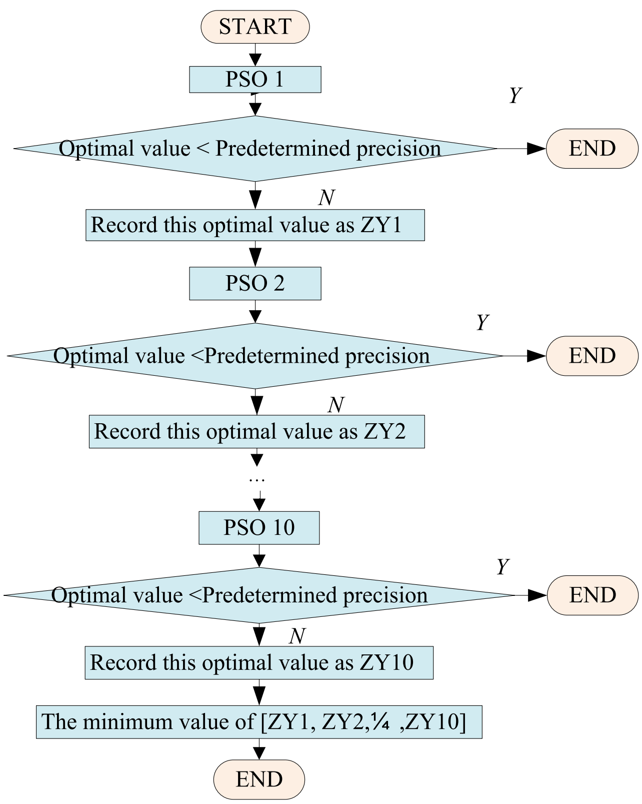

FIGURE 8. The process of the improved PSO [36].

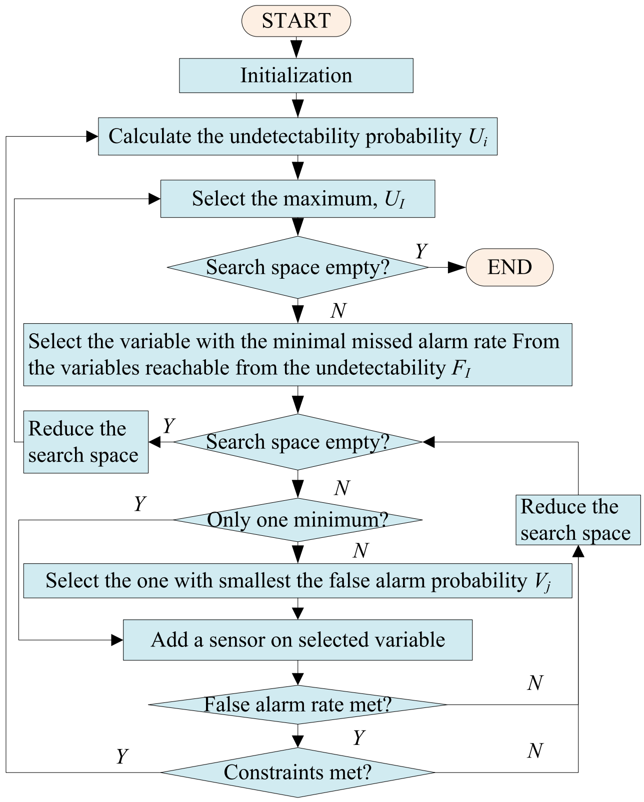

FIGURE 9. Flow chart of the optimization algorithm [62].

algorithm has been developed for the combinatorial optimization of minimizing the maximum unobservability [62], [72]. The algorithm is illustrated in Figure 9 and it obtains an optimal sensor set by iteratively reducing the search space. Tyagi *et al.* [44] proposed a highly optimized tolerance inspired heuristic to solve an E-optimality based sensitivity criterion of the fixture layout quality in a multi-station assembly. Compared to a single optimization algorithm [66], the combined optimization algorithm shows better optimization ability. He *et al.* [26] proposed an improved shuffled frog leaping algorithm (SFLA) to manage the multi-objective sensor optimization distribution problem. Based on traditional simulated annealing [20] and evolutionary algorithms [93], Shukla *et al.* [46] proposed a chaos-embedded fast-simulated annealing to minimize the number of sensors and maximize the determinant of Fisher information matrix with the minimum effect of noise in the sensor data to locate the optimal sensor distribution.

Owing to the complexity of the manufacturing system, there are numerous optimization algorithms for sensor placement to diagnose the manufacturing system. Because of the different focus in the sensor arrangement, it is hard to determine whether one optimization strategy is better than another. The main optimization algorithms applied for sensor placement in manufacturing systems are evolutionary algorithms (such as GA, PSO, and SFLA), greedy algorithms, FEM, exchange algorithms, gradient-based search, and IP. Other optimization algorithms such as the effective independence method [32, 94], fuzzy clustering algorithm [95], Bayesian sensor placement optimization algorithms [67], and Powell's direct search [31] have been less widely employed. Figure 10 shows the optimization algorithms applied for sensor arrangement in manufacturing systems.

D. PERFORMANCE ASSESSMENT

Optimal sensor placement for monitoring/diagnosis can be different for performance assessment in a complex manufacturing system. Presentation of evaluation criteria for optimal

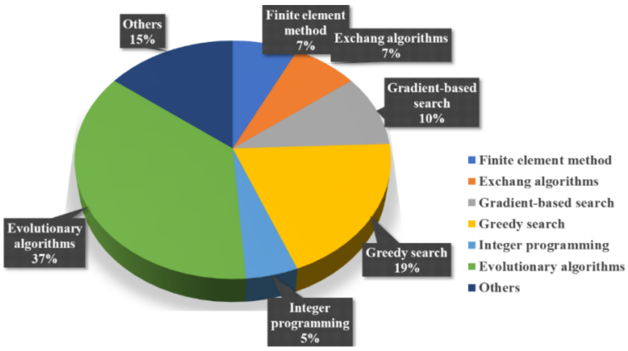

FIGURE 10. Frequency of usage of optimization algorithms for sensor deployment to diagnose manufacturing systems.

sensor systems in a unified way would be very helpful to engineers and scientists working in the monitoring/diagnosis field in a complex manufacturing process.

Maximizing the degree of observability is usually presented as a reliability criteria for optimal sensor location from a fault diagnosis perspective in complex manufacturing systems [13], [96]. A minimum unobservability criteria of the optimal sensor distribution is proposed to ensure system reliability [58]–[62], [86]. Wu *et al.* [25] proposed an optimized sensor deployment with the goal to achieve the minimum unobservability and cost under the constraints of detectability for accurately diagnosing manufacturing systems. For discrete-event systems, Jiang and Garcia [97] determined the optimal sensor set that provided minimal yet sufficient events observational information for the task such as estimation, diagnosis, or control. Bruant *et al.* [49] proposed an optimal location of piezoelectric sensors to ensure system observability under minimum piezoelectric elements requirement. Shaker and Tahavori [45] maximized the trace of the generalized observability Gramian to determine the optimal sensor locations for unstable systems. He et al. [26] proposed a sensor deployment strategy by minimizing the fault unobservability and cost, and maximizing the system stability under the constraints of detectability, stationarity, and limited resources for manufacturing process monitoring.

