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Multi-station Fixture Layout Design Using Simulated Annealing*

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ABSTRACT

Automotive and aircraft assembly process rely on fixtures to support and coordinate parts and sub-assemblies. Fixture layout in multi-station panel assemblies has a direct dimensional effect on final products and thus presents a quality problem. This paper describes a methodology for fixture layout design in multi-station assembly processes. An optimal fixture layout improves the robustness of a fixture system against environmental noises, reduces product variability, and eventually leads to manufacturing cost reduction. One of the difficulties raised by multi-station fixture layout design is the overwhelmingly large number of design alternatives. This makes it difficult to find a global optimality and, if an inefficient algorithm is used, may require prohibitive computing time. In this paper, simulated annealing is adopted and appropriate parameters are selected to find good fixture layouts. A four-station assembly process for a sport utility vehicle (SUV) side frame is used throughout the paper to illustrate the efficiency and effectiveness of this methodology.

Keywords: Simulated annealing, Fixture layout design, Multi-station manufacturing system

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1. INTRODUCTION

Dimensional quality control is one of the more difficult problems in the panel assembly process. In the automotive industry, for example, about two-thirds of the quality related problems during new product launches were caused by dimensional problems [5]. The automotive body assembly process is a typical multistage assembly process involving up to 70 stations to fabricate the structural frame of the automobile, the Body-in-White (BIW). In such an assembly process, dimensional variation originates from fixture locators at every station, accumulates and propagates along the production stream, and finally results in defective assembly. This complexity of assembly processes combined with the requirement of fixtures places high demands on the fixture design for improving the dimensional quality of the final product.

Three aspects need to be incorporated in the solving of these high dimensional design optimization problems: (1) a variation propagation model that links fixture variation inputs on every station to overall product dimensional variation; (2) a quantitative design criteria that benchmarks the sensitivity of different fixture layouts; (3) optimization algorithms that efficiently find the optimal fixture layout. In the recent progress regarding quality improvement and variation reduction, a state space model has been developed in [6,11] to characterize the variation propagation and accumulation in a multistage manufacturing process (MMP). Furthermore, multi-layered process sensitivity indices are also proposed in Ding *et al.* [7] and Kim and Ding [13] to numerically present the inherent response of an MMP to input variation. In Ding *et al.* [7], the proposed sensitivity indices are expressed in terms of process configuration such as fixture layout and shift scheme; different design configurations are compared and evaluated by using the sensitivity index. Despite failure to address the optimal process design, those works provided the foundation for a more robust design of a multistage assembly process. Quantitative design measures used to find an optimal design also discussed in Kim and Ding's work [13].

In this paper, the variation propagation model and quantitative design criteria which were developed from previous works [7, 13] are used. Robust designs regarding fixture layout/position has been studied with different objectives. Menassa and DeVries [14] proposed an optimization procedure for fixture support position such that the workpiece deformation is minimized. Cai and Hu [2] explored the optimal design of fixture configuration with emphasis on part flexibility and springback effects. The above two papers primarily utilized finite element methods to calculate deformation of compliant workpieces as an objective function in their optimization scheme. Robust fixture design for a 3-D rigid workpiece has been studied by Wang [17] and Soderberg and Carlson [16] for minimizing the influence of fixture deviation on workpiece positioning accuracy. Those works only focus on the fixture layout of a single work station. Research of robust fixture designs for a multistage assembly process, however, is very limited. The major obstacles are the lack of process-level models which relate the fixture errors from different stations to dimension quality of the final assembly and the nonexistence of a quantitative measure which can indicate the sensitivity of a multi-station assembly process.

Following this introduction, Chapter 2 briefly describes our example, and Chapter 3 presents the implementation of the variation propagation model and the selection of design criteria. The optimization algorithms are presented in Chapter 4 and applied in Chapter 5. Finally, Chapter 6 concludes this paper with a summary and suggestions for future work.

2. PROBLEM DESCRIPTION

In a panel assembly process, locating pins and NC blocks are widely used to determine the location and orientation of a subassembly. Figure 1 shows a typical 3-2-1 fixture used in the panel assembly process. It consists of three key tooling elements: (1) a 4-way pin that controls part motion in both X- and Y- directions, denoted as P_{4way}; (2) a 2-way pin that controls part motion in Y-direction, denoted as P_{2way}; (3) and three NC blocks that constrain other degrees of freedom of the workpiece, denoted as $NC_{1\text{-}3}$. More than three NC blocks may be needed in order to reduce part deformation if the part is not a flat or rigid body panel. An n-2-1 fixture layout, denoted by $\{P_{4way}, P_{2way}, NC_i, i = 1,2, \cdots, n\}$, is a more generic expression of the panel assembly processes.

