Optimal Design of Fixture Layout in Multistation Assembly Processes

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***Abstract*—This paper presents a methodology for the optimal design of fixture layouts in multistation assembly processes. An optimal fixture layout improves the robustness of a fixture system against environmental noises, reduces product variability, and leads to manufacturing cost reduction. Three key aspects of the multistation fixture layout design are addressed: a multistation variation propagation model, a quantitative measure of fixture design, and an effective and efficient optimization algorithm. One of the challenges raised by this multistation design is that a high-dimension design space, which usually embeds a lot of local optimums, will have to be explored. Consequently, it makes a global optimality more difficult and, if an inefficient algorithm is used, may require prohibitive computing time. In this paper, exchange algorithms, originally developed in the research of optimal experimental design, are adopted and further revised to optimize fixture layouts in a multistation process. The revised exchange algorithm provides a good tradeoff between optimality and efficiency: it remarkably reduces the computing time without sacrificing the optimal value. A four-station assembly process for a sports utility vehicle sideframe is used throughout the paper to illustrate the relevant concepts and the resulting methodology.**

***Note to practitioners*—This paper was motivated by the problem of planning a fixture locator layout in a multistation assembly process. Existing approaches generally focused on planning fixture locator layouts on a single workstation. In a multistation production process, such as an automobile body assembly process, the fixture locating holes used on one station will be reused on different stations, which could cause a station-to-station coupling in variation propagation. In other words, dimensional variation could originate from fixture elements on every station, propagate along the production line, and accumulate on the final assembly. Station-wise fixture layout design may not necessarily lead to a good solution because it overlooks the variation coupling and propagation effect. In this paper, we modeled the variation propagation across multiple stations and provided a quantitative characterization of the performance of fixture layout with the presence of environmental noises. Then, we recommended an efficient computation algorithm to solve for the optimal fixture layout. Our results showed that the multistation layout design is different from a single station one; some intuitions gained from single-station design work may not be still valid. The current work is based on a two-dimensional, rigid panel assembly model. The extension to accommodate more sophisticated two-dimensional, complaint-part assembly processes is much needed in the future research.**

***Index Terms*—D-optimality, E-optimality, exchange algorithm, fixture layout design, multistation manufacturing system.**

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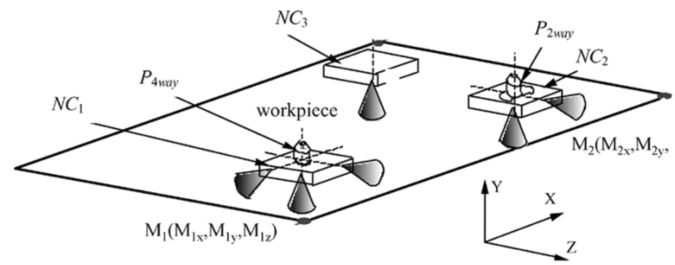

Fig. 1. Illustration of a 3-2-1 fixture.

I. Introduction

DIMENSIONAL quality control is one of the major challenges in discrete-part manufacturing. In the automotive and aviation industries, for instance, dimensional problems contribute to about two-thirds of all quality-related problems during a new product launch [1], [2]. Automotive and aircraft assembly processes are typical multistation panel assembly processes, in which fixtures are used extensively to provide physical support and to coordinate reference to parts and subassemblies. As a result, fixture design greatly affects the dimensional accuracy of the final products.

Fig. 1 illustrates a typical 3-2-1 fixture used in panel assembly processes. It consists of two locating pins, $P_{4\text{way}}$ and $P_{2\text{way}}$, and three net contact (NC) blocks, NC_{1-3}. The two locating pins constrain three degrees of freedom in the X-Z plane, where the 4-way pin controls part motion in both X- and Z-directions and the 2-way pin controls part motion in Z-direction. Three NC blocks constrain other degrees of freedom of the workpiece. When a workpiece is nonrigid, more than three NC blocks may be needed in order to reduce part deformation. An n-2-1 fixture layout, denoted by $\{P_{4\text{way}}, P_{2\text{way}}, \text{NC}_i, i = 1, 2, \ldots, n\}$, is a more generic setting in panel assembly processes.

Product dimensional variations resulting from locating pins and NC blocks are generally different: variation from locating pins causes a (global) rigid-body motion of a workpiece while variation from NC blocks can cause (local) deformations. In this study, we are more interested in the global variation phenomena related to locating pins. Hence, we use $\{P_{4\text{way}}, P_{2\text{way}}\}$ as a simplified representation of an n-2-1 fixture layout.

A real panel assembly process always consists of multiple assembly stations. For example, an assembly line in an automotive body-shop could involve up to 80 stations to assemble 150 to 250 sheet-metal parts into the structure of a vehicle. Consider the assembly process of the sideframe of a sports utility vehicle (SUV) in Fig. 2. The final product, the *inner-panel complete*, comprises four components: A-pillar, B-pillar, rail-roof side panel, and rear quarter panel, which are assembled on three

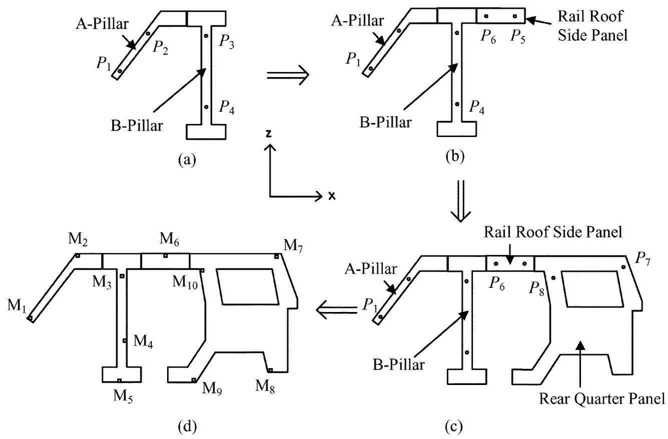

Fig. 2. Assembly process of an SUV sideframe. (a) Station I, (b) Station II, (c) Station III, and (d) Station IV: Key product features.

stations (Stations I, II, and III). Then, the final assembly is inspected at Station IV [M_1–M_{10} marked in Fig. 2(d) are key dimensional features].

In such a multistation process, the aforementioned 3-2-1 fixture is used on every station to ensure product dimensional accuracy. In Fig. 2, P_1–P_8 are the so-called principal locating points (PLP), which are the pinholes used to position a part on an assembly station. However, the same symbols are also used interchangeably to represent locating pins. Thus, a fixture layout in a multistation process can be represented using these PLPs as follows:

$$\begin{aligned}\{\{P_1, P_2\}, \{P_3, P_4\}\}_{\mathrm{I}} &\rightarrow \{\{P_1, P_4\}, \{P_5, P_6\}\}_{\mathrm{II}} \\ &\rightarrow \{\{P_1, P_6\}, \{P_7, P_8\}\}_{\mathrm{III}} \\ &\rightarrow \{\{P_1, P_8\}\}_{\mathrm{IV}}\end{aligned}$$

where the assembly process starts from Station I (indicated by the subscript) and the arrow represents a transition from one station to the next. As an example, $\{\{P_1, P_4\}, \{P_5, P_6\}\}_{\mathrm{II}}$ means that at Station II the first workpiece, the subassembly "A-pillar+B-pillar," is located by P_1 and P_4 and the second workpiece, the rail roof side panel, is located by P_5 and P_6.

In a multistation assembly process, dimensional variation could originate from fixture elements on every station, propagate along the production line, and accumulate on the final assembly. The dimensional quality of the final assembly depends on: 1) input variation level and 2) process sensitivity to variation inputs. The former issue is usually addressed by tolerance design. This paper focuses on the second issue, i.e., an optimal design of fixture layouts in a multistation assembly process so that the process is insensitive to variation input.

Fixture layout design in a multistation process determines the locations of fixtures on every assembly station. The problem is equivalent to the determination of PLP locations on an assembly product. Three aspects that should be addressed are:

1) a variation propagation model that links fixture variation inputs on every station to product dimensional variation;
2) a quantitative design measure that benchmarks the sensitivity of different fixture layouts;
3) optimization algorithms that find the optimal fixture layout.

Following this introduction, Section II reviews the research relevant to fixture design. In Section III, we briefly discuss the variation propagation model and explain major variation phenomena in a panel assembly process. Section IV discusses the selection of design measures. The optimization algorithms, illustrated by solving the fixture-layout in the SUV sideframe assembly process, are presented in Section V. Finally, we conclude this paper in Section VI.

II. Related Work

Earlier research on fixture design employed kinematical and mechanical analysis to explore accessibility, detachability, and location uniqueness of a fixture, aiming at the automatic generation of fixture layouts [3]. Heuristic algorithms were developed for automatic generation of fixture configurations [4], [5]. Trappery and Liu [6] summarized the research before 1990 on fixture-design automation and a more recent summary can be found in [7, Sec.1].

These fixture designs are considered *deterministic* approaches because they consider neither random manufacturing errors of fixture elements nor workpiece positioning errors induced by fixturing operations. Since a workpiece or a fixture element is unavoidably subject to manufacturing error, researchers studied the problem of robust fixture design in a stochastic environment [7]–[21].

