

Research Article

Sensor Optimization for Variation Diagnosis in Multistation Assembly Processes

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Appropriate sensor deployment is the key to the efficient diagnosis of product variation. Yet, optimizing sensor placement in complex manufacturing systems remains challenging. We propose a variation propagation analysis (VPA)-based sensor deployment strategy for variation diagnosis in multistation assembly processes. A state-space model is employed to analyze the influences of fixture faults and workpiece dimensional deviations on assembly variation. Based on matrix transformation, the assembly variation propagation characteristics are quantified and a VPN-based causal graph is constructed to represent the causality between assembly variation and sensor measurement. To ensure the diagnosability of over-tolerance of assembly variation (OAV) and the economics of the sensor system, an optimal sensor deployment scheme is presented. It uses the enhanced shuffled frog-leaping algorithm to minimize the OAV unobservability per unit cost and the sensor cost under the constraint of detectability. Finally, the effectiveness of the proposed approach is illustrated by a case study of sensor deployment for variation diagnosis in a multistation automobile differential assembly process.

1. Introduction

In the multistation assembly processes used in current manufacturing industries, variation diagnosis is an important issue that remains to be solved. In product assembly processes, condition monitoring based on distributed sensor networks (DSNs) is an effective and reliable way to ensure the assembly quality of product parts. In multistation assembly processes, fixture failure is the main source of dimensional variation in assembled parts [1], especially in the automotive and aerospace industries, where about 70% of product assembly variations are caused by fixture failure [2]. Therefore, in multistation assembly processes, an effective, real-time strategy is needed to monitor the sources of variation that cause product assembly quality defects, so as to effectively diagnose and control product variation.

In complex multistation assembly processes, product variation diagnosability depends on the ability of sensors to determine abnormal states in the system [3]. However, this is constrained by many aspects, such as the assembly process,

the sensor characteristics and arrangement, and the characteristics of the variation sources. Improper sensor placement may fail to provide sufficient and accurate data, thereby reducing the diagnostic capabilities of the system. Although a saturated sensor arrangement can effectively overcome this, it may produce a large amount of irrelevant or conflicting data, increasing the difficulty of data processing [1] and reducing system diagnosability. For this reason, there has been much research on optimizing sensor arrangements for condition monitoring during assembly processes.

Initial sensor placement strategies for variation diagnosis mainly focused on single-station placement. Khan et al. [4] proposed an optimized sensor arrangement for fault identification in automobile body assembly fixtures. The fixture design specification was incorporated into the sensor field plan to optimize the sensor arrangement for single-fixture fault diagnosis and reduce the variation in automobile body assembly. They also proposed a multilayer, two-step, and hierarchical optimized sensor arrangement based on Computer Aided Design (CAD) assembly data for multifixture

fault diagnosis during stamped part assembly processes, which improved the multifixture fault diagnosability by maximizing the minimum single-fixture diagnosis vector norm [5]. Liu et al. [6] proposed a causal network approach to characterize the causal relationship between assembly variation sources and measurement features. Based on a causal network, they used information entropy to evaluate the sensitivity of measurement features to the source of assembly variation. Then, a sensor optimization algorithm was used to obtain the minimum number of features and optimal sensor arrangement for fully identifying the sources of assembly variation. Li et al. [7] proposed a grey relational analysis (GRA)-based quantitative causal diagram (QCD) sensor allocation strategy, which considers the influence of the propagation of fault risks. Fault-to-sensor and fault-to-fault causal relationships are expressed by the QCD and the propagation coefficients of fault risk, which are calculated by GRA. However, they only considered sensors of a single type. He et al. [8, 9] proposed a quantitative fuzzy bipartite graph model to characterize the causal relationship between sensors and fault/assembly variation sources. The sensor layout is optimized for condition monitoring of a single-station and multistep manufacturing process by efficiently integrating sensor and fault/variation source features into cause-and-effect diagrams. However, this approach is limited by the single-station sensor layout and a lack of systematic analysis of the inherent causal relationships between various fault/variation sources.