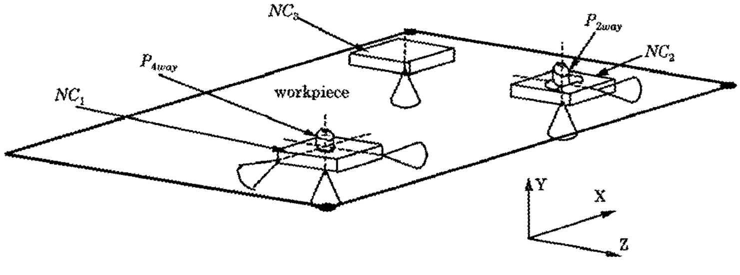

Figure 1. Illustration of a 3-2-1 fixture

Product dimensional variations generated from locating pins and NC blocks are quite different. The NC blocks usually hold a variation caused by local deformation and the locating pins support a variation that comes from global rigid body motion. Because our interest is more focused on the global variation phenomena, our optimization object is the locating pins. Thus, we use $\{P_{4way}, P_{2way}\}$ as a simplified n-2-1 fixture layout representation.

Let us consider the assembly process of sports utility vehicle (SUV) side frame in Figure 2. The product *inner-panel-complete* consists of four components: A-pillar, B-pillar, side roof panel, and rear quarter panel. Three stations (Stations I, II, III) are involved in fabrication as shown in Figure 2. At the first station, A-pillar and B-pillar are joined together. The subassembly "A-pillar+B-pillar" is welded with the side roof panel at the second station. Finally, the subassembly of first three panels is assembled with the rear quarter panel at the third station. Then, the final step is the inspection station where ten key dimensional features (marked as M_1-M_{10}) are used.