One branch of robust fixture design aims at finding optimal fixture positions that minimize the deflection of a compliant workpiece under working load [8]–[14]. This research usually does not consider manufacturing errors of fixture elements. However, fixture-related local deformation and micro-slippage are considered error sources [10], [11].

Another branch of robust fixture design is known as the *variational* approach because it considers fixture error or workpiece surface error and tries to find an optimal fixture layout that makes the positioning accuracy of a workpiece insensitive to input errors [7], [15]–[17]. Variational fixture design often starts with developing a sensitivity measure that characterizes the robustness of a fixture system. This sensitivity measure is determined by fixture layout and is independent of fixture error input. The smaller the sensitivity, the more robust the fixture system. For example, Wang [15] maximized the determinant of the information matrix (D-optimality), which is the inverse of the sensitivity matrix, and Cai *et al.* [7] minimized the Euclidean norm of their sensitivity matrix. Meanwhile, heuristic or rule-based methods have also been developed for designing robust fixture layout [17]. Research work in [18]–[21] is also relevant in the sense that it provides variation/tolerance analysis of a fixture system while the difference is that the issue of fixture synthesis is not addressed.

Past variational fixture designs were conducted mainly at the single-machine level rather than at the multistation system level, i.e., the fixture layout being optimized is limited to a single workstation. Based on our description of the 3-2-1 fixture used in panel assembly processes, it is apparent that a station-wise optimization of fixture layout is different from a system-wide optimization. Suppose that one had optimized the positions

TABLE I
COMPARISON OF FIXTURE-DESIGN METHODOLOGIES

<table>
<tr><th colspan="4">Problem Domain</th><th colspan="2">Methodologies</th></tr>
<tr><td rowspan="5">Fixture Design</td><td colspan="3">Deterministic</td><td colspan="2">Asada and By [3], Chou et al. [4], Ferreira et al. [5], Trappey and Liu [6]</td></tr>
<tr><td colspan="3">Robust design for minimal deflection</td><td colspan="2">Menasa and DeVries [8], Rearick et al. [9], DeMeter [10], Melkote [11], Hockenberger and DeMeter [12], Cai and Hu [13], Huang and Hoshi [14]</td></tr>
<tr><td rowspan="3">Varia-tional Robust Design</td><td colspan="2">Single Station</td><td colspan="2">Cai et al. [7], Wang [15], Wang and Pelinescu [16], Soderberg and Carlson [17], Rong et al. [18], Choudhuri and DeMeter [19], Carlson [21]</td></tr>
<tr><td colspan="2" rowspan="2">Multi-Station</td><td>Modeling & analysis</td><td>Rong and Bai [26], Jin and Shi [22], Camelio et al.[24], Ding et al. [20,23], Zhou et al. [25], Xiong et al. [27,28]</td></tr>
<tr><td>Fixture optimization</td><td>To be presented in this paper</td></tr>
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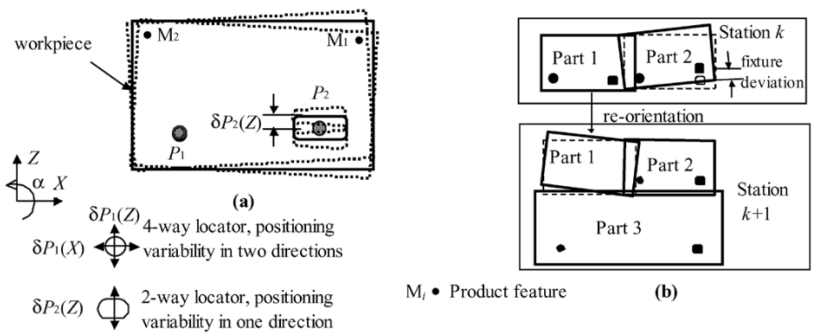

Fig. 3. Fixture-related variation sources.

of P_1, P_2, P_3, and P_4 on Station I. Note that P_1 and P_4 (the PLPs on A-pillar and B-pillar, respectively) will be reused on Station II. Thus, when a station-wise optimization is carried out on Station II, one could choose to optimize all fixtures on Station II as if P_1 and P_4 were not optimized on Station I or he/she can keep the optimized positions of P_1 and P_4 and only optimize the fixture layout (P_5 and P_6) that supports the newly added part. Obviously, neither approach will lead to an overall optimal fixture-layout in a multistation process.

Research on multistation fixture optimization is very limited because of the inherent difficulty resulting from multistation variation modeling, development of design criteria, as well as choice of efficient optimization methods. Recent research work addresses the issue of multistation variation modeling using either a station-indexed state–space model [22]–[25] or a datum-machining surface relationship graph (DMG) [26]. Xiong *et al.* [27], [28] further studied nonlinear fixturing models for variation prediction in multistation aluminum welded assemblies. Based on linear variation models developed for panel assembly processes [22]–[24], this paper will continue the development of design criteria and optimization algorithms for multistation fixture design.

One more note is on fixture *diagnosis* [29]–[32], which is to pinpoint malfunctioning fixtures based on in-line measurements from Optical CMMs. It is apparent that fixture diagnosis is an *in-line* technique that complements the *off-line* fixture design method. It is not surprising, though, that both types of research share the common theoretical background of variation modeling and analysis. Overall, the methodologies reviewed in this section are summarized in Table I.

III. STATE–SPACE VARIATION MODEL

Dimensional variation models that link fixture variation to dimensional measurements are developed using standard kinematics analysis [33]. A few variation propagation models were recently developed for multistation assembly processes using a state-space representation [22]–[24]. Since this model is an integral part of multistation fixture design, we briefly explain key elements in the modeling procedure and then present a general model structure. A two-dimensional (2-D) assembly process is modeled in this paper.

There are two major fixture-related variation sources, as illustrated in Fig. 3. One is the variation contributed by fixture locators on station k [Fig. 3(a)] and another is the variation induced when a subassembly is transferred to the next station where a different fixture layout is used to position the subassembly [Fig. 3(b)].

The modeling procedure starts with an individual station k. Denote the product dimensional state of part i on station k as $\mathbf{x}_{i,k} = [\delta X_{i,k}\ \ \delta Z_{i,k}\ \ \delta\alpha_{i,k}]^T$, which are the deviations associated with its three degrees of freedom, where δ is the perturbation operator and α is the orientation angle. Suppose that this part is located by the jth fixture pair $\{P_1, P_2\}$ on station k, whose random deviations are denoted as $\mathbf{u}_{j,k} = [\delta P_1(X)\ \ \delta P_1(Z)\ \ \delta P_2(Z)]^T$. Apparently, $\mathbf{x}_{i,k}$ can be related to $\mathbf{u}_{j,k}$ through a linearization

$$\mathbf{x}_{i,k} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & \frac{1}{P_1(X)-P_2(X)} & \frac{1}{P_2(X)-P_1(X)} \end{bmatrix} \cdot \mathbf{u}_{j,k} + \mathbf{w}_{i,k} \tag{1}$$

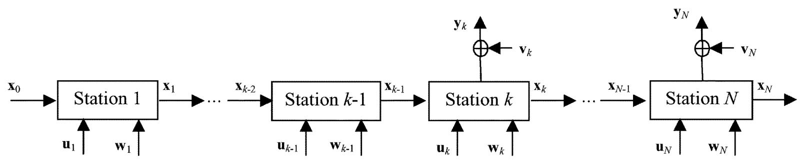

Fig. 4. Diagram of a multistation manufacturing process.

where $P_1(X)$ and $P_2(X)$ are the nominal coordinates of locators P_1 and P_2, respectively, and $\mathbf{w}_{i,k}$ includes the unmodeled higher order terms.

Generally, the state of the product, which comprises n_p parts, is represented by $\mathbf{x}_k \equiv [\mathbf{x}_{1,k}^T \ \cdots \ \mathbf{x}_{n_p,k}^T]^T$. If part i has not yet appeared on station k, the corresponding $\mathbf{x}_{i,k} = \mathbf{0}$. The fixture deviation vector on station k is $\mathbf{u}_k = [\mathbf{u}_{1,k}^T \ \cdots \ \mathbf{u}_{n_k,k}^T]^T$, where n_k is the number of fixture pairs on station k. Product measurements at station k are included in $\mathbf{y}_k$. For the example in Fig. 3(a), $\mathbf{y}_k = [\delta \mathrm{M}_1(X) \ \delta \mathrm{M}_1(Z) \,|\, \delta \mathrm{M}_2(X) \ \delta \mathrm{M}_2(Z)]^T$, which are the deviations associated with product features M_1 and M_2.

The basic idea of a state–space variation model is to consider a multistation process as a sequential system but replace the time index in a traditional state–space model with a station index. For the process in Fig. 4, the station-indexed state–space model can be expressed as

$$\mathbf{x}_k = \mathbf{A}_{k-1}\mathbf{x}_{k-1} + \mathbf{B}_k\mathbf{u}_k + \mathbf{w}_k$$

and

$$\mathbf{y}_k = \mathbf{C}_k\mathbf{x}_k + \mathbf{v}_k, \qquad k \in \{1, 2, \ldots, N\} \tag{2}$$

where N is the number of stations and $\mathbf{v}_k$ represents measurement noises. In this variation model, $\mathbf{B}_k$ models the effect of fixture variation $(\mathbf{u}_k)$ on the product dimensional state $(\mathbf{x}_k)$. It aggregates transformation matrices, each of which is similar to the one in (1), for modeling all n_k fixture pairs. Matrix $\mathbf{C}_k$ includes the information of key product features (the number and locations of those features on station k). In the process described in Fig. 2, $\mathbf{C}_{1,2,3} = \mathbf{0}$ and $\mathbf{C}_4 \neq \mathbf{0}$ because key product features are measured only on Station IV after assembly operations on Stations I, II, III.