Compared with local single-station sensor arrangements, multistation arrangements based on distributed sensing at the system level have received increasing attention. Based on matrix transformation of a state-space model, Ding et al. [1] analyzed the transmissibility of variation between stations and the variation diagnosability of single stations. They then derived a corresponding performance measurement index for variation diagnosis in multistation assembly processes. However, the characteristic differences between sensors were ignored. Yu et al. proposed a novel approach that integrates statistical analysis with domain knowledge. The relationships between key control and product characteristics are revealed by a variation propagation model. The fault diagnosis problem is transformed into a search for a sparse solution to abnormal variance changes in process faults. Based on the non-negative property of a covariance matrix, a Bayesian hierarchical model was developed to allow sparse estimation of the variance in underdetermined multistage assembly processes [10]. Shukla et al. [11] presented a novel method of sensor allocation for multistation assembly processes. It minimizes the effect of noise on sensor placement by maximizing the determinant of a Fischer information matrix. The state-space method is used to simulate the variation propagation pertaining to the transfer of parts within a multistation assembly process. The influence of sensor coupling noise was added to an optimization objective function, and a chaotic embedded fast simulated annealing algorithm (CEFSA) was proposed to optimize the objective function. An optimal sensor arrangement with minimal noise impact was obtained. Ren and Ding [12] proposed a distributed sensor

placement strategy to maximize assembly variation diagnosability in multistation assembly processes. They defined a sensitivity index to characterize the diagnostic capability of sensor networks and employed a data-mining-guided evolutionary approach for the nonlinear optimization of sensor layouts. However, only sensors of the same type were considered. Bastani et al. [13] proposed an optimal sensor layout method based on compressive sensing for fault diagnosis in multistation assembly processes. It is based on the ability of compressed sensing theory to deal with indeterminate equations by seeking the minimum average cross-correlation coefficient to maximize the system fault diagnosability. Liu and Shi [14] proposed a sensor arrangement method for real-time system fault diagnosis based on distributed sensor networks. They used a Bayesian network to determine the causal relationships between system faults and sensor measurements. The sensor placement problem was transformed into a sensor set coverage problem to minimize the system cost and meet the diagnosability constraints. Finally, the optimal sensor arrangement was obtained via an intelligent searching algorithm of minimum placement subsets. Using a discrete-time nonlinear state-space model, Qu et al. [15] developed a more accurate multistation assembly process variation propagation model, which provides a mathematical representation for process-oriented positioning reference system design. They proposed a design parameter model that includes a positioning reference system and established the quantitative relationship between key control characteristics and key product characteristics. Shukla et al. [16] proposed an optimal sensor placement method based on key product features for product quality variation diagnosis in multistation assembly processes. Firstly, a genetic algorithm is used to maximize the number of key feature points, and then a search method is used to further optimize the sensor network to obtain its optimal arrangement. Although, the concept of key quality characteristics was proposed, there was no analysis of the internal correlations between them.

It can be seen from the above literature that whether a single- or multistation sensor arrangement strategy is used, variation diagnosis in assembly variation transmission, causal model construction, and multiobjective optimization still have the following problems that the present study aimed to solve the following:

- (1) Although many studies have considered variation transfer characteristics in multistation assembly processes, the inherent correlations between the variation source characteristics and the assembly process, as well as the influences of sensor and variation source characteristics on multistation sensor arrangements, still require further analysis and improvement.
- (2) In multistation assembly processes, the status information provided by different types of sensors and variation source features influences the network diagnosis accuracy. Effectively integrating such information into causal models has received little attention in research on multistation sensor optimal arrangement.

- (3) The optimization of sensor arrangements for multistation assembly variation diagnosis is currently limited to single-objective optimization approaches. The introduction of an effective intelligent optimization algorithm into a multiobjective optimization approach warrants further research.

2. Sensor Layout Methodology

2.1. Multistation Assembly Variation Propagation Analysis (VPA). Multistation assembly refers to a process where products/parts are assembled at multiple stations. For example, the assembly of automobile main reducers, bodies in white, and engines are completed at multiple stations. In the assembly process, positioning pins and NC positioning blocks are widely used for precise positioning during workpiece assembly. The 3-2-1 fixture and rigid part assumptions are made in the derivation. For rigid parts, the 3-2-1 principle is the most common layout method [17]. It mainly includes locating pins P_1 limited to four degrees of freedom, a locating pin P_2 restricted to two degrees of freedom, and an NC block restricted in a single direction. At each assembly station, a fixture failure can directly cause assembly misalignment, producing an error declination $\Delta\alpha_{P_{2,1}}$. If the fixture is excessively worn, the positioning point is moved from P_2 to $P_{2,2}$, resulting in a deviation angle $\Delta\alpha_{P_{2,2}}$. In some special cases, if the workpiece itself has a dimensional deviation, such as in the size of a positioning hole, the resulting deviation angle $\Delta\alpha_{P_{2,1}}$ is equivalent to the deviation angle $\Delta\beta_{P_2}$, as shown in Figure 1.