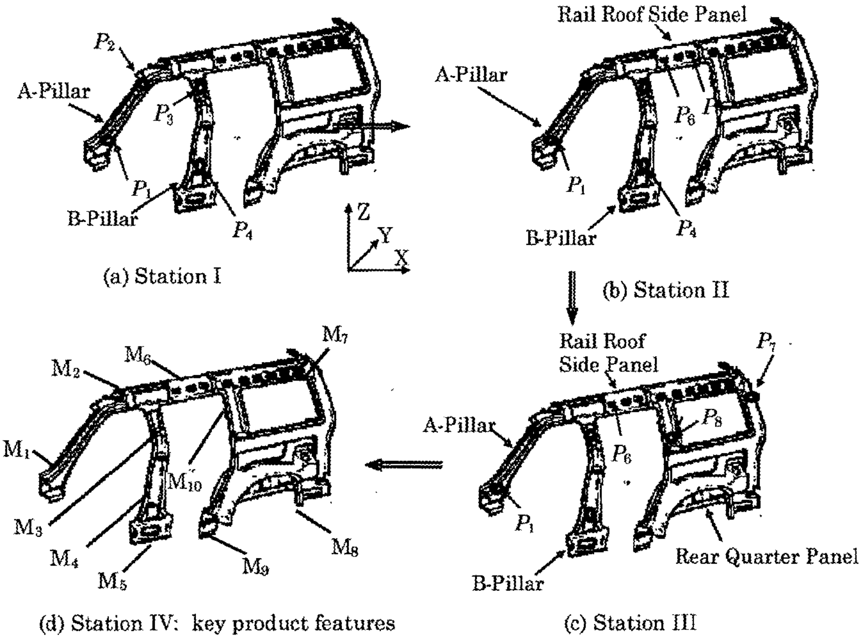

Figure 2. Assembly process of an SUV side frame

In a multi-station process such as this, the aforementioned 3-2-1 fixture is used on every station to ensure product dimensional accuracy. In Figure 2, P_1–P_8 are the so-called principal locating points (PLP) on the assembly. They correspond to the pinholes used to position the part on each station. In this example, all P's with odd subscripts (P_1, P_3, P_5, P_7) are the 4-way circular holes while the P's with even subscripts (P_2, P_4, P_6, P_8) are the 2-way slots. After two parts are assembled, more than one set of PLPs are used for positioning. For example, at Station II, there are two sets of PLPs $\{P_1, P_2\}$ and $\{P_3, P_4\}$ on the subassembly "A-pillar+B-pillar". In order to position this subassembly, one of four combinations can be used - $\{P_1, P_2\}$, $\{P_3, P_4\}$, $\{P_1, P_4\}$, and $\{P_3, P_2\}$. Thus, fixturing layout shifts from station to station during a multistage assembly process. We use the following shift notation to indicate which pair of PLPs is selected at a station.

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

In the above notation, the assembly starts from the first station and the arrow indicates transition from one station to another. As an example, $\{\{P_1, P_4\},\{P_5, P_6\}\}$ means that at the second station, the first part (subassembly A-pillar+B-pillar) is located by P_1 and P_4 and the second part on station two (rail roof side panel) is held by P_5 and P_6.

Fixture layout design in a multi-station process determines the locations of fixtures on every assembly station, meaning the problem is equivalent to the determination of PLP locations on an assembly product. In the above example, there are eight locations to be determined (P_1 - P_8). Since the position of a locator is determined by its X and Y coordinates, this translates into a fixture layout design problem involving the selection of 16 parameters for the purpose of minimizing quality costs subject to satisfying specific geometric constraints.

The design space has 16 parameters and is continuous - meaning that there are infinite number of design alternatives. We can generate a finite candidate design space via discretization, say, using the resolution of 10 millimeters on each panel. 10 millimeter is the size of a locator's diameter and the variation difference is negligible. This resolution level will result in the number of candidate locations on each panel being 308, 905, 396, and 6204 respectively. The total number of design alternatives is therefore $C_2^{308} \times C_2^{905} \times C_2^{369} \times C_2^{6204} \approx 4.65\times10^{23}$, where C_a^b is a combinational operator. The number of design alternatives is very large and a lot of local optima are embedded in the 16-dimension design space.

3. STATE SPACE MODEL AND DESIGN CRITERIA

A multi-station assembly process such as automotive body assembly has been described in detail in Ceglarek *et al.* [4]. A diagram is shown in Figure 3 for a process with N assembly stations.

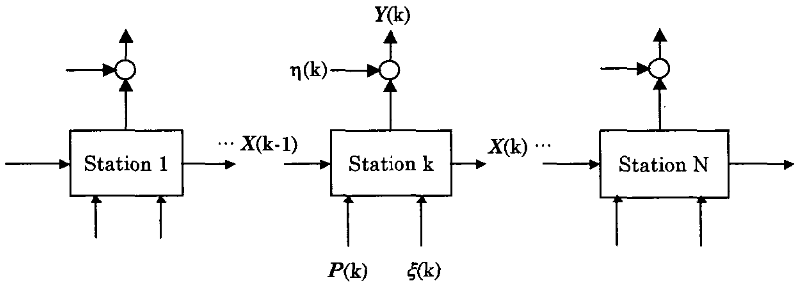

Figure 3. Diagram of an assembly process with N stations

The state space model of such a process can be expressed as

$$\boldsymbol{X}(k) = \boldsymbol{A}(k-1)\boldsymbol{X}(k-1) + \boldsymbol{B}(k)\boldsymbol{P}(k) + \xi(k), \quad \mathrm{k} \in \{1, 2, \ \ , \mathrm{N}\} \tag{1}$$

$$\boldsymbol{Y}(k) = \boldsymbol{C}(k)\boldsymbol{X}(k) + \boldsymbol{\eta}(k), \quad \mathrm{k} \in \{1, 2, \ \ , \mathrm{N}\} \tag{2}$$

where $\boldsymbol{X}(k)$ is the part accumulative deviation, $\boldsymbol{P}(k)$ is fixture deviation contributed at station k, $\boldsymbol{Y}(k)$ is the measurement obtained at station k, and $\boldsymbol{\xi}, \boldsymbol{\eta}$ are mutually independent noises. The first equation, known as the state equation implies that part deviation at station k is influenced by two sources: the accumulative quality value up to station k-1, and variation contributed at the current station. The second equation is on observation equation.