One difference between a multistation variation model and a single-station model is the existence of matrix $\mathbf{A}$ that links product states $(\mathbf{x})$ across different stations. Matrix $\mathbf{A}$ depends on fixture layouts on two adjacent stations. The procedure to determine $\mathbf{A}$ is conceptually similar to that of determining $\mathbf{B}$ or $\mathbf{C}$ but algebraically complicated (for more details, please refer to [22], [23], or [24]). If there is no change in fixture layouts across stations, $\mathbf{A}$ simply becomes an identity matrix (e.g., the process described in [34]), and then the multistation model in (2) becomes a simple summation of multiple single-station models.

However, in the multistation panel assembly process described in Section I, a change in fixture layouts occurs when the subassembly proceeds to a new station. Fig. 3(b) illustrates the effect due to the change in fixture layouts; it results in a reorientation of the subassembly. If there were fixture deviations in previous stations, the reorientation-induced error could happen to a part even if fixtures at the current station are free of error [e.g., part 1 in Fig. 3(b)].

This reorientation is almost unavoidable for a multistation panel assembly process because a subset of PLPs is necessary to reposition a subassembly on a downstream station. Due to this reorientation effect, $\mathbf{A}$ in the multistation variation model takes a structure other than an identity matrix. More importantly, and maybe surprisingly, $\mathbf{A}$ is singular throughout the process. This singularity issue was identified for a multistation assembly process in [31].

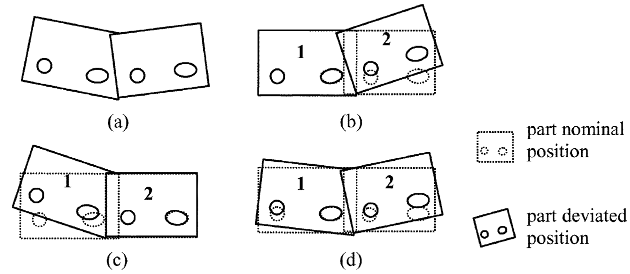

Fig. 5. Singularity of $\mathbf{A}$ due to reorientation. (a) Observed assembly. (b) Fixture-pair one: normal and fixture-pair two: faulty. (c) Fixture-pair one: faulty and fixture-pair two: normal. (d) Fixture-pair one: faulty and fixture-pair two: faulty.

We present an intuitive explanation for why $\mathbf{A}$ is singular when fixture layouts change across stations. Consider the simple example in Fig. 5, where several possible fixture errors on an upstream station could have caused the same resulting pattern of part deviation.

When this resulting deviation pattern is observed on Station $k+1$ [Fig. 5(a)], the faulty fixture pair on Station k causing the deviation pattern could be either fixture-pair one [Fig. 5(c)], fixture-pair two [Fig. 5(b)], or both fixture pairs [Fig. 5(d)]. Assembly deviation at one station is related to its deviation incurred at the previous station through matrix $\mathbf{A}$, i.e., $\mathbf{x}_{k+1} = \mathbf{A}_k\mathbf{x}_k$, by neglecting other terms. Noticing that, given $\mathbf{x}_{k+1}$, there is no unique solution for $\mathbf{x}_k$ because of the above-mentioned ambiguity, we can conclude that $\mathbf{A}_k$ is singular. The singularity of matrix $\mathbf{A}$ is a general problem existing in panel assembly processes and will affect our choice of design criterion during later development.

Following the modeling procedure in [22] and [23], we developed a state-space variation model for the four-station assembly process of the SUV sideframe in Fig. 2. In this model, the fixture used on Station IV is considered well maintained and calibrated with much higher repeatability than those on a regular assembly station. Thus, fixture locators on the measurement station are assumed free of error, i.e., $\mathbf{u}_4 = \mathbf{0}$, while deviation inputs from fixtures on three assembly stations, $\mathbf{u}_1$, $\mathbf{u}_2$, and $\mathbf{u}_3$, are included. Thus, the state–space model is

$$\begin{cases} \mathbf{x}_k = \mathbf{A}_{k-1}\mathbf{x}_{k-1} + \mathbf{B}_k\mathbf{u}_k + \mathbf{w}_k, & k = 1, 2, 3 \\ \mathbf{x}_4 = \mathbf{A}_3\mathbf{x}_3 + \mathbf{w}_4 \\ \mathbf{y}_4 = \mathbf{C}_4\mathbf{x}_4 + \mathbf{v}_4 \end{cases} \tag{3}$$

where $\mathbf{x}_0$ represents product error resulting from the part-fabrication process (which is a stamping process for panel assembly) prior to the assembly process. Due to limited space, numerical

TABLE II
INTERPRETATION OF SYSTEM MATRICES

Symbol	Name	Relationship	Interpretation	Assembly Task
$\mathbf{A}$	Dynamic matrix	$\mathbf{x}_{k-1} \xrightarrow{\mathbf{A}_{k-1}} \mathbf{x}_k$	Change of fixture layout between two adjacent stations	Assembly transfer
$\mathbf{\Phi}$	State transition matrix	$\mathbf{x}_i \xrightarrow{\mathbf{\Phi}_{k,i}} \mathbf{x}_k$	Change of fixture layout across multiple stations	Assembly transfer
$\mathbf{B}$	Input matrix	$\mathbf{u}_k \xrightarrow{\mathbf{B}_k} \mathbf{x}_k$	Fixture layout at station k	Part positioning
$\mathbf{C}$	Observation matrix	$\mathbf{x}_k \xrightarrow{\mathbf{C}_k} \mathbf{y}_k$	Key product features at station k	Inspection

expressions of $\mathbf{A}$'s, $\mathbf{B}$'s, and $\mathbf{C}$ are included in the Appendix. It is easy to verify that $\mathbf{A}_1, \mathbf{A}_2$, and $\mathbf{A}_3$ are all singular.

Finally, we summarize the physical interpretation of $\mathbf{A}, \mathbf{B}$, and $\mathbf{C}$ in Table II, where $\mathbf{\Phi}_{k,i} \equiv \mathbf{A}_{k-1}\mathbf{A}_{k-2}\cdots\mathbf{A}_i$ and $\mathbf{\Phi}_{i,i} \equiv \mathbf{I}$, and include a few more remarks regarding the state–space variation model as follows.

Remark 2.1: The state–space variation model in this paper assumed a linear model structure. We acknowledge that its applications are limited to linear systems where the magnitude of fixturing error is much smaller than the distance between locators and when the process error is not strongly coupled with the fixturing error. Nonlinearity could be resulted from strong error-coupling and a relatively large fixturing error, which cases have been addressed in some most recent work [21], [27], [28].

Remark 2.2: Because we are more interested in the global variation resulted from locating pins in this paper, we assume that the NC blocks are not the major variation contributors and thus modeled only a 2-D product. In situations when the NC blocks indeed significantly affect the assembly variation, a 3-D locating model is more appropriate. State space models with the same structure but different matrix dimensions and parameters were used to model complicated 3-D processes, e.g., the 3-D machining model in [25]. It should be noted that the subsequent development of fixture design criteria and optimization methods is generally applicable to any linear system model instead of depending on particular values of parameters or matrix dimensions.

Remark 2.3: In this study, the variation model for a single station is implemented to treat a point geometry of the locating contacts for a fixture pair. However, products with complicated surface profile are located using a greater number of fixture elements and product quality may also be affected by local surface properties of the locator-workpiece system. Researcher has recently spent efforts [15], [35], and [36] to address these problems that may be critical to meet a high-precision requirement in fixturing small parts with complex geometry. The resulting models in [15], [35], [36] adopt a linear structure, which makes it not difficult to incorporate them in the state–space model. For example, the fixture-quality relations for a more general product surface, modeled by (8) in [35] or (5) in [15], are mathematically equivalent to the term $\mathbf{B}_k\mathbf{u}_k$ in (2) so that $\mathbf{B}_k\mathbf{u}_k$ can be simply replaced by these relations. The local fixture contact properties modeled by (28) in [36] cannot directly replace $\mathbf{B}_k\mathbf{u}_k$, though, because they are expressed in velocity not in displacement (or deviation). In that case, either the state vector should be augmented to include both velocity and deviation, as it is usually expressed in dynamic state–space models, or a model for deviation from the integral of (28) in [36] should be used.