To effectively describe the evolution of the variation information in the multistation assembly process and reveal the causal relationship between this information and sensor measurements, a state-space model is used to characterize the multivariate input and output relationship of the assembly variation information flow [17], as shown in Figure 2. The model is as follows:

$$\begin{aligned} X_k &= A_{k-1}X_{k-1} + B_kU_k + e_k, \\ U_k &= F_{k,i} + P_{k,j}, \\ Y_k &= C_kX_k + w_k, \end{aligned} \quad (1)$$

$i, j, k \in \{1, 2, \dots, N\}$,

where k is the station index and N is the number of stations. The product dimensional state, which describes random dimensional deviations, is denoted as $X_k \in \mathfrak{R}^{n_k \times 1}$ ($k = 1, 2, \dots, N$). $U_k \in \mathfrak{R}^{n_k \times 1}$ ($k = 1, 2, \dots, N$) represents the variation information introduced at station k . $F_{k,i} \in \mathfrak{R}^{n_k \times 1}$ and $P_{k,j} \in \mathfrak{R}^{n_k \times 1}$ describe the variation information introduced by the i^{th} fixture failure and j^{th} workpiece dimensional deviation, respectively. Product measurements at the station are included in $Y_k \in \mathfrak{R}^{m_k \times 1}$. However, if Y_k is not specifically measured, then $C_k = 0$. ν_k, μ_k, γ_k respectively represent the dimensions of its vector. Additional process variation, including unmodeled higher-order terms, is represented by e_k . Sensor noise, denoted by w_k , is a vector of uncorrelated random variables with zero means. A_k is known as a dynamic matrix that characterizes assembly reorientation during part

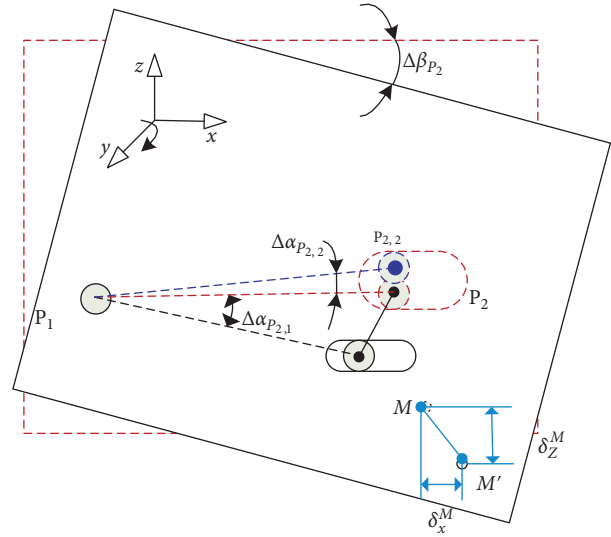


FIGURE 1: Assembly deviation due to locating pin P_2 .

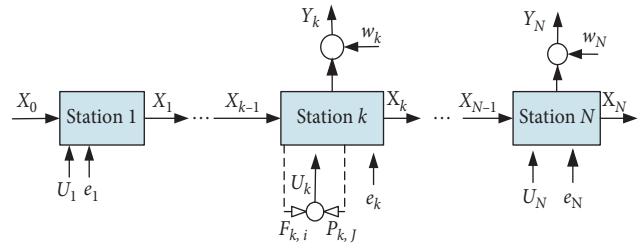


FIGURE 2: Multistation assembly variation information flow.