System matrices ***A***, ***B***, and ***C*** are determined by process/product design. ***A***, known as the dynamic matrix, characterizes deviation changes due to part transfer among stations. Matrix ***B*** is the input matrix determining how the fixture deviation affects the part deviation, depending on the geometry of the fixture layout at each station. Matrix ***C*** contains the information about sensor positions at a station. For more details of the model, please refer to Jin and Shi [11], Ding et al. [6], and Kim and Ding [13]. In this paper, the reformulation of the state-space model into a suitable format is used for the design optimization and then the model for the process in Figure 2 is implemented in MATLAB.

For this paper, E-optimality, which minimize the upper sensitivity bound of the fixture system, addressed by Kim and Ding [13] was used as objective sensitivity for determining a robust fixture system in a multi-station panel assembly process. The design parameters are the locations of PLPs, denoted as $\boldsymbol{\theta}$ = $[X_1 \; Y_1 \cdots X_{n_{PLP}} \; Y_{n_{PLP}}]^T$, where n_{PLP} is the total number of PLPs, i.e., $n_{PLP} = 8$ for the process in Figure 2. Mathematically, the optimization scheme is expressed as

$$\begin{aligned} &\min_{\theta} \quad S(\theta) \equiv \lambda_{\max}(D^T D) \\ &\textit{subject to} \quad G(\theta) \geq 0 \end{aligned} \tag{3}$$

where $G(\cdot)$ represents the appropriate geometrical constraints on PLP locations as imposed by the geometries of the parts and λ is the eigenvalue of $\mathbf{D}^T\mathbf{D}$.

4. OPTIMIZATION AGOLRITHM AND PROCEDURE

Simulated annealing is used for finding optimization procedures for solving combinatorial optimization problems based on stochastic computational techniques though it also considers many aspects related to iterative improvements algorithm. The application of iterative improvement algorithms presupposes the specific definition of the problem. This includes the definition of configurations, neighborhood, cost of the configuration, and an initial configuration. The generation mechanism defines a neighborhood for each configuration, consisting of all configurations that can be reached with one transition.

Kirkpatrick *et al.* [12] introduced the first annealing technique that corresponds to an increase in the cost function in a limited way. It is generally known as simulated annealing due to the analogy with the simulation of the annealing of solids it is based upon. It is also known as Monte-Carlo annealing, statistical cooling, probabilistic hill climbing, or the probabilistic exchange algorithm. Solutions obtained by simulated annealing do not depend on the initial configuration and have a very good solution. Further, it is possible to give a polynomial upper bound for the computation time for some implementations of the algorithm.

The generic parameters to be determined before experiments are: initial temperature (T), cooling ratio (k_B), known as the Boltzmann constant, and the stopping criterion. An initial configuration is also needed, and is generally selected at random from all design configuration alternatives. The specific procedure is controlled as a function based on initial temperature and cooling ratio. Δ is defined as the difference in cost between the current solution and the neighboring solution; if the difference means reduction in objective function, then the process is continued with the new solution. If the difference means an increase in objective function, the new solution is accepted according to the specific probability, which is expressed as $e^{(-\Delta/k_B T)}$ where T is the control parameter. A random number ra is selected from the interval [0,1]. If $ra < e^{(-\Delta/k_B T)}$ then the step is accepted or otherwise denied. This probability depends highly on the Boltamann constant k_B, and this condition means that the simulated annealing algorithm can violate local optimality in its quest for a global optimum.

The stopping criterion which will determine the system is cool enough affects the efficiency of the solution as it depends on the number of iterations per each temperature, the total number of temperature changes, and the configuration changes at each temperature stage. The algorithm proceeds until the temperature reaches the final temperature, which corresponds in the analogy to the frozen or solid temperature.

To find a good solution quality within a comparably short period of time using this simulated annealing algorithm, the parameters must be chosen carefully. The choice of parameters is discussed in the next Chapter.

5. EXAMPLE

In order to facilitate the job of optimization, the geometry of the original inner-panel-complete part is simplified by using polygons along its contour. The feasible area allowing a PLP hole/slot is smaller than the edge contour of the part because the remaining material will not be strong enough if the PLP hole/slot is too close to the edge. Based on our industry experience, the width of the edge area is selected as 35 mm. The simplified geometry is shown in Figure 4, where the solid line represents the part contour and the dashed line indicates the actual boundary for PLPs. The search for optimal PLP locations is constrained within the dashed line. In Figure 4, the marks of 1, 2, 3 and 4 correspond to A-pillar, B-pillar, side roof panel, and rear quarter panel, respectively.