IV. DESIGN CRITERIA

We first reformulate the state-space model in (2) into an input–output linear model by eliminating all intermediate state variables $\mathbf{x}_k$. We have

$$\mathbf{y}_N = \sum_{k=1}^{N} \mathbf{C}_N \mathbf{\Phi}_{N,k} \mathbf{B}_k \mathbf{u}_k + \mathbf{C}_N \mathbf{\Phi}_{N,0} \cdot \mathbf{x}_0 + \sum_{k=1}^{N} \mathbf{C}_N \mathbf{\Phi}_{N,k} \mathbf{w}_k + \mathbf{v}_N. \quad (4)$$

In this fixture design problem, our focus is on the first term in the above equation, $\sum_{k=1}^{N} \mathbf{C}_N \mathbf{\Phi}_{N,k} \mathbf{B}_k \mathbf{u}_k$, because it represents fixture error inputs from all N stations. Therefore, we simplify (4) as

$$\hat{\mathbf{y}} \equiv \mathbf{D}\mathbf{u} = \sum_{k=1}^{N} \mathbf{C}_N \mathbf{\Phi}_{N,k} \mathbf{B}_k \mathbf{u}_k \quad (5)$$

where $\mathbf{D} \equiv [\mathbf{C}_N\mathbf{\Phi}_{N,1}\mathbf{B}_1 \;\; \mathbf{C}_N\mathbf{\Phi}_{N,2}\mathbf{B}_2 \;\; \cdots \;\; \mathbf{C}_N\mathbf{B}_N], \mathbf{u}^T \equiv [\mathbf{u}_1^T \;\; \cdots \;\; \mathbf{u}_N^T]$, and $\hat{\mathbf{y}}$ is the fixture-induced product variation. Subscript N is dropped from $\hat{\mathbf{y}}$ hereafter without causing ambiguity. For the model in (3), because $\mathbf{u}_4$ is assumed zero, $\mathbf{D} = [\mathbf{C}_4\mathbf{\Phi}_{4,1}\mathbf{B}_1 \;\; \mathbf{C}_4\mathbf{\Phi}_{4,2}\mathbf{B}_2 \;\; \mathbf{C}_4\mathbf{\Phi}_{4,3}\mathbf{B}_3]$.

We use $\hat{\mathbf{y}}^T\hat{\mathbf{y}}$, the sum of squares of product deviations, to benchmark the overall level of product dimensional nonconformity. Thus, product quality is optimized if $\hat{\mathbf{y}}^T\hat{\mathbf{y}}$ is minimized. Given $\hat{\mathbf{y}}^T\hat{\mathbf{y}} = \mathbf{u}^T\mathbf{D}^T\mathbf{D}\mathbf{u}$, the problem is equivalent to minimizing $\mathbf{u}^T\mathbf{D}^T\mathbf{D}\mathbf{u}$. However, $\mathbf{u}^T\mathbf{D}^T\mathbf{D}\mathbf{u}$ is an input-dependent quantity. Since our goal is to find a fixture layout in which product quality is insensitive to fixture variation input, we need a design criterion or a sensitivity index that is determined only by fixture design information (modeled by $\mathbf{D}$) and is independent of variation input (represented by $\mathbf{u}$).

For a single input–output pair, the sensitivity can be defined as $S_{i,j} = y_i/u_j$, where y_i is the ith product feature and u_j is the jth fixture error input. For the entire assembly system with multiple inputs and multiple features, an intuitive way to define the sensitivity index is as

$$S \equiv \frac{\hat{\mathbf{y}}^T\hat{\mathbf{y}}}{\mathbf{u}^T\mathbf{u}} = \frac{\mathbf{u}^T\mathbf{D}^T\mathbf{D}\mathbf{u}}{\mathbf{u}^T\mathbf{u}}. \quad (6)$$

The difficulty associated with this definition is that S is still input dependent.

Apparently, $\mathbf{D}^T\mathbf{D}$ plays a determining role in the above definition, which motivates researchers to define the sensitivity index using a measure of $\mathbf{D}^T\mathbf{D}$. Research conducted in experimental design has studied a similar problem and proposed several optimality criteria [37]–[39]. The often used criteria include D-optimality $(\min \det(\mathbf{D}^T\mathbf{D}))$, A-optimality

$(\min \mathrm{tr}(\mathbf{D}^T\mathbf{D}))$, and E-optimality (minimize the extreme eigenvalue of $\mathbf{D}^T\mathbf{D}$), where $\mathrm{tr}(\cdot)$ and $\det(\cdot)$ are the trace and the determinant of a matrix, respectively. These three measures are related to each other through eigenvalues of $\mathbf{D}^T\mathbf{D}$, $\{\lambda_i\}_{i=1}^p$, where p is the column number of $\mathbf{D}$. They can be expressed as

$$D_{\mathrm{opt}}\colon \det(\mathbf{D}^T\mathbf{D}) = \Pi_{i=1}^p \lambda_i \quad A_{\mathrm{opt}}\colon \mathrm{tr}(\mathbf{D}^T\mathbf{D}) = \sum_{i=1}^p \lambda_i$$
$$E_{\mathrm{opt}}\colon \lambda_{\min} \text{ or } \lambda_{\max}. \tag{7}$$

The D-optimality criterion is the most widely used in experimental designs due to the following two reasons [37], [38].

1) For experimental designs, this criterion has a clear interpretation. D-optimality is equivalent to minimizing the prediction variance from an estimated model or the variances of least-squares estimates of unknown parameters.
2) It possesses an invariant property under scaling, i.e., experiments can be designed using a group of standardized dimensionless variables (say, all variables are in $[-1, 1]$) instead of the original physical variables. In fact, this D-optimality criterion was also used in solving problems of fixture design and sensor placement by Wang and his colleagues [15], [16], [35].

However, the singularity of matrix $\mathbf{A}$ in our variation propagation model (2) requires us to reconsider the design criterion. Because $\mathbf{A}$ is singular, the state transition matrix $\mathbf{\Phi}_{k,i}$ is also singular. It suggests that each term $\mathbf{C}_N\mathbf{\Phi}_{N,i}\mathbf{B}_i$ in $\mathbf{D}$ is less than full rank even if $\mathbf{C}$ and $\mathbf{B}$ matrices are of full rank. As a result, matrix $\mathbf{D}$ is less than full rank so that $\mathbf{D}^T\mathbf{D}$ is singular.

When $\mathbf{D}^T\mathbf{D}$ is singular, at least one of its eigenvalues is zero, i.e., $\det(\mathbf{D}^T\mathbf{D}) = 0$. Recalling the reason why $\mathbf{A}$ is singular (explained in Section III), we know that this singularity issue cannot be resolved by simply changing the positions of fixture locators on a station. It is an inherent problem caused by the fixturing mechanism in a multistation panel assembly process. This fact implies that even if we choose new positions for fixture locators, $\det(\mathbf{D}^T\mathbf{D})$ is always zero. It is fair to conclude that $\det(\mathbf{D}^T\mathbf{D})$ is noninformative in this multistation fixture design.

Given the singularity problem of design matrix $\mathbf{D}$, we consider that A-optimality or E-optimality is an informative criterion for multistation fixture design. We recommend the use of E-optimality because it has a clearer physical interpretation. It is known [40] that

$$S \equiv \frac{\mathbf{u}^T\mathbf{D}^T\mathbf{D}\mathbf{u}}{\mathbf{u}^T\mathbf{u}} \leq \lambda_{\max}(\mathbf{D}^T\mathbf{D}), \qquad \text{for any } \mathbf{u} \neq \mathbf{0}. \tag{8}$$

That is, E-optimality, which minimizes $\lambda_{\max}(\mathbf{D}^T\mathbf{D})$, is equivalent to minimizing the upper sensitivity bound of the fixture system. This criterion can also be derived using the concept of matrix 2-norm. Defining the upper bound of sensitivity as $S_{\max}$, it follows the definition of matrix 2-nom [40] that

$$S_{\max} \equiv \sup_{\mathbf{u}\neq\mathbf{0}} \frac{\mathbf{u}^T\mathbf{D}^T\mathbf{D}\mathbf{u}}{\mathbf{u}^T\mathbf{u}} = \|\mathbf{D}\|_2^2 = \lambda_{\max}(\mathbf{D}^T\mathbf{D}). \tag{9}$$

In other words, E-optimal condition is the square of the 2-norm of design matrix $\mathbf{D}$.

We cannot rule out the possible use of A-optimality in this multistation fixture design problem. Since an eigenvalue of $\mathbf{D}^T\mathbf{D}$ represents the sensitivity level related to one particular input–output pair for a canonical variation model, $\mathrm{tr}(\mathbf{D}^T\mathbf{D})$ is the summation of sensitivities related to all input–output pairs, representing the overall sensitivity level of the fixture system. Using A-optimality can be considered to be minimizing the summation of sensitivities.

Compared with A-optimality, E-optimality is a little conservative because it attempts to reduce the maximum sensitivity index. This conservativeness actually makes E-optimality more easily to be accepted by practitioners because minimization of the maximum sensitivity is consistent with the pareto principle in quality engineering. Our experience with the automotive industry indicates the same tendency.

Based on our experience with this multistation fixture design, we caution the use of D-optimality in general engineering system designs. Engineering system designs are different from experimental designs in many aspects. The differences could cause the advantages of using D-optimality in an experimental design to be inapplicable to an engineering design problem. The major differences include the following.