transfer between stations. B_k is an input matrix that determines how fixture failure and workpiece dimensional deviation affect the product assembly variation state at station k . C_k is an observation matrix that includes sensor deployment information [17]. A detailed analysis of a multistation system modeled by equation (1) was reported in [1]. The recursive expression in equation (1) can be formulated into an input-output relation as

$$\begin{aligned} X_k &= A_{k-1}X_{k-1} + B_kU_k + e_k \\ &= \prod_{j=k-1}^{i-1} A_j X_{i-1} + \begin{bmatrix} B_k \\ \prod_{j=k-1}^{k-1} A_j B_{k-1} \\ \prod_{j=k-1}^{k-2} A_j B_{k-2} \\ \vdots \\ \prod_{j=k-1}^i A_j B_i \end{bmatrix} \begin{bmatrix} U_k \\ U_{k-1} \\ U_{k-2} \\ \vdots \\ U_i \end{bmatrix} + \begin{bmatrix} I \\ \prod_{j=k-1}^{k-1} A_j \\ \prod_{j=k-1}^{k-2} A_j \\ \vdots \\ \prod_{j=k-1}^i A_j \end{bmatrix} \begin{bmatrix} e_k \\ e_{k-1} \\ e_{k-2} \\ \vdots \\ e_i \end{bmatrix} \\ &= G_{i-1 \rightarrow k} X_{i-1} + \begin{bmatrix} G_{k \rightarrow k} B_k \\ G_{k-1 \rightarrow k} B_{k-1} \\ G_{k-2 \rightarrow k} B_{k-2} \\ G_{k-3 \rightarrow k} B_{k-3} \\ \vdots \\ G_{i \rightarrow k} B_i \end{bmatrix} \begin{bmatrix} U_k \\ U_{k-1} \\ U_{k-2} \\ U_{k-3} \\ \vdots \\ U_i \end{bmatrix} + \begin{bmatrix} G_{k \rightarrow k} \\ G_{k-1 \rightarrow k} \\ G_{k-2 \rightarrow k} \\ G_{k-3 \rightarrow k} \\ \vdots \\ G_{i \rightarrow k} \end{bmatrix} \begin{bmatrix} e_k \\ e_{k-1} \\ e_{k-2} \\ e_{k-3} \\ \vdots \\ e_i \end{bmatrix}, \end{aligned} \quad (2)$$

where a state transition matrix for a state-space approach may be defined as $G_{i \rightarrow k} = \left\{ \prod_{j=k-1}^i A_j, \text{ when } i \leq k-1; I, \text{ when } i = k \right\}$. The linear input-output relations between the observation vector Y_k and variation sources U_k is illustrated based on the SOVA model, as shown in (1) [17]. The input-output model is

$$S_i \rightarrow Y_{1 \rightarrow k} = Z_{1 \rightarrow k} U_{1 \rightarrow k} + \Theta_{1 \rightarrow k}, \quad (3)$$

where S_i indicates that the i^{th} sensor is installed at the k^{th} station. $\Delta_{1 \rightarrow k}$ indicates the accumulated error information at the k^{th} station ($\Delta = Y, U$). $\Theta_{1 \rightarrow k}$ represents the independent noise source accumulated at the k^{th} station, $\Theta_{1 \rightarrow k} = \sum_{i=1}^k C_k G_{j \rightarrow k} e_i + w_k$. The coefficient of the first term in equation (2), $Z_{1 \rightarrow k}$, can be defined as

$$Z_{1 \rightarrow k} = \begin{bmatrix} C_1 B_1 & 0 & 0 & 0 \\ C_2 G_{1 \rightarrow 2} B_1 & C_2 B_2 & \dots & 0 \\ C_3 G_{1 \rightarrow 3} B_1 & C_3 G_{2 \rightarrow 3} B_2 & \dots & 0 \\ C_4 G_{1 \rightarrow 4} B_1 & C_4 G_{2 \rightarrow 4} B_2 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ C_k G_{1 \rightarrow k} B_1 & C_k G_{2 \rightarrow k} B_2 & \dots & C_k B_k \end{bmatrix}. \quad (4)$$