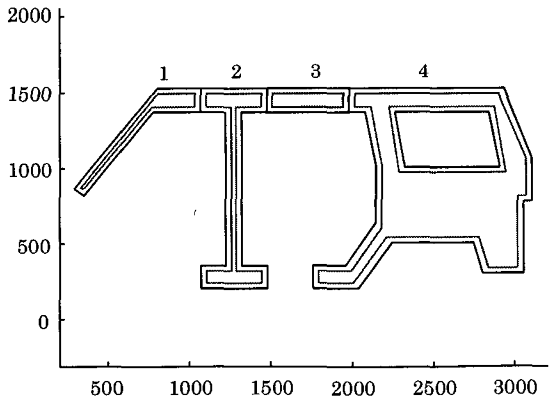

Figure 4. The simplified geometry of inner–panel–complete

Let us first consider the fixture layout and shift scheme used in the current industry practice. The coordinates of this layout $\boldsymbol{\theta}$ are given in Table 1.

Table 1. The currently used layout (unit: mm)

Part #	4-way PLP (X, Y)	2-way PLP (X, Y)
1	(367.8, 906)	(667.4, 1295.3)
2	(1272, 1275)	(1272.7, 537.3)
3	(1579.9, 1453)	(1879.9, 1453)
4	(2910, 1421)	(2180.3, 1302.8)

The state space representation can be set up for this multi-station process after which the sensitivity index is calculated based on system matrices $S(\boldsymbol{\theta})$=5.401. The value of 5.401 represents the capacity of the assembly process in the response to variation input. If the multiple noise inputs at three assembly stations have unit variance in terms of their Euclidean norm, the upper bound of the variance of KPCs could be as high as 5.401, which is considered not robust enough to resist the influence of noise. Optimization should be carried out to reduce the system sensitivity level.

The simulated annealing algorithm is applied following procedure. In our example, the number of configuration is selected as the number of fixtures (i.e. eight).

Step 1. Generate an initial random solution $\boldsymbol{\theta}_0$ and calculate $S(\boldsymbol{\theta}_0)$
Step 2. Loop while $\boldsymbol{i}$ (the number of $\boldsymbol{T}$ changes) <= 100
Loop while $\boldsymbol{j}$ (the number of configuration changes) <= $\boldsymbol{n}$ (the number of Configurations) * 10 or $\boldsymbol{it}$ (the number of iterations) <= $\boldsymbol{n}$ * 100
Generate an alternative random solution $\boldsymbol{\theta}_1$ and $S(\boldsymbol{\theta}_1)$
d = $S(\boldsymbol{\theta}_1)$ - $S(\boldsymbol{\theta}_0)$
$\boldsymbol{ra}$ = random[0,1]
If d <= 0 or $\boldsymbol{ra}$ < exp(-d / T) then
$S(\boldsymbol{\theta}_0) = S(\boldsymbol{\theta}_1)$, $\boldsymbol{\theta}_0 = \boldsymbol{\theta}_1$
$\boldsymbol{j} = \boldsymbol{j} + 1$
end if
$\boldsymbol{it} = \boldsymbol{it} + 1$
End Loop
$\boldsymbol{T} = \boldsymbol{T} * k_B$ (cooling ratio)
$\boldsymbol{j} = 0$, $\boldsymbol{it} = 0$, $\boldsymbol{i} = 0$
End Loop

The above algorithm is implemented in solving our multi-station fixture layout design problem in the SUV assembly process. The number of configuration changes to be attempted at each temperature and the number of iterations are set proportional to the number of fixtures at ($100n$) and ($10n$), respectively. The total number of temperature steps, which affects the run time of the procedure, is set at 100 iterations. Generally, the most important parameters in using simulated annealing is the initial temperature $\boldsymbol{T}$ and the cooling ratio k_B.