1) Engineering design problems are often accompanied by complex constraints, for example, the geometric constraints imposed by the shape of a part in the SUV side-frame assembly process. This type of complexity makes it almost impossible to design an engineering system based on a group of dimensionless standardized variables. In this regard, the invariant property of D-optimality becomes much less attractive to general engineering designs.
2) The complexity of engineering systems often results in ill-conditioned systems with some eigenvalue of $\mathbf{D}^T\mathbf{D}$ close to zero or even singular systems (such as our multistation fixture system). Since the purpose of D-optimality is to minimize the product of all eigenvalues, it is possible in the presence of ill-conditioned systems that the near-zero eigenvalue is forced to become zero while leaving other eigenvalues uncontrolled as if a perfect D-optimal condition was achieved. Obviously, this is actually an undesirable result. This problem is less likely to occur, though, in an experimental design or to a well-posed system (see [35] for a detailed discussion).
3) The physical interpretation of D-optimality in engineering system designs may not be as clear as that in experimental designs. For instance, what $\det(\mathbf{D}^T\mathbf{D})$ represents in this fixture design problem is not obvious.

In the rest of this paper, we will use E-optimality criterion for determining a robust fixture system in a multistation panel assembly process. The design parameters are the locations of PLPs, denoted as $\boldsymbol{\varphi} = [X_1 \ Z_1 \ \cdots \ X_{n_{\mathrm{PLP}}} \ Z_{n_{\mathrm{PLP}}}]^T$, where n_{PLP} is the total number of PLPs, e.g., $n_{\mathrm{PLP}} = 8$ for the process in Fig. 2. The PLP layout is denoted as $\boldsymbol{\varphi}_0$, the initial or reference fixture layout. It is straightforward to calculate $S_{\max}(\boldsymbol{\varphi}_0) = 5.397$. Mathematically, the optimization scheme is expressed as

$$\begin{aligned}&\min_{\varphi} S_{\max} \equiv \lambda_{\max}(\mathbf{D}^T\mathbf{D})\\ &\text{subject to } G(\boldsymbol{\varphi}) > 0\end{aligned} \tag{10}$$

where $G(\cdot)$ captures geometrical constraints on PLP locations, imposed by geometries of parts.

V. Optimization Methods

A. Overview of Optimization Methods

The objective function $\lambda_{\max}(\mathbf{D}^T\mathbf{D})$ is a nonlinear function of design parameter $\boldsymbol{\varphi}$, and (10) thus states a constrained nonlinear optimization problem. The performance of an optimization algorithm is often benchmarked by: 1) its effectiveness, measured by the closeness of its solution to the global optimum; and, 2) its efficiency, usually measured by the time it takes to find the optimal value. Unless the objective function is of a simple form such as a quadratic function (and our objective function is apparently not), the difficulty with nonlinear optimization is that the global optimum is not guaranteed for almost all available algorithms without an exhaustive search.

A multistation fixture design problem, when expressed in the format of (10), might appear to be no different from a single-station fixture design. However, the challenge that a multistation fixture design raises is that a much higher dimension design space will have to be explored. For example, even in the 2-D four-panel SUV assembly process, we need to determine the positions of eight PLPs, which constitutes a sixteen-dimension design space. A general car body assembly that is made of over 100 panels will then correspond to a design space of hundreds of dimensions. Consequently, a high-dimension design space, embedding a lot of local optimums, makes a global optimality much more difficult and requires prohibitive computer time if an exhaustive search is used. Therefore, we soften our goal a bit in this paper. Instead of looking for *the* global optimum, we try to find an algorithm that yields a substantial improvement in our design criterion with a reasonable cost of computer-time.

A gradient-based search such as sequential quadratic programming or the like [41] is a widely used method in solving fixture design problems (e.g., in [7]–[9], and [13]). Many commercial nonlinear programming packages implement this method, e.g., the MATLAB function "*fmincon*." The gradient-based method usually converges quickly because it calculates the derivative at each searching point and follows the steepest ascent/descent direction. The major drawback is that it can easily be entrapped in a local optimum. For example, if we use *fmincon* to solve the fixture design in the SUV assembly process, the sensitivity value of the final fixture layout $\boldsymbol{\varphi}_f$, is $S_{\max}(\boldsymbol{\varphi}_f) = 5.300$ and it takes about 10 s to converge in the MATLAB environment. The result shows merely an 1.8% improvement from the current design layout.

Another nonlinear optimization method is the simplex search [42], also available in MATLAB as "*fminsearch*." It is a direct search method that does not require gradients or other derivative information. Its performance is similar to the gradient-based method: it easily stops at a local optimum and does not take long to compute. The final sensitivity that it reaches is better than that from *fmincon* but takes a little bit more time. Our calculation reveals that $S_{\max}(\boldsymbol{\varphi}_f) = 4.420$ (a further 16.3% improvement) and it takes 85.6 s to converge in the same MATLAB environment on the same machine, AMD-Athlon 1.13 GHz (other algorithms below are also executed under the same software and hardware computing conditions). Both the gradient-based method and the simplex search operate on a continuous design space.

In the research of optimal experimental design, exchange algorithms were developed to solve combinatorial optimizations based on various design criteria mentioned earlier, such as D-, E-, A-optimality [37], [38], [43]. Most of these algorithms are variants on the basic idea of an exchange, explained as follows. First, discretize the continuous design space to yield N_c candidate fixture-locator positions. Then, randomly select n_d locations from N_c candidate positions as an initial design and calculate $S_{\max}$ (in our problem, we actually already have an initial design). In each exchange, do the following.

- EA1) For each one of the N_c candidate locations, calculate $S_{\max}$ as if the ith location in the current design was exchanged with the candidate location. Record the smallest $S_{\max}(i)$ and the corresponding candidate location.
- EA2) Repeat EA1) for $i = 1, \ldots, n_d$ locations in the current design space.
- EA3) Find the smallest value among $\{S_{\max}(i)\}_{i=1}^{n_d}$ and exchange the corresponding location in the design space and its according candidate location.
- EA4) Iterate until $S_{\max}$ cannot be improved further.

The above procedure is known as the "basic exchange algorithm" [43]. The pioneer work applying this idea to fixture design was carried out by Wang and his colleagues in solving a single-station fixture design problem based on the D-optimality criterion [15], [16].

Indeed, this basic exchange algorithm can yield a remarkably smaller value of $S_{\max}$ when it is applied to the SUV assembly process. However, the basic exchange algorithm was initially designed to determine efficient experiments for fitting simple regression models rather than for optimization problems with a high design space. It would run too slowly given a large N_c, i.e., a large number of the candidate locations. In this study, we discretized the continuous design space on each panel with candidate points 10 mm apart (10 mm is roughly the size of a locator's diameter). We feel that this resolution of discretization is sufficient to generate a fine enough grid on a panel. Given that the panels in the SUV assembly process have a size of several hundred millimeters, this discretizing resolution results in a total of $N_c = 7813$ candidate positions on four panels. Applying the basic exchange algorithm, we reduce $S_{\max}$ down to 3.922 at the computing cost of 1955.9 s.

The value of $S_{\max}$ from the basic exchange algorithm renders a further 11.3% reduction of the maximal sensitivity level of the fixture system from the simplex search method (or a 27.3% reduction in sensitivity from $\boldsymbol{\varphi}_0$). Our empirical experience indicates that this $S_{\max}$ value, even if it may not be the smallest sensitivity, should be close to the global optimum. However, the basic exchange algorithm takes too much computing time, which limits its applicability in a larger scale fixture design problem with more panels on more stations. Thus, our goal is to make the exchange algorithm faster without sacrificing too much of its effectiveness in reducing the sensitivity level of a fixture system.

B. Revised Exchange Algorithm

The fact that only one fixture location in the initial design is replaced in each iteration makes the basic exchange algorithm expensive to use. Within each iteration, the algorithm loops through all candidate sets n_d times, which makes the total computation of sensitivity function at the order of $n_d \cdot N_c$ per iteration. Meanwhile, all the PLPs in the initial design are likely to be replaced eventually. Thus, the overall computation complexity is at the order of $(n_d)^2 \cdot N_c$. It is clear that we should reduce N_c and the number of iterations to make the exchange algorithm faster. Toward this goal, we implemented the following three improvements.

1) Increase the Number of Exchanges Per Iteration: In order to increase the number of exchanges, after Step EA1) in the basic exchange algorithm, we can carry out the exchange that minimizes $S_{\max}(i)$. Then, the number of exchanges is n_d for each iteration. This method is known as "modified Fedorov exchange" and was first suggested by Cook and Nachtsheim [43].

Another way of increasing the exchange number is to perform the exchange whenever there is an improvement in the objective function. In this way, the exchange is performed much more frequently. However, it is easier for this algorithm to be entrapped in a local optimum since it is so rushed for an exchange. This method is seldom recommended in the literature.

Alternatively, we can combine the above modifications that are made to a basic exchange algorithm. The purpose of a combined modification is to exchange the candidate locations in the upper tail of the distribution of improvements in design criterion among all the candidate locations. A similar procedure is suggested by Lam *et al.* [44] for a uniform coverage design in molecule selection.