According to equations (2) and (3), whether the sensor S_i should be arranged at station k or not is closely related to the matrix $G_{i \rightarrow k} B_i$. After $\pi(\bullet)$ matrix transformation [1], $\pi(G_{i \rightarrow k} B_i)$ can be obtained, whose rank $R_{i \rightarrow k} = \text{Rank}\{\pi(G_{i \rightarrow k} B_i)\}$ represents the number of assembly variation sources transmitted from station i to station k . Assuming that there are v_i workpiece/part assemblies at station i , the assembly variation transfer rate from station i to station k is $R_{i \rightarrow k}/3v_i$. When the number of workpieces/parts is joined at station i and the coordinates of the positioning pins are known, it is easy to obtain the assembly variation transfer coefficient [18]. If v_i independent workpieces/parts are assembled at the i^{th} station, the variation transfer coefficient from station i to station k , $c_{i \rightarrow k}$, can be expressed as

$$c_{i \rightarrow k} = \begin{cases} 0.667 v_i = 2, R_{k-1 \rightarrow k} = 4, \\ 0.833 v_i = 2, R_{k-1 \rightarrow k} = 5, \\ 1 v_i \geq 3, \text{ or } i = k. \end{cases} \quad (5)$$

To objectively evaluate the system diagnostic capability, it is crucial to effectively integrate the assembly variation and sensor characteristics (especially of heterogeneous sensors) into the sensor layout optimization process [3]. Here, the failure mode effect analysis (FMEA) of 6Sigma is used to effectively quantify the characteristics of the sensor and assembly variation source itself, such as the occurrence rate (f) of over-tolerance of assembly variation (OAV). The causal analysis tool of 6 Sigma is used based on VPA to build a causal model of sensor measurement and multistation assembly variation.

2.2. Optimal Sensor-Distribution Strategy. The reliability of the diagnostic network is not only restricted by the assembly process, but also by the characteristics of the sensor and the

source of assembly variation itself. To match the assembly variation source node with the sensor node, it is necessary to minimize the unobservability of the OAV of the entire system; that is, to minimize the probability that sensor failure and OAV occur at the same time [3]. This also minimizes the sensor layout cost [7]. The detectability of assembly variation is taken as the constraint condition. Mathematically, this can be expressed as

$$\text{Min: } U = \frac{\sum_{k=1}^N \sum_{i=1}^M [\log(f_{k,i}) + \sum_{j=1}^m (d_{i,j} \times \log(\text{Pr}_{k,j}) \times x_j)]}{\sum_{k=1}^N \sum_{j=1}^m c_{k,j} x_j},$$

$$\text{Min: } C = \sum_k \sum_j c_{k,j} x_j,$$

Subject to:

$$\left(\sum_{j \in S} d_{i,j} x_j \right) | \forall i \in X > 0. \quad (6)$$

These equations mean that an OAV is only unable to be observed when it occurs at the moment of sensor failure. Here, U is the OAV unobservability index per unit cost, C is the system layout cost, $f_{k,i}$ is the OAV occurrence probability, $\text{Pr}_{k,j}$ is the sensor failure probability, $d_{i,j}$ is the entry of a binary bipartite matrix ($d_{i,j} = 1$ if the OAV affects sensor S_j or is zero otherwise), and x_j and $c_{k,j}$ are decision variables related to how many j^{th} sensors need to be used, and their price, respectively. We notice that the primary objective is the OAV unobservability index per unit cost (U). The system layout cost (C) is the secondary objective function that needs to be minimized under the constraints of detectability. The proposed approach to direct sensor deployment is shown in Figure 3.

3. Results and Discussion

To illustrate the proposed sensor deployment approach for multistation assembly system diagnosis, a case study of an automobile differential assembly process is presented below.

An automobile differential assembly line (Figure 4) owned by the project team was used to demonstrate the proposed sensor deployment approach. Optimization of the sensor arrangement was carried out for this multistation assembly process. Figure 5 shows the assembly process. Four stations are analyzed, of which three parts are joined at Station 1, which has an assembly variation transfer coefficient $c_{1 \rightarrow k} = 1, 1 < k \leq 4$. At Station 2, two parts are joined, and their 4-DOF positioning pins have the same Z -coordinate, which means $R_{k-1 \rightarrow k} = 4$. Therefore, its assembly variation transfer coefficient is $c_{2 \rightarrow k} = 0.667, 2 < k \leq 4$. Similarly, at Station 3, the assembly variation transfer coefficient is $c_{3 \rightarrow k} = 0.833, 3 < k \leq 4$. Station 4 is the end inspection station. Based on variation propagation analysis of the above assembly process, a VPA-based causal diagram was constructed (Figure 6). Among them, $X_k (k = 1, 2,$