Considering the uncertainty of the sensor system, accuracy/sensitivity is also employed as the optimality criteria for the optimal design of sensor location [36], [38], [67], [98]. This involves the optimization of maximizing the smallest eigenvalue of the Fisher information matrix. The accuracy index is usually the sensitivity index that is regarded as the estimation accuracy of variation sources in a manufacturing process [43]. Ren *et al.* [30], [93] proposed to maximize the sensitivity to minimize the deviation at the fixture locators on different stations. Mendibil *et al.* [34] studied the effects of input parameters variation on sensor signals in different locations inside the mould, with experiments demonstrating that the sensor located in the micro-featured cavity showed higher sensitivity to process variations than the sensor in the runner. Shukla et al. [42] developed a sensitivity index, which is regarded as having sensor measurement capability to detect variation and to characterize the sensor layout in automotive assembly processes. Lu *et al.* [36] defined sensitivity indices as the sensor deployment criteria for the process variance detection in the specific context of a panel assembly process. Tyagi *et al.* [44] proposed an E-optimality based sensitivity criterion for the fixture quality measurement to determine the optimal design of fixture layout in a multi-station assembly process.

In discrete-part manufacturing processes, diagnosability of the process faults is usually regarded as the performance measures for the optimization design of sensor configuration. In general, diagnosability is expressed as a mathematical condition under which the variance component is uniquely identifiable. Full diagnosability of system is determined by whether the diagnostic matrix is singular or not [31], [32], [47], [53], [99]. Bastani *et al.* [39] proposed an optimal sensor placement by minimizing the average mutual coherence to maximize the diagnosability in multi-station assembly processes. Sun *et al.* [72] proposed three indices, namely detectability, locatability, and isolability to measure system diagnosability in a multi-station manufacturing system. Ding *et al.* [24] developed a diagnosability index to quantify the effectiveness of a distributed sensor system in a multi-station assembly process. In addition, an optimal sensor distribution by maximizing the minimum variation pattern distance to perform variation diagnosis has also been employed in a complex assembly system [33], [74]–[76]. The performance usually involves the distance among the variation pattern vectors. The larger the distance, the better the sensor system can perform variation diagnosis.

The optimization design of sensor configurations should be based on a systematic analysis relative to operational and economic considerations [100]. Therefore, the minimum cost of the sensor layout network is usually regarded as an evaluation benchmark under specified detectability requirements [46], [65], [66]. Conversely, it is difficult for a single optimization target to meet the actual fault diagnosis requirements. We note that the most recent development in the field of sensor optimization arrangement is the emergence of the multi-objective optimization, such as false alarm rate, detection rate [87], cost and reliability [64], real time, costs, and scalability [78].

III. STRATEGY IMPLEMENTATION

For different application objects in a manufacturing systems, owing to the differences of process configuration, sensor system homogeneity, and variation sources [69], the implementation of sensor layout strategy also varies. When multiple sensors are considered, a homogeneous or heterogeneous sensor system is involved. In a general sense, the description of the variation source in the monitor-oriented sensor-distribution strategy is associated with nothing more specific than an occurrence probability, whereas in the diagnosis-oriented sensor distribution strategy it is concerned with the statistical properties of process variables [69]. Based on the

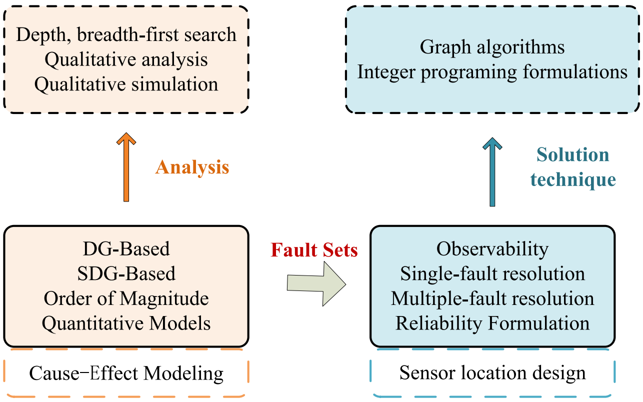

FIGURE 11. **Two-level sensor location strategy [58].**

issues mentioned above, considerable research has occurred into the development of sensor deployment strategies.

In the early stage of research on strategy implementation of sensor deployment, the majority of the literature only took into account the methodologies that handled homogeneity among sensor properties, as well as the single-objective optimization [61]. Figure 11 shows the philosophy of strategy implementation, and that one of the key ideas of the location problem from a fault diagnosis perspective is the decoupling of the cause-effect modeling. Usually, the cause-effect information is denoted by a bipartite matrix in which rows correspond to faults and the columns correspond to sensor nodes. The cause-effect modeling is integrated with the optimization benchmark based on the fault sets and the sensor sets are generated based on it. The various performance assessments such as observability, single-fault resolution, multiple-fault resolution, reliability, and cost can be applied to the optimization benchmark. Cause-effect modeling can be decoupled by effective quantitative analysis or simulation, which will facilitate the use of a variety of algorithms to solve a specific sensor layout problem (such as graph algorithm, IP, heuristic algorithm, and so on). Thus, the sensor layout problem can be solved [58], [59]. Based on the above ideas, BNs are employed for modeling, updating, and reasoning the causal relationships and uncertainties. Information metrics are proposed to assess the potential information gained from each sensor placement scenario. The optimized sensor placement can be identified based on the amount of reliability information provided by the sensor placement network [67]. Compared to this complicated decoupling process, Ghani *et al.* [80] proposed a FEM determining the optimum locations of strain gauge to measure the cutting tool deflection during the turning process. Stress analysis was conducted using ANSYS software. Based on the simulation results, two strain gauges were mounted on the tool holder at two different locations from the cutting point. The optimum location was determined by analyzing the cutting force picked up by two strain gauges. Comparatively speaking, the strategy implementation of sensor placement based on dynamic information modeling is more intuitive and simple; however, it lacks dynamic signal mechanism analysis. A similar implementation strategy is shown in Figure 12 [98]. The time-domain measurements $y_1(t); y_2(t); \cdots, y_n(t)$ from sensors at n locations $(L_1; L_2; \cdots; L_n)$ are accepted as inputs. Based on the discrete Fourier transform, the discrete frequency spectrum Y is obtained and the amplitude a and frequency ω of each of the frequencies are given. The sensitive frequency parser will then sieve out these frequencies from the spectrum provided by the frequency domain pre-processing. Radial basis function is chosen to infer the vibration spectrum at the critical location Y_{ri}, which will be summed up to yield the overall frequency spectrum Y_r at the critical location.