The initial temperature is determined by identifying the lowest value at which at least 80 percent of a certain number of random configuration changes are accepted [12]. Extremely high initial temperatures without relatively long iteration times can not guarantee favorable solutions since they provide too many chances to accept an inferior objective function value and hence the procedure could stop before it reaches a solid state that is the best solution. Alternatively, assigning too small of a value for initial temperatures will make the simulated annealing algorithm behave as a steepest descent algorithm, which does not allow uphill moves, and it may easily become trapped in a local optimum. For our problem, $\boldsymbol{T}$ is tested from 10 to 20. There was no appreciable difference in the objective function value and $\boldsymbol{T} = 12.5$ was selected as a best initial temperature.

The cooling ration k_B is determined by the multiple experiments. Table 2 shows the results when the cooling ratio k_B is changed from 0.85 to 0.99 with initial temperature $\boldsymbol{T} = 12.5$. We can observe that the objective function value decreases with lower cooling ratio, but if we consider the efficiency as well we find that $k_B = 0.90$ or $k_B = 0.95$ is a good trade off between optimality and efficiency.

Table 2. Result comparison from different cooling ratio (k_B)

		$k_B = 0.85$		$k_B = 0.90$		$k_B = 0.95$		$k_B = 0.99$	
	initial $S(\boldsymbol{\theta})$	$S(\boldsymbol{\theta})$	time	$S(\boldsymbol{\theta})$	time	$S(\boldsymbol{\theta})$	time	$S(\boldsymbol{\theta})$	Time
1	43.8925	3.8647	1051.3	3.8854	640.09	3.9609	309.205	7.1499	206.958
2	16.8125	3.8834	1080.2	3.8185	722.028	3.9571	313.851	9.3755	213.357
3	27.4431	3.8208	1092.1	3.821	655.773	3.9095	310.196	4.4019	213.237

Table 3 shows the comparisons between existing methods and simulated annealing method. It uses randomly generated initial designs as an initial seed location and the performance data is the average of 10 trials. The results from simulated annealing are compared with a non-linear optimization method available in MATLAB and several modified exchange algorithms. A gradient-based search such as the Sequential Quadratic Programming or the like [10] is widely used in solving fixture design problems (e.g., in [2, 14]). In this paper, the MATLAB function "*fmincon.*" was used among many of the commercial non-linear programming packages. The gradient-based method usually calculates the derivative at each searching point and follows the steepest ascent/descent direction, so it finds a solution quickly but it does not guarantee a global optimum. For example, if we use *fmincon* to solve the fixture design in our example, the sensitivity value of the final fixture layout is $S(\boldsymbol{\theta}) = 5.300$ when current fixture layout was used as an initial design on 2.20GHz P4 processor (other algorithms below are also executed under the same software and hardware computing conditions). It takes about 20 seconds to converge and this result shows merely a 1.9% improvement from the current design layout.

Simplex search [15] is also used as another non-linear method. It is also available in MATLAB as "*fminsearch*". It does not require gradients or other derivative information. Its performance is similar to the gradient-based method but also easily stops at a local optimum. The final sensitivity that it reaches is better than that from *fmincon* but takes a little bit more time. Our calculation reveals that $S(\boldsymbol{\theta})$=4.420 (a 22.19% improvement) when current fixture layout was used as an initial design and it takes 85.6 seconds to converge in the same MATLAB environment on the same machine. Both the gradient-based method and the simplex search operate on a continuous design space.

Some previous works solve the optimal fixture layout problem by using the exchange algorithm[17]. The exchange algorithm is used to solve optimal designs in design experiments. Wang and Pelinescu [18] used this algorithm in a single station fixture layout problem. The modified Fedrov exchange algorithm use less iterations and more greedily searches for an optimal solution. Because the modified Fedrov exchange algorithm uses fewer iterations, it takes less time to find solution than the basic exchange algorithm. These two exchange algorithms are also applied to compare the results from the non-linear programming method and simulated annealing.

We can find from the results comparison in Table 3 that the basic exchange algorithm can yield a small objective function value of $S(\boldsymbol{\theta})$ when it is applied to an optimal fixture layout problem in a multi-station environment on random initial designs. But because it is initially designed to find an optimal design in experiments with only a few parameters, the total running time is extremely high. The modified Fedrov exchange algorithm can find quite good designs in a faster time than the basic exchange algorithm.

The best design is found when we use the simulated annealing algorithm with cooling ratio(k_B) = 0.9 at the cost of 655.8 seconds of computation time.