In doing so, we should record the improvement in design criterion that a candidate location can make if the corresponding exchange is indeed carried out. The distribution of the improvement can be approximated by the recorded values. Denote the Δ as the improvement in the $S_{\max}$ criterion, i.e., $\Delta \equiv S_{\max}^{\text{old}} - S_{\max}^{\text{new}}$. Record all Δ_j's $(j = 1, \ldots, N_c)$ when we loop through the N_c candidate locations. Sort the value of Δ_j's in a descending order as $\Delta_{(1)} \geq \Delta_{(2)} \geq, \ldots,$ and so on. Select an integer number q, set $\Delta_{(q)}$ as the threshold. If there is an improvement greater than $\Delta_{(q)}$, then carry out the exchange.

It is apparent that the above combined modification is similar to the modified Fedrovo exchange algorithm if $q = 1$; and, if q is the value corresponding to $\Delta_{(q)} = 0$, it is the same as the one that performs an exchange whenever there is an improvement. This combined exchange algorithm is more versatile for broader applications.

In implementing this algorithm, we need to determine the value of q. Since we will likely replace all the initial design points in the final design, we decide to select $q = n_d$ so that we can replace n_d points in each iteration. However, in our fixture design, panels have a natural boundary and therefore an exchange between a design point and a candidate point can only be performed for those locations on the same panel. For this reason, we should implement the above algorithm for individual panels. Given that $n_d = 2$ for a panel (i.e., two locators per panel), we set $q = 2$. Moreover, the initial distribution of Δ is determined in the same way as in [44], i.e., it is approximated by Δ-values of 100 randomly selected locations in the candidate set.

2) Reduce the Number of Locations in the Candidate Set: It is obvious to us that the large value of N_c is one of key reasons that the basic exchange algorithm is computationally expensive. The N_c can be reduced if we use a coarse grid on each panel when we discretize the continuous design space. However, a coarse grid could miss those low-sensitivity PLP locations and thus sacrifice the algorithm's effectiveness.

If we could rule out some areas that are unlikely to yield a "good" location, we can then discard the candidate locations in those areas entirely and thus reduce N_c. A part positioning deviation is more sensitive to locating deviations when both locators are close to each other than when they are distantly apart. This simple rule suggests that the final position of a locator is unlikely to fall into the geometrical central area on a panel. The geometrical center of a panel, which coincides with its gravity center when the panel has a homogenous density, is defined as

$$X_i = \frac{\iint_{\text{Panel } i} X dX dZ}{A_i} \quad \text{and} \quad Z_i = \frac{\iint_{\text{Panel } i} Z dX dZ}{A_i} \tag{11}$$

where A_i is the area of panel i.

The geometrical central area on a panel is considered to be the neighborhood of a panel's gravity center. The determination of this neighborhood is illustrated in Fig. 6(a). The distance between the gravity center and a vertex on the polygonal panel is calculated. Then, the median of these distances is chosen to represent the size of the panel, denoted as d_0. A hypothetical circle is drawn on the panel with the gravity as its center and $d_0/2$ as its radius. The area inside this hypothetical circle is considered to be the neighborhood of the gravity center. Only candidate locations outside the neighborhood will be used for exchanges with a design point. The use of the median of all gravity-to-vertex distances in determining d_0, rather than their mean value, makes the resulting d_0 less sensitive to a very large or a very small gravity-to-vertex distance on panels with an irregular shape (recall that median is a more robust statistic than mean

[45]). We apply this rule to four SUV sideframes. The resulting candidate areas are shown as the dark areas in Fig. 6(b). One may also notice that there is a gap (35 mm) between the candidate areas and the edge of a part. This 35-mm gap is determined by engineering safety requirement because a locating hole that is too close to the edge may not be able to endure the load exerted during fixturing. The resulting candidate area contains a total of $N_c = 4642$ candidate locations, which is 59.4% of the original N_c. The density of candidate locations is kept the same.

3) Reduce the Number of Candidate Locations After Each Iteration: After each iteration, the improvement in design criterion Δ_j is recorded for all candidate locations and sorted in a descending order. Those candidate locations with a low Δ value are less likely to be picked up by the exchange algorithm in the next iteration. Therefore, we propose removing half of the candidate locations whose Δ value is among $[\Delta_{(N_c/2+1)}, \Delta_{(N_c)}]$ after each iteration. Then, N_c becomes $N_c/2$ after each iteration. Our implementation of this action shows that it not only reduces the number of candidate locations but also makes convergence faster, i.e., the program will stop after fewer iterations.

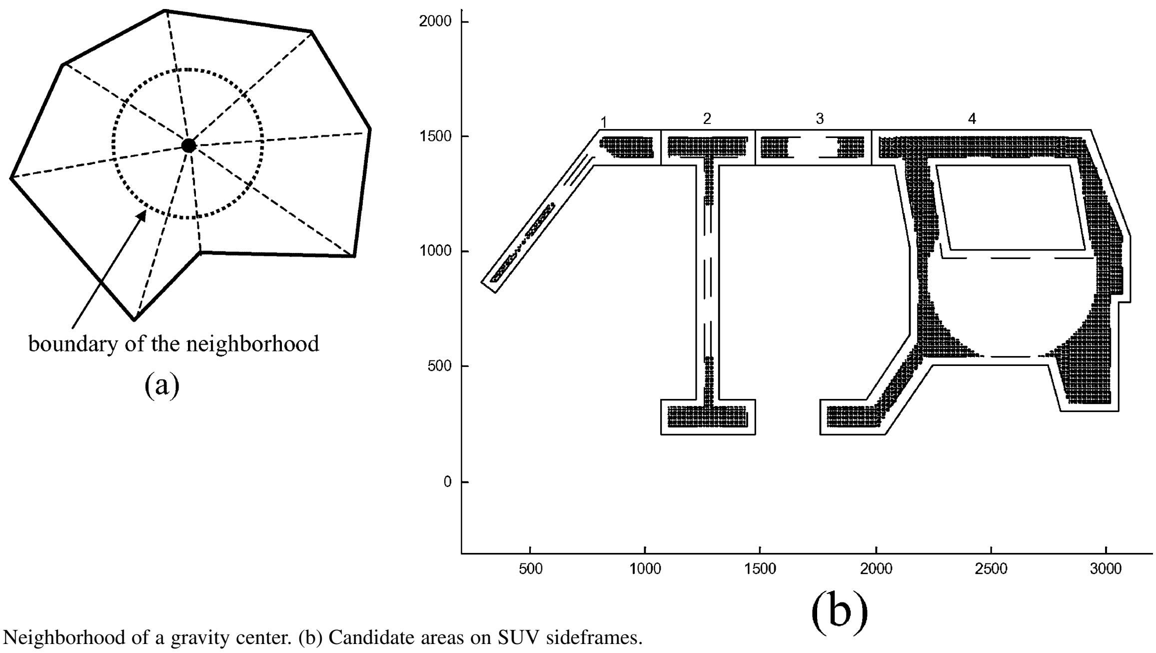

Fig. 6. (a) Neighborhood of a gravity center. (b) Candidate areas on SUV sideframes.

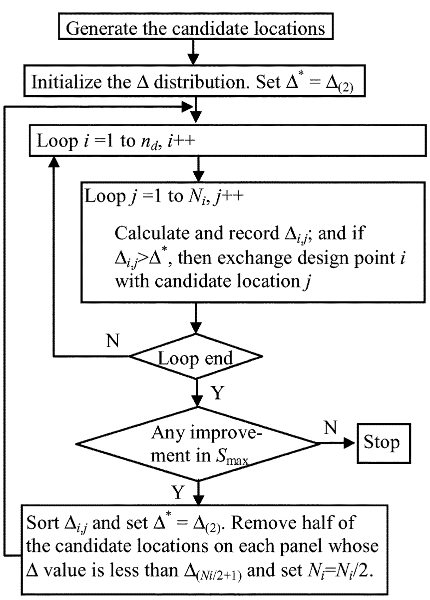

Fig. 7. Flowchart of the revised exchange algorithm.

By incorporating Section V-B1–B3, our revised exchange algorithm is summarized as follows and a flow chart is shown in Fig. 7 to illustrate the algorithm.

Step 1) Generate the candidate locations in the candidate areas as shown in Fig. 6(b). The resolution for discretization is 10 mm between two adjacent candidate locations.

Step 2) Initialize the Δ distribution. Randomly select 100 candidate locations on each panel. Calculate their Δ values and sort them in a descending order. Set $\Delta^* = \Delta_{(q)}$, where $q = 2$.

Step 3) For $i = 1$ to n_d (loop for each one of the current design points)

For $j = 1$ to N_i (loop through the candidate locations; N_i is the number of candidate locations on the panel that contains design point i)

• Calculate and record $\Delta_{i,j}$;

• If $\Delta_{i,j} > \Delta^*$, then exchange design point i with candidate location j.

End of the j-indexed loop

If there is no exchange during the last j-indexed loop, then exchange design point i with the

candidate point that maximizes $\Delta_{i,j}$ (for $j = 1, \ldots, N_i$).

End of the i-indexed loop.

Step 4) If there is no improvement in the $S_{\max}$ criterion during last loop (we check if $(\max_{i,j} \Delta_{i,j})/(S_{\max}^{\text{old}}) < 0.1\%$), then stop. Otherwise, sort $\Delta_{i,j}$; set $\Delta^* = \Delta_{(q)}$; remove half the candidate locations on each panel whose Δ value is less than $\Delta_{(N_i/2+1)}$; set $N_i = N_i/2$; go to Step 3 until the stopping criterion is met.