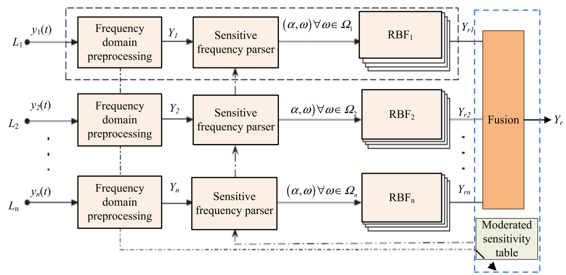

FIGURE 12. **Block diagram of the proposed framework [98].**

The method mentioned above, however, does not take into account fault transmissibility. A product usually needs to go through more processing stations, especially in a complex multi-station manufacturing system. Therefore, the product-related fault information (mostly fixture failures) also has variation transmissibility between stations. This transfer characteristic of fault information cannot be negligible for sensor optimization arrangements. In general, based on the mechanism of variation transmissibility between stations and variation detectability at individual stations in a multi-station assembly process, a diagnosability index is developed to identify the sensing station. For example, as shown in Figure 13,

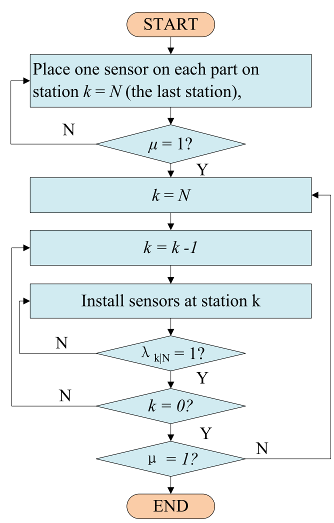

FIGURE 13. **Sensor distribution strategy for diagnosability in a multi-station assembly process [24].**

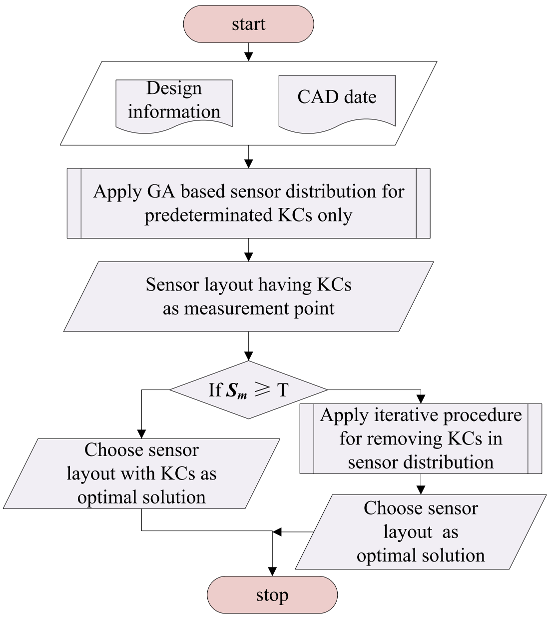

FIGURE 14. **Feature-based approach to identify optimal sensor layout in multi-station assembly processes; S_m is the mean-detecting sensitivity [42].**

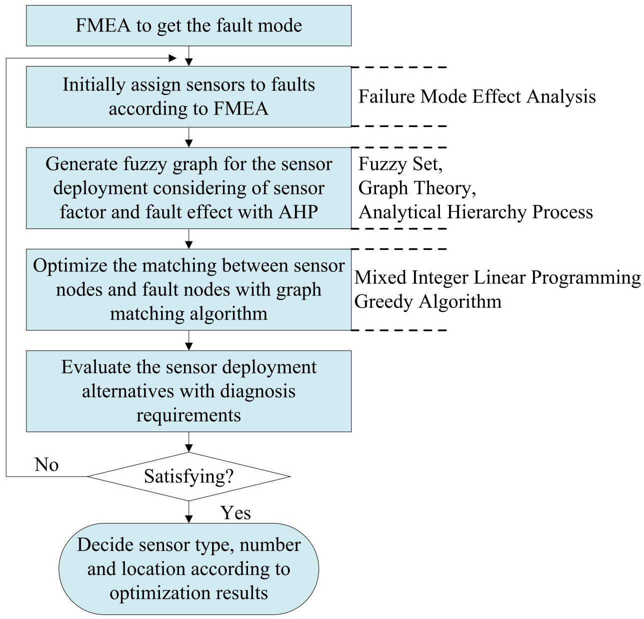

FIGURE 15. **Sensor deployment optimization strategy [25].**

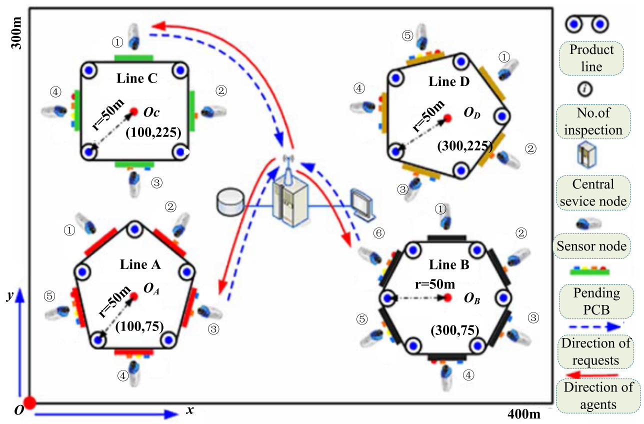

FIGURE 16. **Quality inspection by mobile agents on manufacturing [89].**

μ is the diagnosability index, and if $\mu < 1$ then the kth station is the sensing station. Identification methods usually include the backward-propagation strategy [24], compressive sensing theory [39], E-optimality [43], [44], and bottom-up and top-down approaches [75]. In addition to the fixture fault, some product and process design features, called key characteristics (KCs), are integrated into the sensor optimization arrangement [42], [50]. The feature-based approach is presented in Figure 14. The Computer-aided design data provides the KCs and the design information provides the details about the KCs in the form of features and points on the parts. Then, GA is employed to select the measurement points from available KCs. The sensor layout obtained by GA is accepted if its sensitivity index (S_m) is greater than the threshold value T, otherwise, an iterative procedure of removing KC(s) from the sensor layout will continue until $S_m > T$. The process design feature is employed first to solve the sensor distribution problem. However, it ignores the influence of sensor features on the sensor layout. Compared to the former strategy implementations of sensor distributions that are time consuming with complex analysis and calculation processes, and do not have intuitive principles according to the process configuration, Xinmin *et al.* [53] presented a simplified strategy that is based on two problems. The first is calculating the transmissibility ratio at each station and the second is how to place sensors at the station when the transmissibility ratio is less than 1 to optimize sensor distribution for a full diagnosis in multi-station assembly processes.