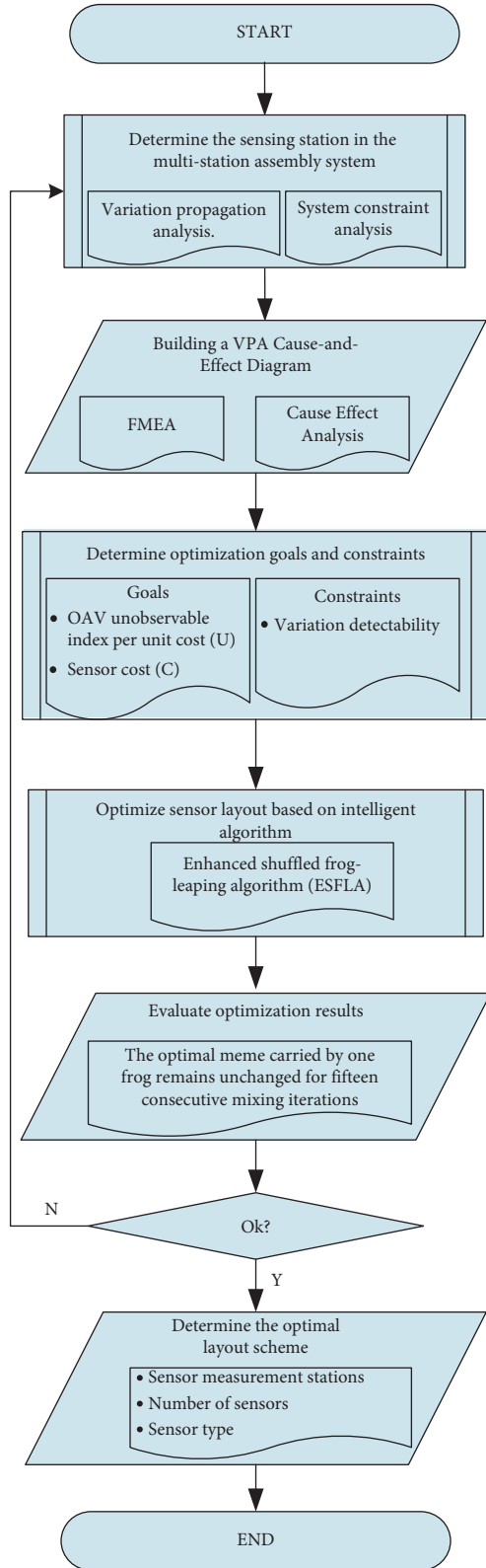


FIGURE 3: VPA-based approach to optimizing sensor layout in multistation assembly processes.

..., 4) denotes the accumulated assembly variation information at the k^{th} station, $F_{i,j}$ is the fixture fault information introduced when the j^{th} part is joined at the i^{th} station, and



FIGURE 4: Automobile differential assembly stations.

$P_{i,j}$ is the workpiece dimensional deviation information introduced, when the j^{th} workpiece is joined at the i^{th} station. Table 1 shows the sensor features and assembly variation characteristics based on FMEA.

The final design of an optimized sensor arrangement must be based on a systematic analysis of operability and economy [19]. To this end, the enhanced shuffled frog-leaping algorithm (ESFLA) is adopted to minimize the OAV unobservability per unit cost, thereby improving the diagnosability and economy of the sensor network system. Here, the “sensor layout position” refers to the position of the assembly variation feature to be detected, rather than the physical position of the sensor actually installed [1]. For the convenience of comparison, a backward propagation (BP)-based sensor layout strategy [1, 11, 12, 18], end-of-line (EOL) sensing, and saturated sensing are also discussed. The optimization variables are exactly the same for all four compared optimization schemes and were derived from the sensor and assembly variation characteristics (Table 1) and their causal relationship based on VPA (Figure 6). In addition, the basic parameters of the ESFLA were as follows. Number of memeplexes $m_g = 50$, number of frogs in each memeplex $n_g = 60$, number of frogs in a submemeplex $q_g = 50$, iteration number within each submemeplex $L_{\max} = 30$, and maximum step size $S_{\max} = 1$. The convergence criteria are met if at least one frog carries the “best memetic pattern so far” for fifteen consecutive shuffles. The results are shown in Table 2.