C. Comparison and Discussion

We implemented the above optimization algorithms in solving the multistation fixture-layout design problem in the SUV assembly process. The overall results are compared in Table III. Please note that our coding of exchange algorithms in MATLAB is not compiled and includes some inefficient for-loops that run slower than those highly optimized and complied standard MATLAB functions. For this reason, we do not compare the computation time between the exchange algorithms and the MATLAB functions such as *fmincon* and *fminsearch* in an absolute percentage sense. Rather the gains in efficiency calculated below are among the different versions of exchange algorithms. The actual computation time of exchange algorithms should be able to be further reduced if using C or FORTUNE complied codes.

TABLE III
COMPARISON OF OPTIMIZATION METHODS

	Initial PLP design			Random initial designs		
	$S_{max}(\varphi_f)$	Time (sec.)	# of iterations	$S_{max}(\varphi_f)$	Time (sec.)	# of iterations
Gradient-based	5.303	10.6	-	7.783	26.4	-
Simplex search	4.420	85.6	-	5.666	74.6	-
Basic Exchange	3.922	1955.9	5	4.022	1868.9	5.1
Modified Fedorov	3.952	780.312	2	3.894	1614.4	4.4
Revised Exchange (B.1-B.3)	3.903	443.528	4	3.940	373.1	3

TABLE IV
OPTIMAL FIXTURE LAYOUT (φ_f) FROM EXCHANGE ALGORITHMS (UNITS: MILLIMETERS)

Part #	Fixture layout with the smallest $S_{max}(\varphi_f)$		From the revised exchange algorithm	
	4-way PLP (X, Z)	2-way PLP (X, Z)	4-way PLP (X, Z)	2-way PLP (X, Z)
1	(523.8, 1091.1)	(1033.8, 1490)	(337.9, 871.9)	(1027.9, 1490)
2	(1434.5, 1418.8)	(1274.5, 248.7)	(1264.5, 1378.6)	(1424.5, 318.8)
3	(1720.9, 1460)	(1940.9, 1480)	(1620.9, 1420)	(1940.9, 1460)
4	(2973.5, 450.1)	(2923.5, 1150.1)	(2033.5, 286.6)	(2163.5, 1160.1)

Optimization methods are compared based on two kinds of initial designs, one is the design currently used in industry; and the other uses randomly generated initial designs and the performance data is the average of ten trials. The reason to include the random initial design is to avoid any serious bias resulting from the comparison using a fixed initial design.

The comparison apparently shows that the revised exchange algorithm significantly reduces computing time. When we use PLP design φ_0, the computing time of the revised exchange algorithm is less than one-fourth (22.6%) of that needed for the basic exchange algorithm or is 56.8% of that needed for the modified Fedorov algorithm. Surprisingly, the $S_{\max}(\boldsymbol{\varphi}_f)$ value from the revised exchange algorithm is even smaller than that from the basic exchange algorithm. It indicates that more exchanges per iteration may help an algorithm escape from a local optimum and thus can improve the algorithm's effectiveness. When we use φ_0, the modified Fedorov exchange demonstrates a 60% shorter run time than the basic exchange algorithm yet yields a slightly larger $S_{\max}(\boldsymbol{\varphi}_f)$. When we use random initial designs, the revised exchange algorithm runs about five times faster on average than the basic exchange algorithm or four times faster than the modified Fedorov algorithm. The $S_{\max}(\boldsymbol{\varphi}_f)$ it finds is slightly (1.2%) larger than the one found by the modified Fedorov but smaller than that from the basic exchange algorithm. The number of iterations in the random initial design is roughly consistent with our previous analysis. The basic exchange algorithm used 5.1 iterations to replace all eight initial locators. The modified Fedorov exchange algorithm uses less iterations since more than one locator is replaced with a good candidate per iteration. The revised exchange algorithm further reduces the iteration to three times, about half of what the basic exchange algorithm used. Due to the nature of the stopping rule for exchange algorithms (comparing two subsequent $S_{\max}$'s), the minimum number of iterations is two. We feel that the potential for reducing the iteration number is being pushed to its limit by the revised exchange algorithm.

Using random initial designs, the modified Fedorov exchange yields a lower $S_{\max}(\boldsymbol{\varphi}_f)$ value on average. The lowest value of $S_{\max}(\boldsymbol{\varphi}_f) = 3.82$ during those trials is also found by the modified Fedorov exchange. Since this value is only 2% lower than 3.922, it does not invalidate our prior conjecture that $S_{\max}(\boldsymbol{\varphi}_f) = 3.922$ should be close to the global optimum.

The coordinates of the optimal fixture layout with the lowest $S_{\max}(\boldsymbol{\varphi}_f)$ value during our trials and the one determined by our revised exchange algorithm are listed in Table IV as well as shown in Fig. 8, where "$+$" represents a $P_{4\text{way}}$ and "$\cdot$" represents a $P_{2\text{way}}$.

One interesting phenomenon that one may observe from Fig. 8 is that the resulting optimal fixture layout on the rear quarter panel apparently does not have the largest possible distance between the pair of locators. We perform fixture optimization for this panel alone and display the resulting positions also in Fig. 8(b), which are indicated by a "$*$" for $P_{4\text{way}}$ and an "o" for $P_{2\text{way}}$. The pair of locators from the single-panel optimization indeed have much greater distance between them and is consistent with our intuition about a robust fixture layout. If we substitute this pair of PLP locations from the single-panel optimization into the multistation assembly, we have the overall system-level $S_{\max} = 3.958$, which is in fact larger than the optimal $S_{\max}$. This phenomenon implies that our intuitive largest-distance rule is not necessarily always right in a multistation fixture design due to the fact that fixture locators are reused on different stations and their interaction complicates the sensitivity analysis. Thus, we should rely on an integrated variation propagation model and an effective optimization method, as developed in this paper.

The fact that both PLPs on the rear quarter panel in this optimal fixture layout are on the same side of the panel's gravity center does not cause a problem here because in our application, the panels are positioned on a horizontal platform (refer to Fig. 1). If the panels are in fact vertically positioned, a force closure constraint in addition to the geometrical constraint $G(\cdot)$

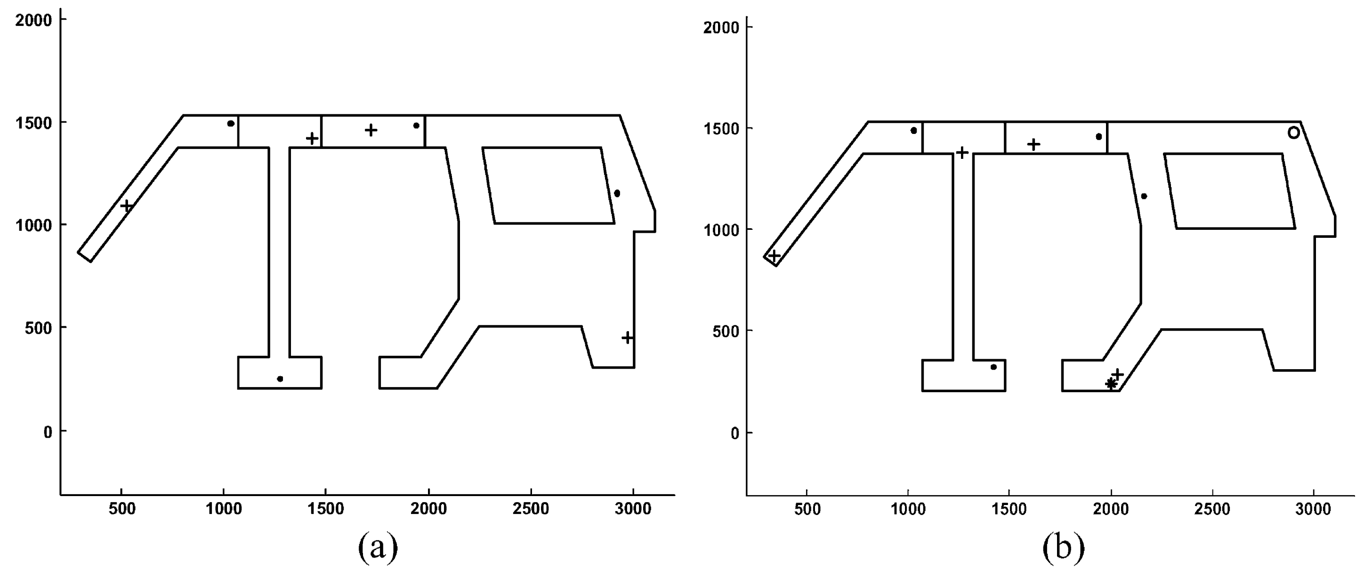

Fig. 8. Optimal fixture layouts. (a) Fixture layout with the lowest $S_{\max}(\varphi_f)$ value. (b) Fixture layout from revised exchange algorithm.

should be included in the optimization scheme [i.e., (10)] to ensure the resultant force and moment to be zero. Under that circumstance, the resulting optimal fixture layout could be different. For a robust fixture design considering force closure, please refer to [15].