In the actual complex manufacturing system, only considering single-objective optimization and homogeneity among sensor properties for optimal sensor deployment strategy is not adequate. Therefore, the methodology that deals with heterogeneity of sensor properties and considers multiple-objective optimization involved in sensor arrangement has been investigated. The strategy implementation is shown in Figure 15. Failure mode effect analysis is employed to decide system fault modes, which is integrated effectively into the causal model. A fuzzy graph is developed to model the cause-effect relationship between fault nodes and sensor nodes in sensor deployment. Diagnosis requirements are represented by mathematical formula that are optimized by an efficient optimization algorithm to decide sensor type, number, and location [25], [26]. With the development of wireless communication technology, a wireless sensor network is potentially introduced in industrial systems [77], [101]. The reliability, real time, costs, energy consumption, and scalability are usually the main questions that need to be discussed in the strategy implementation of sensor arrangements [78]. As shown in Figure 16, wireless sensor networks

TABLE 3. Modeling characterization involved in strategy implementation.

Modelling technique	Sensor/fault characteristics	Target characteristics	Optimal objective	Main application	Ref.
Graph-based approach	Not considered	Single-objective	Fault observability	Chemical process	[61]
	Considered	Multi-objective	Reliability and cost of the monitoring system	Chemical process	[58]
			Unobservability of fault and Cost	Manufacturing systems.	[25], [26]
	Not considered	Single-objective	Maximal spread of the fault vectors	Multi-fixture sheet-metal assembly	[75]
Bayesian approach	Not considered	Single-objective	System reliability	Power transformer	[67].
Vibration profile analysis	Not considered	Single-objective	Sensitivity	Manufacturing systems	[30]
State-space model	Not considered	Single-objective	Sensing cost/ percentage of KCs/ sensitivity index/ average mutual coherence	Multi-station assembly process	[24],[42, 44],[39] [53].
Linear diagnostic model	Considered	Single-objective	Mean/variance component sensitivity indices	Multi-station assembly process	[43].
			Uncertainty	Multi-station machining processes	[50].
Genetic Algorithms	Not considered	Multi-Objective	Coverage, cost, connectivity/ energy and sensors number	Smart communications /active vibration control of flexible structures/ quality inspection.	[77, 101] [49],[89]
Branch-and-bound algorithm.	Not considered	Single-objective	Thermal behavior of hardware resources	Reconfigurable systems at the post manufacturing stage	[102].
Pareto-based evolution algorithms	Not considered	Multi-Objective	Reliability, real time, cost, performance, scalability	Industrial wireless sensor networks	[78].

are introduced to inspect the printed circuit board in a distributed system [89]. The causal model was constructed based on an integrated metric. The integrated metric is designed based on three key factors: creation sequence, priority of agents, and energy consumption. A genetic algorithm is employed to determine the optimal sequence of mobile agents in the task queue. The reciprocal of the integrated metric is regarded as the fitness function. Therefore, the higher the fitness, the better the deployment sequence of mobile agents. The optimized deployment strategy decreases the energy consumption and time delay under the constraint of bandwidth when the numbers of nodes and mobile agents increase. In fact, the multitarget-based sensor layout strategy is also based on the hierarchical optimization due to the priorities of optimization goals. Therefore, multi-objects related to sensor arrangements are optimized one by one.

In summary, there are various fault diagnosis requirements based on sensor optimization layouts for different application objects; therefore, the strategy implementation presents different characteristics in complex manufacturing systems, as shown in Table 3.

IV. OPEN-ENDED ISSUES

Sensors and sensing technologies constitute the fundamental basis for condition monitoring/fault diagnosis. Integrating multiple sensors into manufacturing systems enables flexible control to determine the potential root causes for abnormal behaviors and product quality improvement. Optimized sensor deployment, which is the foundation of robustly diagnosing manufacturing systems, has attracted the attention of many researchers. Although great effort has taken place to investigate the sensor deployment strategy and modeling characteristics, these are both highly complex and interact with a large number of factors, thus preventing the efficiency of sensor measurements on faulty symptoms. Therefore, the main recommendations and challenges in sensor deployment include, but are not limited to, the following:

(1) Although a lot of effort has occurred in studying the sensor deployment strategy, there is still a lack of integrated strategy that effectively involves more uncertainty information of sensors and faults characteristics into the sensor deployment, as well as integrates the optimal sensor placement into manufacturing systems, thus adjusting the sensor deployment network by employing the feedback of system output. Therefore, a dynamic sensor deployment optimization system could be put into practice.

(2) Compared to the cumbersome mathematical terms, graph theories, such as BN, DG, SDG, have been applied to model the cause-effect relationship between system faults and sensor measurements in the optimal sensor deployment. However, their application for sensor optimization arrangements is still very limited in complex manufacturing systems.

(3) The current benchmark for optimal sensor location for diagnosing manufacturing systems still does not incorporate the uncertainty information of the sensor and faults, such as signal noise ratio, sensitivity, resolution, accuracy, fault occurrence rate, and fault detection speed, thus providing a more realistic sensor optimal layout model in actual manufacturing settings.

(4) Although many types of heuristic methods, such as greedy search, genetic algorithm, and particle swarm optimization algorithm, are often employed in the current optimal

sensor deployment to obtain a better solution, their convergence speeds are relatively slow and the solution may not be the optimal one. Therefore, the combinatorial optimization algorithm integrated with various integer optimization approaches needs more research effort.

(5) An optimal sensor deployment strategy is a high level operational strategy after simplifying and parameterizing the optimization target of systems such as the parameter observability or the fault diagnosability. However, insights from these physically meaningful variables and parameters cannot fully reveal the actual operating state of the system. Therefore, the realistic model must be expanded into sensor distribution studies.

V. CONCLUSIONS

In an optimized sensor deployment, a wide variety of factors, including cause-effect model, optimization benchmark, optimization approach, performance assessment and strategy implementation, have major influence on the reliability of monitoring/diagnosing the manufacturing system. A great amount of theoretical and experimental research has occurred and a lot of promising results have been acquired. In summary, key information concerning optimal sensor deployment to diagnose a manufacturing system can be shown as follows:

(1) Modeling the cause-effect relationship between system faults and sensor measurements is the foundation for diagnosing manufacturing systems. Many complex mathematical models, such as the linear model, the effective independence method, the Fisher information matrix, and station-indexed state-space model have been used to model the cause-effect relationship between system faults and sensor measurements. At present, graph theories, such as DG, SDG, QCEG, fuzzy graph, and BN have been employed for determining the influence of the sensor location on assessing the complex manufacturing system status.