It can be seen from Table 2 that compared with the other three sensor placement strategies, the proposed VPA-based causal graph achieves a lower OAV unobservability index per unit cost (U) and a lower network placement cost (C), demonstrating better system diagnosability and economy.

The BP-based sensor deployment for multistation assembly variation diagnosis takes into account the transfer characteristics of assembly variations between different stations but ignores the influences of the sensor and assembly variation characteristics on the optimization of the sensor distribution. Therefore, BP-based sensing has a higher OAV unobservability index per unit cost ($U_{BP} = -0.0017 > U_{VPA} = -0.0021$) and a higher network placement cost ($C_{BP} = 2700 > C_{VPA} = 2000$).

The traditional EOL sensor deployment approach ignores the assembly variation propagation characteristics between different stations during the assembly process. This

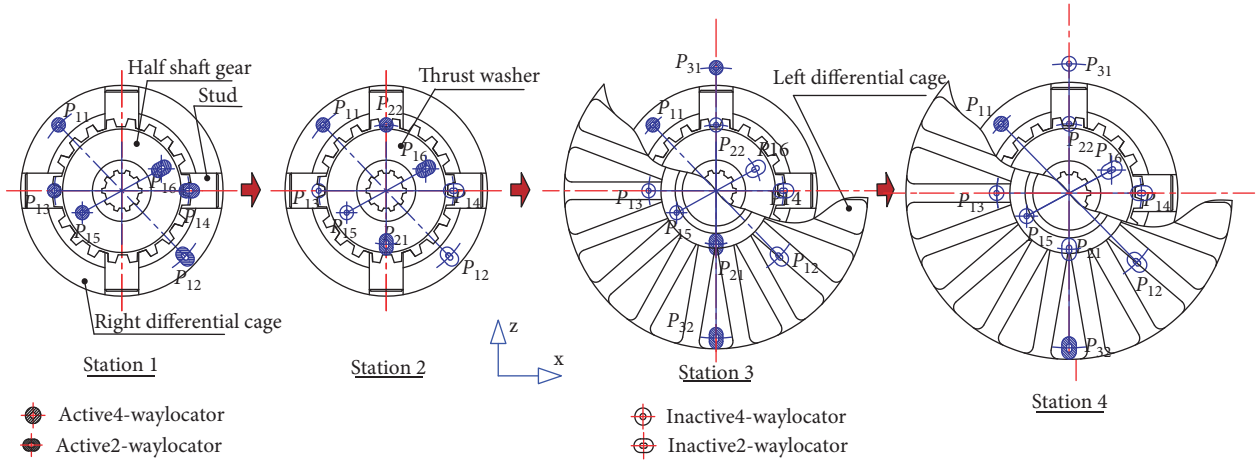


FIGURE 5: Automobile differential assembly sequence.

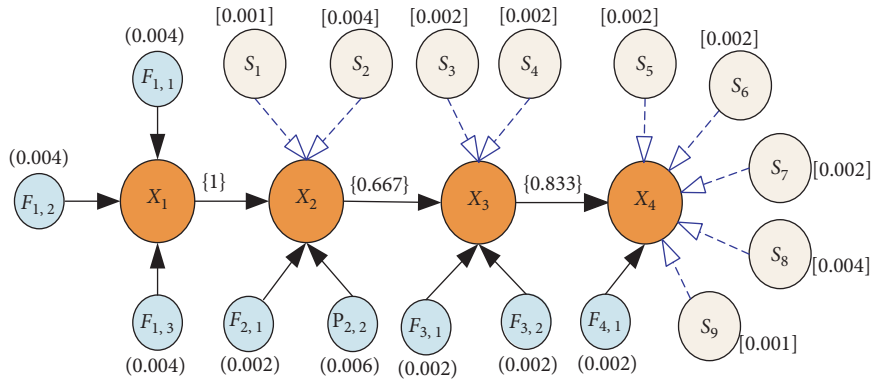


FIGURE 6: VPA-based causal diagram.

TABLE 1: Assembly variations and sensors used in the differential assembly process.