VI. Concluding Remarks

This paper investigates various aspects of optimal fixture layout design in multistation panel assembly processes: variation modeling, design criteria, and optimization methods. Due to the singularity of the design matrix of a multistation fixture system, the widely used D-optimal criterion is not an appropriate design measure. Instead, the E-optimality criterion is recommended, which minimizes the maximum sensitivity level of a fixture system to the input variation. Different optimization methods are explored and compared. The exchange algorithm, originated from the research of optimal experimental design, is adopted and further revised to solve a high-dimension optimization for multistation fixture layout designs.

For the fixture system used in a four-station SUV sideframe assembly process, the revised exchange algorithm yields the optimal fixture design whose maximal sensitivity level is only 72.3% of the currently used fixture layout design. The resulting optimal fixture layout is more robust to the environmental noise—the reduction of 27.7% in sensitivity implies the same amount of reduction in product variation level under the same variation inputs, according to the definition of sensitivity in (6). The improvement in product quality will lead to a remarkable cost reduction in manufacturing systems.

For a nonlinear optimization problem such as this multistation fixture-layout design, it may be too costly, sometimes even impossible, to find the global optimum. The revised exchange algorithm is a good tradeoff between optimality and algorithm efficiency. This revised exchange algorithm takes less than one-fourth of the computing time that a basic exchange algorithm needs and yields a fixture layout whose $S_{\max}$ is only 2.1% larger than that of the best fixture layout we obtained during all the trials. Furthermore, although the algorithm is discussed in the specific context of fixture layout design, we feel that the variation propagation model, the selection of design criterion, and the resulting revised exchange algorithm are fairly general and should be applicable to other engineering system designs.

Appendix

System matrices $\mathbf{A}, \mathbf{B}, \mathbf{C}$ for the initial design are as follows:

$$\mathbf{A}_1 = \left[\begin{array}{cccccc:c} 0 & 0 & 0 & 0 & 0 & 0 & \\ 0 & 0 & 0 & 0 & 0 & 0 & \\ 0.0004 & 0.0009 & 1.0000 & -0.0004 & -0.0009 & -0.2855 & \\ -1.1425 & -0.3497 & 0 & 1.1425 & 0.3497 & 105.3621 & \mathbf{0}^{6\times 6} \\ 0.3492 & -0.1430 & 0 & -0.3492 & 0.1430 & -258.1800 & \\ 0.0004 & 0.0009 & 0 & -0.0004 & -0.0009 & 0.7145 & \\ \hdashline \multicolumn{6}{c:}{\mathbf{0}^{6\times 6}} & \mathbf{I}^{6\times 6} \end{array}\right]_{12\times 12}$$

$$\mathbf{A}_2 = \left[\begin{array}{ccc:c:ccc:c} 0 & 0 & 0 & & 0 & 0 & 0 & \\ 0 & 0 & 0 & \mathbf{0}^{3\times 3} & 0 & 0 & 0 & \mathbf{0}^{3\times 3} \\ -0.0003 & 0.0007 & 1 & & 0.0003 & -0.0007 & 0.2056 & \\ -0.8859 & -0.2529 & 0 & & -0.1141 & 0.2529 & -75.8764 & \\ -0.2797 & -0.3802 & 0 & \mathbf{I}^{3\times 3} & 0.2797 & -0.6198 & 185.9280 & \mathbf{0}^{3\times 3} \\ -0.0003 & 0.0007 & 0 & & 0.0003 & -0.0007 & 0.2056 & \\ -0.8308 & -0.3749 & 0 & & 0.8308 & 0.3749 & -112.4780 & \\ -0.4677 & 0.0364 & 0 & \mathbf{0}^{3\times 3} & 0.4677 & -0.0364 & 310.9287 & \mathbf{0}^{3\times 3} \\ -0.0003 & 0.0007 & 0 & & 0.0003 & -0.0007 & 1.2056 & \\ \hdashline \multicolumn{3}{c:}{\mathbf{0}^{3\times 3}} & \mathbf{0}^{3\times 3} & \multicolumn{3}{c:}{\mathbf{0}^{3\times 3}} & \mathbf{I}^{3\times 3} \end{array}\right]_{12\times 12}$$

$$\mathbf{A}_3 = \left[\begin{array}{ccc:c:ccc} 0 & 0 & 0 & & 0 & 0 & 0 \\ 0 & 0 & 0 & \mathbf{0}^{3\times 6} & 0 & 0 & 0 \\ -0.0000 & 0.0000 & 1 & & 0.0000 & -0.0000 & 0.0004 \\ -0.0010 & -0.0002 & 0 & & -0.0000 & 0.0002 & -0.1468 \\ -0.0001 & -0.0005 & 0 & & 0.0001 & -0.0005 & 0.3597 \\ -0.0000 & 0.0000 & 0 & \mathbf{I}^{6\times 6} & 0.0000 & -0.0000 & 0.0004 \\ -0.0009 & -0.0003 & 0 & & -0.0001 & 0.0003 & -0.2176 \\ -0.0002 & -0.0002 & 0 & & 0.0002 & -0.0008 & 0.6015 \\ -0.0000 & 0.0000 & 0 & & 0.0000 & -0.0000 & 0.0004 \\ -0.0009 & -0.0003 & 0 & & 0.0009 & 0.0003 & -0.2049 \\ -0.0003 & 0.0003 & 0 & \mathbf{0}^{3\times 6} & 0.0003 & -0.0003 & 1.0133 \\ -0.0000 & 0.0000 & 0 & & 0.0000 & -0.0000 & 0.0014 \end{array}\right]_{12\times 12}$$

$$\mathbf{B}_1 = \left[\begin{array}{c|c} \begin{matrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0.0016 & -0.0012 & -0.0016 & 0.0012 \end{matrix} & \mathbf{0}^{3\times 4} \\ \hline \mathbf{0}^{3\times 4} & \begin{matrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ -0.0014 & 0 & 0.0014 & 0 \end{matrix} \\ \hline \multicolumn{2}{c}{\mathbf{0}^{6\times 8}} \end{array}\right]_{12\times 8}$$

$$\mathbf{B}_2 = \left[\begin{array}{c|c} \begin{matrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ -0.0004 & -0.0009 & 0.0004 & 0.0009 \\ 1.1425 & 0.3497 & -0.1425 & -0.3497 \\ -0.3492 & 0.1430 & 0.3492 & 0.8570 \\ -0.0004 & -0.0009 & 0.0004 & 0.0009 \end{matrix} & \mathbf{0}^{6\times 4} \\ \hline \mathbf{0}^{6\times 4} & \begin{matrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0.0000 & 0.0033 & -0.0000 & -0.0033 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{matrix} \end{array}\right]_{12\times 8}$$

$$\mathbf{B}_3 = \left[\begin{array}{c|c} \begin{matrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0.0003 & -0.0007 & -0.0003 & 0.0007 \\ 0.8859 & 0.2529 & 0.1141 & -0.2529 \\ 0.2797 & 0.3802 & -0.2797 & 0.6198 \\ 0.0003 & -0.0007 & -0.0003 & 0.0007 \\ 0.8308 & 0.3749 & 0.1692 & -0.3749 \\ 0.4677 & -0.0364 & -0.4677 & 1.0364 \\ 0.0003 & -0.0007 & -0.0003 & 0.0007 \end{matrix} & \mathbf{0}^{9\times 4} \\ \hline \mathbf{0}^{3\times 4} & \begin{matrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ -0.0002 & 0.0013 & 0.0002 & -0.0013 \end{matrix} \end{array}\right]_{12\times 8}$$

$$\mathbf{C}_4 = \left[\begin{array}{c|c|c|c} \begin{matrix} 1 & 0 & 46 \\ 0 & 1 & -89.8 \\ 1 & 0 & -62.9 \\ 0 & 1 & 43.2 \end{matrix} & \mathbf{0}^{4\times 3} & \mathbf{0}^{4\times 3} & \mathbf{0}^{4\times 3} \\ \hline \mathbf{0}^{6\times 3} & \begin{matrix} 1 & 0 & -25 \\ 0 & 1 & 3 \\ 1 & 0 & 641.5 \\ 0 & 1 & 34.5 \\ 1 & 0 & 1074 \\ 0 & 1 & -27.5 \end{matrix} & \mathbf{0}^{6\times 3} & \mathbf{0}^{6\times 3} \\ \hline \mathbf{0}^{2\times 3} & \mathbf{0}^{2\times 3} & \begin{matrix} 1 & 0 & -82 \\ 0 & 1 & -149.9 \end{matrix} & \mathbf{0}^{2\times 3} \\ \hline \mathbf{0}^{8\times 3} & \mathbf{0}^{8\times 3} & \mathbf{0}^{8\times 3} & \begin{matrix} 1 & 0 & -114 \\ 0 & 1 & 30 \\ 1 & 0 & 1115.9 \\ 0 & 1 & -108.7 \\ 1 & 0 & 1221 \\ 0 & 1 & -877.1 \\ 1 & 0 & 71 \\ 0 & 1 & -830 \end{matrix} \end{array}\right]_{20\times 12}$$

$\mathbf{A}_0$ is an identity matrix with appropriate dimensions.

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