(2) As revealed by the referenced literature, the majority of the optimization approaches explored in the literature include gradient-based search algorithms, exchange algorithms, and lexicographical mixed integer linear programming. In addition, intelligent optimization algorithms, such as greedy algorithm, PSO algorithm, and GA are also employed. Performance assessment of optimization design of sensor configuration are mainly focused on fault observability, system accuracy/sensitivity, system economy, and fault diagnosability.

(3) Early-stage research on sensor arrangement optimization only took into account methodologies that handled homogeneity among sensor properties, as well as the single-objective optimization. For the multi-station manufacturing system, the fault transmissibility is taken into account; however, the sensor property is not considered. Currently, the majority of current literature attempts to present methodologies that handle heterogeneity of sensor properties and consider multiple-objective optimization involved in sensor arrangement. For different application scenarios (e.g., single-objective optimization, multi-station manufacturing system, and multi-objective optimization), strategy implementation of sensor deployment also presents their respective different characteristics.

REFERENCES

[1] W. Qiao and D. Lu, "A survey on wind turbine condition monitoring and fault diagnosis—Part I: Components and subsystems," *IEEE Trans. Ind. Electron.*, vol. 62, no. 10, pp. 6536–6545, Apr. 2015.

[2] M. Riera-Guasp, J. A. Antonino-Daviu, and G.-A. Capolino, "Advances in electrical machine, power electronic, and drive condition monitoring and fault detection: State of the art," *IEEE Trans. Ind. Electron.*, vol. 62, no. 3, pp. 1746–1759, Mar. 2015.

[3] Y. Lei, J. Lin, Z. He, and M. J. Zuo, "A review on empirical mode decomposition in fault diagnosis of rotating machinery," *Mech. Syst. Signal Process.*, vol. 35, nos. 1–2, pp. 108–126, Feb. 2013.

[4] Y. Lei, J. Lin, M. J. Zuo, and Z. He, "Condition monitoring and fault diagnosis of planetary gearboxes: A review," *Measurement*, vol. 48, pp. 292–305, Feb. 2014.

[5] B. K. N. Rao, "The need for condition monitoring maintenance management in industries," in *Handbook Condition Monitor*. Oxford, U.K.: Elsevier, 1996, pp. 1–37.

[6] D. K. Pradhan, "Types of fault tolerance," in *Fault-Tolerant Computer System Design*. Upper Saddle River, NJ, USA: Prentice-Hall, 1996, pp. 1–30.

[7] R. Isermann, "Integration of fault detection and diagnosis methods," in *Issues of Fault Diagnosis for Dynamic Systems*. London, U.K.: Springer, 2013, pp. 15–49.

[8] A. Siddhpura and R. Paurobally, "A review of flank wear prediction methods for tool condition monitoring in a turning process," *Int. J. Adv. Manuf. Technol.*, vol. 65, nos. 1–4, pp. 371–393, Mar. 2013.

[9] A. J. Torabi, M. J. Er, X. Li, B. S. Lim, and G. O. Peen, "Application of clustering methods for online tool condition monitoring and fault diagnosis in high-speed milling processes," *IEEE Syst. J.*, vol. 10, no. 2, pp. 721–732, May 2016.

[10] J. B. Ali, N. Fnaiech, L. Saidi, B. Chebel-Morello, and F. Fnaiech, "Application of empirical mode decomposition and artificial neural network for automatic bearing fault diagnosis based on vibration signals," *Appl. Acoust.*, vol. 89, pp. 16–27, Mar. 2015.

[11] Y. Lei, D. Han, J. Lin, and Z. He, "Planetary gearbox fault diagnosis using an adaptive stochastic resonance method," *Mech. Syst. Signal Process.*, vol. 38, no. 1, pp. 113–124, Mar. 2013.

[12] J. Pons-Llinares, J. A. Antonino-Daviu, M. Riera-Guasp, S. B. Lee, T.-J. Kang, and C. Yang, "Advanced induction motor rotor fault diagnosis via continuous and discrete time–frequency tools," *IEEE Trans. Ind. Electron.*, vol. 62, no. 3, pp. 1791–1802, Sep. 2015.

[13] M. Askarian, G. Escudero, M. Graells, R. Zarghami, F. Jalali-Farahani, and N. Mostoufi, "Fault diagnosis of chemical processes with incomplete observations: A comparative study," *Comput. Chem. Eng.*, vol. 84, pp. 104–116, Jan. 2016.

[14] Z. Gao, C. Cecati, and S. X. Ding, "A survey of fault diagnosis and fault-tolerant techniques—Part I: Fault diagnosis with model-based and signal-based approaches," *IEEE Trans. Ind. Electron.*, vol. 62, no. 6, pp. 3757–3767, Mar. 2015.

[15] K. Bastani, Z. Kong, W. Huang, X. Huo, and Y. Zhou, "Fault diagnosis using an enhanced relevance vector machine (RVM) for partially diagnosable multistation assembly processes," *IEEE Trans. Autom. Sci. Eng.*, vol. 10, no. 1, pp. 124–136, Oct. 2013.

[16] Y. Liu, X. Ye, and S. Jin, "A bayesian based process monitoring and fixture fault diagnosis approach in the auto body assembly process," *J. Shanghai Jiaotong Univ. (Sci.)*, vol. 21, no. 2, pp. 164–172, Apr. 2016.

[17] H. Shui, X. Jin, and J. Ni, "An anomaly detection and diagnosis method based on real-time health monitoring for progressive stamping processes," in *Proc. ASME Int. Manuf. Sci. Eng. Conf.*, Charlotte, NC, USA, 2015, p. V002T005A021.

[18] F. Franceschini, M. Galetto, D. Maisano, and L. Mastrogiacomo, "A review of localization algorithms for distributed wireless sensor networks in manufacturing," *Int. J. Comput. Integr. Manuf.*, vol. 22, no. 7, pp. 698–716, Apr. 2009.

[19] H. Arslan, A. O. Er, S. Orhan, and E. Aslan, "Tool condition monitoring in turning using statistical parameters of vibration signal," *Int. J. Acoust. Vibrart.*, vol. 21, no. 4, pp. 371–378, Dec. 2016.