Sensor candidates	Sensor failure rate (P_r , %)	Sensor cost (C, \$)	Part candidate	Possible variations	OAV occurrence rate (f , %)
Displacement sensor S_1	0.1	200	Fixture $F_{2,1}$	Excessive wear	0.2
Thickness sensor S_2	0.4	400	Thrust washer $P_{2,2}$	Thickness deviation	0.6
Displacement sensor S_3	0.2	300	Left diff. cage $F_{3,1}/F_{3,2}$	Fixture failure	0.2
Displacement sensor S_4	0.2	300	Left diff. cage $F_{3,1}/F_{3,2}$	Fixture failure	0.2
Displacement sensor S_5	0.2	300	Right diff. cage $F_{1,1}$	Fixture failure	0.4
Displacement sensor S_6	0.2	300	Stud $F_{1,2}$	Fixture failure	0.4
Displacement sensor S_7	0.2	300	Half-shaft gear $F_{1,3}$	Fixture failure	0.4
Thickness sensor S_8	0.4	400	Thrust washer $P_{2,2}$	Thickness deviation	0.6
Displacement sensor S_9	0.1	200	Left diff.cage/fixture $F_{4,1}$	Excessive wear	0.2

is because the assembly variations generated at Stations 2 and 3 cannot be propagated to the end station (Station 4), while Stations 2 and 3 lack sensor arrangements ($S_1 \sim S_4$). Therefore, the assembly variations generated at Stations 2

and 3 cannot be detected by the system, so system diagnosability cannot be ensured. In addition, the traditional EOL sensor deployment has a high unit OAV unobservability index per unit cost ($U_{EOL} = -0.0005 > U_{VPA} =$

TABLE 2: Comparison of various approaches to automobile differential assembly.

Approach	Sensors selected	OAV unobservability index per unit cost (U)	Cost utilized ($C/\$$)
VPA-based causal graph	$\{S_1, S_2, S_3, S_5, S_6, S_7, S_9\}$	-0.0021	2000
BP-based sensing	$\{S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8, S_9\}$	-0.0017	2700
EOL sensing	$\{S_5(3), S_6(3), S_7(3), S_8(3), S_9(3)\}$	-0.0005	4500
Saturated sensing	$\{S_1(3), S_2(3), S_3(3), S_4(3), S_5(3), S_6(3), S_7(3), S_8(3), S_9(3)\}$	-0.0012	8100

-0.0021), so it cannot ensure the economy of the sensor system.

In industrial applications, to maximize OAV diagnosability, the corresponding sensors are usually arranged at each potential source of assembly variation, resulting in sensor saturation. Here, considering the actual system, *saturation deployment* refers to installing three sensors at each station, which can effectively reduce information loss. However, due to its high OAV unobservability index per unit cost ($U_{Saturate} = -0.0012 > U_{VPA} = -0.0021$), high sensor deployment cost ($C_{Saturate} = 8100 > C_{VPA} = 2000$), and the difficulty of processing massive sensor datasets in the later stage, the diagnosis efficiency and economy of multistation assembly variation are further weakened. This is also the fundamental reason why the sensor network needs to be optimally deployed.

4. Conclusions

Optimal sensor deployment is an important issue in detecting multistation assembly variation. The accurate and efficient collection of sensor signals is also a new challenge. The contributions of this paper are three-fold:

- (1) Based on a state-space model, the influences of fixture faults and workpiece dimensional deviations on multistation assembly variation were analyzed. By matrix transformation of the state-space model, the inherent characteristics of variation propagation between stations were quantified.
- (2) Based on the analysis of the multistation assembly variation process, a VPA-based causal graph was proposed to characterize the causal relationship between sensor measurements and multistation assembly variations. The key characteristics of the sensors and assembly variations were quantified using the 6Sigma tool and effectively fused into a causal graph.
- (3) A multiobjective optimization model was proposed that (1) minimizes the OAV unobservability index per unit cost (U) and sensor layout cost (C) as its optimization objective, (2) takes detectability as the constraint condition, and (3) is optimized by the ESFLA. A case study of sensor deployment for variation diagnosis in an automobile differential multistation assembly process was conducted. It shows that compared with BP-based, traditional EOL, and saturation sensor layout strategies, the

proposed VPA-based causal graph strategy can (1) obtain a lower OAV unobservability index per unit cost and (2) a lower sensor layout cost, and (3) ensure multistation assembly variation diagnosability and sensor deployment economy.

Data Availability

Data are contained within the article.

Conflicts of Interest

The authors declare no conflicts of interest.

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