[20] J. Guo and H. Jafarkhani, "Sensor deployment with limited communication range in homogeneous and heterogeneous wireless sensor networks," *IEEE Trans. Wireless Commun.*, vol. 15, no. 10, pp. 6771–6784, Jul. 2016.
[21] G. Huang, "10 emerging technologies that will change your world," *Technol. Rev.*, vol. 107, no. 1, pp. 32–50, Jun. 2004.
[22] S. Nandi, H. A. Toliyat, and X. Li, "Condition monitoring and fault diagnosis of electrical motors—A review," *IEEE Trans. Energy Convers.*, vol. 20, no. 4, pp. 719–729, Dec. 2005.
[23] A. Widodo and B.-S. Yang, "Support vector machine in machine condition monitoring and fault diagnosis," *Mech. Syst. Signal Process.*, vol. 21, no. 6, pp. 2560–2574, 2007.
[24] Y. Ding, P. Kim, D. Ceglarek, and J. Jin, "Optimal sensor distribution for variation diagnosis in multistation assembly processes," *IEEE Trans. Robot. Autom.*, vol. 19, no. 4, pp. 543–556, Aug. 2003.
[25] Z. Wu, S.-J. Hsieh, and J. Li, "Sensor deployment based on fuzzy graph considering heterogeneity and multiple-objectives to diagnose manufacturing system," *Robot. Comput.-Integr. Manuf.*, vol. 29, no. 1, pp. 192–208, Jul. 2013.
[26] K. He, M. Jia, and Q. Xu, "Optimal sensor deployment for manufacturing process monitoring based on quantitative cause-effect graph," *IEEE Trans. Autom. Sci. Eng.*, vol. 13, no. 2, pp. 963–975, May 2016.
[27] J. Lee, "Teleservice engineering in manufacturing: Challenges and opportunities," *Int. J. Mach. Tool Manuf.*, vol. 38, no. 8, pp. 901–910, Aug. 1998.
[28] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: A survey," *Comput. Netw.*, vol. 38, no. 4, pp. 393–422, 2002.
[29] E. Hummel and I. Hoffmann, "Complexity of nutritional behavior: Capturing and depicting its interrelated factors in a cause-effect model," *Ecol. Food. Nutrition*, vol. 55, no. 3, pp. 241–257, Jan. 2016.
[30] P. V. Er, C. S. Teo, and K. K. Tan, "Approach towards sensor placement, selection and fusion for real-time condition monitoring of precision machines," *Mech. Syst. Signal Process.*, vols. 68–69, pp. 105–124, Feb. 2016.
[31] Y. Wang and S. R. Nagarkar, "Locator and sensor placement for automated coordinate checking fixtures," *J. Manuf. Sci. Eng.*, vol. 121, pp. 709–719, Nov. 1999.
[32] S. Sheng, L. Zhang, and R. X. Gao, "A systematic sensor-placement strategy for enhanced defect detection in rolling bearings," *IEEE Sensors J.*, vol. 6, no. 5, pp. 1346–1354, Oct. 2006.
[33] J. A. Camelio and S. J. Hu, "Sensor placement for effective diagnosis of multiple faults in fixturing of compliant parts," *J. Manuf. Sci. Eng.*, vol. 127, no. 1, pp. 68–74, Feb. 2005.
[34] X. Mendibil, I. Llanos, H. Urreta, and I. Quintana, "In process quality control on micro-injection moulding: The role of sensor location," *Int. J. Adv. Manuf. Technol.*, vol. 89, nos. 9–12, pp. 3429–3438, Apr. 2017.
[35] E. Oromiehie, G. Prusty, P. Compston, and G. Rajan, "*In situ* process monitoring for automated fibre placement using fibre Bragg grating sensors," *Struct. Heath Monitor.*, vol. 15, no. 6, pp. 706–714, Aug. 2016.
[36] S. Lu, M. Jiang, Q. Sui, H. Dong, Y. Sai, and L. Jia, "Acoustic emission location on aluminum alloy structure by using FBG sensors and PSO method," *J. Mod. Opt.*, vol. 63, no. 8, pp. 742–749, Oct. 2016.
[37] C. Mukhopadhyay *et al.*, "Optimization of positioning of an acoustic emission sensor for monitoring hot forging," *Mater. Manuf. Process.*, vol. 21, no. 5, pp. 543–549, Feb. 2006.
[38] D. M. Chang, C. C. Yu, and I.-L. Chien, "Arrangement of multi-sensor for spatio-temporal systems: Application to sheet-forming processes," *Chem. Eng. Sci.*, vol. 56, no. 20, pp. 5709–5717, Oct. 2001.
[39] K. Bastani, Z. Kong, W. Huang, and Y. Zhou, "Compressive sensing–based optimal sensor placement and fault diagnosis for multi-station assembly processes," *IIE Trans.*, vol. 48, no. 5, pp. 462–474, Feb. 2016.
[40] Y. Ding and D. W. Apley, "Guidelines for placing additional sensors to improve variation diagnosis in assembly processes," *Int. J. Prod. Res.*, vol. 45, no. 23, pp. 5485–5507, Oct. 2007.
[41] Y. Chen, J. Jin, and J. Shi, "Integration of dimensional quality and locator reliability in design and evaluation of multi-station body-in-white assembly processes," *IIE Trans.*, vol. 36, no. 9, pp. 827–839, Aug. 2004.
[42] N. Shukla, D. Ceglarek, and M. K. Tiwari, "Key characteristics-based sensor distribution in multi-station assembly processes," *J. Intell. Manuf.*, vol. 26, no. 1, pp. 43–58, Feb. 2015.
[43] C. Q. Liu, Y. Ding, and Y. Chen, "Optimal coordinate sensor placements for estimating mean and variance components of variation sources," *IIE Trans.*, vol. 37, no. 9, pp. 877–889, Feb. 2005.
[44] S. Tyagi, N. Shukla, and S. Kulkarni, "Optimal design of fixture layout in a multi-station assembly using highly optimized tolerance inspired heuristic," *Appl. Math. Model.*, vol. 40, no. 11, pp. 6134–6147, Jun. 2016.
[45] H. R. Shaker and M. Tahavori, "Optimal sensor and actuator location for unstable systems," *J. Vibrat. Control.*, vol. 19, no. 12, pp. 1915–1920, Jul. 2013.
[46] N. Shukla, M. Tiwari, and R. Shankar, "Optimal sensor distribution for multi-station assembly process using chaos-embedded fast-simulated annealing," *Int. J. Prod. Res.*, vol. 47, no. 1, pp. 187–211, Nov. 2009.
[47] Y. Ren and Y. Ding, "Optimal sensor distribution in multi-station assembly processes for maximal variance detection capability," *IIE Trans.*, vol. 41, no. 9, pp. 804–818, Jun. 2009.
[48] H. Oloomi and M. E. Sawan, "Optimal sensor placement in decentralized control systems," *Int. J. Syst. Sci.*, vol. 20, no. 6, pp. 939–943, Jun. 1989.
[49] I. Bruant, L. Gallimard, and S. Nikoukar, "Optimization of piezoelectric sensors location and number using a genetic algorithm," *J. Mech. Adv. Mater. Struct.*, vol. 18, no. 7, pp. 469–475, 2011.
[50] J. V. Abellan-Nebot, J. Liu, and F. R. Subirón, "Quality prediction and compensation in multi-station machining processes using sensor-based fixtures," *Robot. Comput.-Integr. Manuf.*, vol. 28, no. 2, pp. 208–219, Oct. 2012.
[51] J. Jin and J. Shi, "State space modeling of sheet metal assembly for dimensional control," *J. Manuf. Sci. Eng.*, vol. 121, no. 4, pp. 756–762, Nov. 1999.
[52] O. Tonomura, S. Nagahara, J.-I. Kano, M. Kano, and S. Hasebe, "Sensor location for effective fault diagnosis in micro chemical processes," *IFAC Proc.*, vol. 42, no. 11, pp. 309–314, Apr. 2009.
[53] L. Xinmin, T. Zhaoqing, and L. Zhongqin, "A simplified method for optimal sensor distribution for process fault diagnosis in multistation assembly processes," *J. Manuf. Sci. Eng.*, vol. 130, no. 5, p. 051002, Jun. 2008.
[54] V. Venkatasubramanian, R. Rengaswamy, and S. N. Kavuri, "A review of process fault detection and diagnosis: Part II: Qualitative models and search strategies," *Comput. Chem. Eng.*, vol. 27, no. 3, pp. 313–326, 2003.
[55] V. Yegnanarayanan, G. Umamaheswari, and R. J. Lakshmi, "On a graph theory based approach for improved computer vision," in *Proc. Int. Conf. Signal Process. Syst.*, Singapore, 2009, pp. 660–664.
[56] R. Li and X. Wang, "Qualitative/quantitative simulation of process temporal behavior using clustered fuzzy digraphs," *AiChE J.*, vol. 47, no. 4, pp. 906–919, Apr. 2001.
[57] V. Venkatasubramanian, R. Rengaswamy, K. Yin, and S. N. Kavuri, "A review of process fault detection and diagnosis: Part I: Quantitative model-based methods," *Comput. Chem. Eng.*, vol. 27, no. 3, pp. 293–311, 2003.
[58] M. Bhushan and R. Rengaswamy, "Comprehensive design of a sensor network for chemical plants based on various diagnosability and reliability criteria. 1. Framework," *Ind. Eng. Chem. Res.*, vol. 41, no. 7, pp. 1826–1839, Mar. 2002.
[59] M. Bhushan and R. Rengaswamy, "Comprehensive design of a sensor network for chemical plants based on various diagnosability and reliability criteria. 2. Applications," *Ind. Eng. Chem. Res.*, vol. 41, no. 7, pp. 1840–1860, Mar. 2002.
[60] M. Bhushan and R. Rengaswamy, "Design of sensor location based on various fault diagnostic observability and reliability criteria," *Comput. Chem. Eng.*, vol. 24, nos. 2–7, pp. 735–741, Jul. 2000.
[61] R. Raghuraj, M. Bhushan, and R. Rengaswamy, "Locating sensors in complex chemical plants based on fault diagnostic observability criteria," *AiChE J.*, vol. 45, no. 2, pp. 310–322, Feb. 1999.
[62] F. Yang, D. Xiao, and S. L. Shah, "Optimal sensor location design for reliable fault detection in presence of false alarms," *Sensors*, vol. 9, no. 11, pp. 8579–8592, Oct. 2009.
[63] H. Qi, S. S. Iyengar, and K. Chakrabarty, "Distributed sensor networks—A review of recent research," *J. Frank. Inst.*, vol. 338, no. 6, pp. 655–668, Sep. 2001.
[64] M. Bhushan, S. Narasimhan, and R. Rengaswamy, "Robust sensor network design for fault diagnosis," *Comput. Chem. Eng.*, vol. 32, no. 4, pp. 1067–1084, Apr. 2008.
[65] J. Li and J. Jin, "Optimal sensor allocation by integrating causal models and set-covering algorithms," *IIE Trans.*, vol. 42, no. 8, pp. 564–576, May 2010.

[66] K. Liu and J. Shi, "Objective-oriented optimal sensor allocation strategy for process monitoring and diagnosis by multivariate analysis in a Bayesian network," *IIE Trans.*, vol. 45, no. 6, pp. 630–643, 2013.
[67] M. Pourali and A. Mosleh, "A Bayesian approach to sensor placement optimization and system reliability monitoring," *Proc. Inst. Mech. Eng., O, J. Risk Rel.*, vol. 227, no. 3, pp. 327–347, Sep. 2013.
[68] M. S. Sayed and N. Lohse, "Ontology-driven generation of Bayesian diagnostic models for assembly systems," *Int. J. Adv. Manuf. Technol.*, vol. 74, nos. 5–8, pp. 1033–1052, Jun. 2014.
[69] S. S. Mandroli, A. K. Shrivastava, and Y. Ding, "A survey of inspection strategy and sensor distribution studies in discrete-part manufacturing processes," *IIE Trans.*, vol. 38, no. 4, pp. 309–328, Jun. 2006.
[70] A. Kumar, M. Baldea, and T. F. Edgar, "On optimal sensing and actuation design for an industrial scale steam methane reformer furnace," *AiChE J.*, vol. 62, no. 9, pp. 3225–3237, May 2016.
[71] S. Costiner *et al.*, "A probabilistic hybrid sensor fusion and optimization approach for aircraft composite components," *J. Intell. Mater. Syst. Struct.*, vol. 24, no. 17, pp. 2110–2134, Nov. 2013.
[72] J. W. Sun, L.-F. Xi, E.-S. Pan, S.-C. Du, and T.-B. Xia, "Design for diagnosability of multistation manufacturing systems based on sensor allocation optimization," *Comput. Ind.*, vol. 60, no. 7, pp. 501–509, Sep. 2009.
[73] W. Sheng, N. Xi, M. Song, and Y. Chen, "CAD-guided sensor planning for dimensional inspection in automotive manufacturing," *IEEE/ASME Trans. Mechatronics*, vol. 8, no. 3, pp. 372–380, Sep. 2003.
[74] A. Khan, D. Ceglarek, J. Shi, J. Ni, and T. C. Woo, "Sensor optimization for fault diagnosis in single fixture systems: A methodology," *J. Manuf. Sci. Eng.*, vol. 121, pp. 109–117, Feb. 1999.
[75] A. Khan and D. Ceglarek, "Sensor optimization for fault diagnosis in multi-fixture assembly systems with distributed sensing," *J. Manuf. Sci. Eng.*, vol. 122, no. 1, pp. 215–226, Feb. 2000.
[76] A. Khan, D. Ceglarek, and J. Ni, "Sensor location optimization for fault diagnosis in multi-fixture assembly systems," *J. Manuf. Sci. Eng.*, vol. 120, pp. 781–792, Nov. 1998.
[77] M. A. Benatia, M. Sahnoun, D. Baudry, A. Louis, A. El-Hami, and B. Mazari, "Multi-objective WSN deployment using genetic algorithms under cost, coverage, and connectivity constraints," *Wireless Pers. Commun.*, vol. 94, no. 4, pp. 2739–2768, Feb. 2017.
[78] L. Wang, L. An, H.-Q. Ni, W. Ye, M. P. Pardalos, and M.-R. Fei, "Pareto-based multi-objective node placement of industrial wireless sensor networks using binary differential evolution harmony search," *Adv. Manuf.*, vol. 4, no. 1, pp. 66–78, 2016.
[79] G. C. Onwubolu and M. Clerc, "Optimal path for automated drilling operations by a new heuristic approach using particle swarm optimization," *Int. J. Prod. Res.*, vol. 42, no. 3, pp. 473–491, Feb. 2004.
[80] J. A. Ghani, P. S. Jye, C. H. C. Haron, M. Rizal, and M. Z. Nuawi, "Determination of sensor location for cutting tool deflection using finite element method simulation," *Proc. Inst. Mech. Eng. C, J. Mech. Eng. Sci.*, vol. 226, no. 9, pp. 2373–2377, Nov. 2012.
[81] F. Bachmann, A. E. Bergamini, and P. Ermanni, "Optimum piezoelectric patch positioning: A strain energy–based finite element approach," *J. Intell. Mater. Syst. Struct.*, vol. 23, no. 14, pp. 1575–1591, Jun. 2012.
[82] A. Belloli and P. Ermanni, "Optimum placement of piezoelectric ceramic modules for vibration suppression of highly constrained structures," *Smart Mater. Struct.*, vol. 16, no. 5, pp. 1662–1673, Aug. 2007.
[83] J. A. Camelio, S. J. Hu, and H. Yim, "Sensor placement for effective diagnosis of multiple faults in fixturing of compliant parts," *J. Manuf. Sci. Eng.*, vol. 127, no. 1, pp. 373–380, Nov. 2003.
[84] P. Kim and Y. Ding, "Optimal design of fixture layout in multistation assembly processes," *IEEE Trans. Autom. Sci. Eng.*, vol. 1, no. 2, pp. 133–145, Oct. 2004.
[85] R. T. Marler and J. S. Arora, "Survey of multi-objective optimization methods for engineering," *Struct. Multidisciplinary Optim.*, vol. 26, no. 6, pp. 369–395, Apr. 2004.
[86] N. S. S. Sen and K. Deb, "Sensor network design of linear processes using genetic algorithms," *Comput. Chem. Eng.*, vol. 22, no. 3, pp. 385–390, Feb. 1998.
[87] H. Chen, J. A. Clark, J. E. Tapiador, S. A. Shaikh, H. Chivers, and P. Nobles, "A multi-objective optimisation approach to IDS sensor placement," *Comput. Intell. Secur. Inf. Syst.*, vol. 63, pp. 101–108, Nov. 2009.
[88] K. Worden and A. Burrows, "Optimal sensor placement for fault detection," *Eng. Struct.*, vol. 23, no. 8, pp. 885–901, Aug. 2001.
[89] X. Wang, S. Wang, and A. Jiang, "Optimized deployment strategy of mobile agents in wireless sensor networks," in *Proc. ISDA*, vol. 2. Oct. 2006, pp. 893–898.
[90] C. C. Yang and F. W. Ciarallo, "Optimized sensor placement for active visual inspection," *J. Robot. Syst.*, vol. 18, no. 1, pp. 1–15, Nov. 2001.
[91] B. Jung, J. Cho, and W. Jeong, "Sensor placement optimization for structural modal identification of flexible structures using genetic algorithm," *J. Mech. Sci. Technol.*, vol. 29, no. 7, pp. 2775–2783, Jul. 2015.
[92] C. Mendis, S. M. Guru, S. Halgamuge, and S. Fernando, "Optimized sink node path using particle swarm optimization," in *Proc. 20th Int. Conf. Adv. Inf. Netw. Appl.*, Vienna, Austria, 2006, pp. 5–15.
[93] Y. Ren, Y. Ding, and F. Liang, "Adaptive evolutionary Monte Carlo algorithm for optimization with applications to sensor placement problems," *Stat. Comput.*, vol. 18, no. 4, pp. 375–390, Dec. 2008.
[94] D. C. Kammer, "Sensor placement for on-orbit modal identification and correlation of large space structures," *J. Guid. Control Dyn.*, vol. 14, no. 2, pp. 2984–2990 Mar./Apr. 1991.
[95] J. Li, S. Feng, Y. Zhang, C. Wang, and X. He, "Optimized thermal sensor allocation for field-programmable gate array temperature measurements based on self-heating test," *Microelectron. J.*, vol. 60, pp. 55–59, Feb. 2017.
[96] V. Gupta, M. Sharma, and N. Thakur, "Optimization criteria for optimal placement of piezoelectric sensors and actuators on a smart structure: A technical review," *J. Intell. Mater. Syst. Struct.*, vol. 21, no. 12, pp. 1227–1243, Sep. 2010.
[97] S. Jiang, R. Kumar, and H. E. Garcia, "Optimal sensor selection for discrete-event systems with partial observation," *IEEE Trans. Autom. Control*, vol. 48, no. 3, pp. 369–381, Mar. 2003.
[98] S. Wu, S. S. Panikar, R. Singh, J. Zhang, B. Glasser, and R. Ramachandran, "A systematic framework to monitor mulling processes using near infrared spectroscopy," *Adv. Powder Technol.*, vol. 27, no. 4, pp. 1115–1127, Jul. 2016.
[99] S. Zhao, B. M. Chen, and T. H. Lee, "Optimal placement of bearing-only sensors for target localization," in *Proc. Amer. Control Conf. (ACC)*, Montreal, QC, Canada, 2012, pp. 5108–5113.
[100] Y. Edan and S. Y. Nof, "Sensor economy principles and selection procedures," *IIE Trans.*, vol. 32, no. 3, pp. 195–203, Mar. 2000.
[101] E. Mesa-Barrameda, N. Santoro, W. Shi, and N. Taleb, "Sensor deployment by a robot in an unknown orthogonal region: Achieving full coverage," in *Proc. 20th IEEE Int. Conf. Parallel Distrib. Syst. (ICPADS)*, Hsinchu, Taiwan, Dec. 2014, pp. 951–960.
[102] B. H. Lee and T. Kim, "Optimal allocation and placement of thermal sensors for reconfigurable systems and its practical extension," in *Proc. Asia South Pacific Design Autom. Conf.*, Seoul, Korea, 2008, pp. 703–707.

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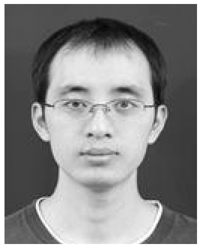

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