The objective sensitivity $S(\boldsymbol{\theta}) = 3.821$-a 41.3% improvement from the current design but it seems that the computation time is still expensive. If we used cooling ratio(k_B) = 0.95, we can reach the close sensitivity value (only 4.2% higher th an what the $k_B = 0.9$ found) but less than one-half of the computational time. This result is quite comparable with the result from revised exchange algorit hm which was developed in [13]. Simulated annealing algorithm can found 3. 1% lower sensitivity objective than revised exchange algorithm when $k_B = 0.9$. If the $k_B = 0.95$ is used, simulated annealing can found the slightly larger so lution (1.1%) in a shorter time than revised exchange algorithm.

We can observe that the computational time and objective sensitivity is highly affected by the cooling ration k_B. The total computation time is decreas ed as the cooling ration is increased. But, if we consider the objective sensiti vity also, cooling ratio(k_B) = 0.9 seems to be the best choice in our particular example.

Table 3. Comparison of optimization methods (random initial designs)

Optimization Methods	$S(\boldsymbol{\theta})$	Time (sec.)
Gradient-based	8.183	22.9
Simplex search	6.825	73.8
Basic Exchange	4.091	1853.1
Modified Fedorov	3.901	1600.2
Revised exchange	3.940	373.1
Simulated Annealing (k_B =0.85)	3.841	1092.1
Simulated Annealing (k_B =0.9)	3.821	655.8
Simulated Annealing (k_B =0.95)	3.982	301.2
Simulated Annealing (k_B =0.99)	7.982	211.5

The limitation of the simulated annealing is the number of evaluations of the objective function. The evaluation of objective functions in some engineering systems is very expensive. For this reason, the efficiency of an optimal design algorithm can sometimes be determined by how often the objective function is evaluated. For $k_B = 0.9$, there were 28,503 number of objective function evaluations and for $k_B = 0.95$, there were 13,606 evaluations. In this example, the time for evaluating objective functions is not really expensive, so simulated annealing could produce a high performance. But if our assembly system contains more stations so that objective function evaluation becomes more expensive, a new approach which can reduce the number of evaluations should be developed.

The coordinates of the optimal fixture layout with the lowest $S(\boldsymbol{\theta})$ value during our trials and the one determined by our simulated annealing are listed in Table 4 as well as shown in Figure 5 where 'o' represents a P_{4way} and "*" represents a P_{2way}.

Table 4. The optimal fixture layout (θ) from simulated annealing (Units: mm)

Part #	Fixture layout with the smallest $S(\boldsymbol{\theta})$	
	4-way PLP (X, Y)	2-way PLP (X, Y)
1	(547.9, 1143.6)	(1027.9, 1440)
2	(1414.5, 1468.8)	(1224.5, 238.6)
3	(1510.9, 1430)	(1920.9, 1490)
4	(2843.5, 460.1)	(2933.5, 1170.1)

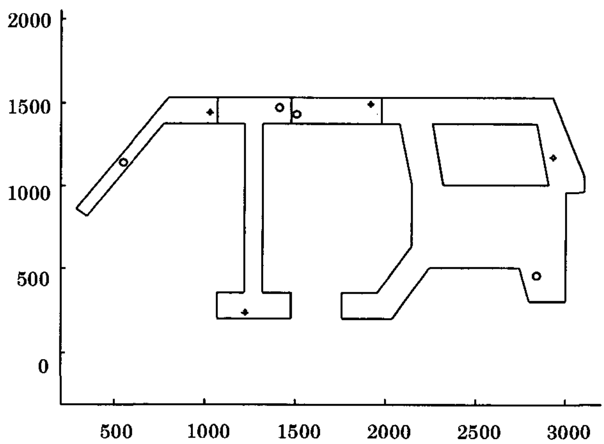

Figure 5. Optimal fixture layouts

To hold a single panel in a single station we know that the variation is minimized when two fixtures are located as far apart as possible, but from Figure 5 we find that this is not always true for multi-station assembly processes. Especially for the rear quarter panel, the two fixtures do not have the largest distance between locators. This phenomenon comes from the fact that the shift change for each station and the reused fixture locators make the sensitivity analysis difficult. From this example, we learn that the location should be selected based on the variation propagation model and an effective algorithm.

5. CONCLUSIONS

This paper presents a simulated annealing aided optimal design method. The method is applied to facilitate the optimal design of fixture layout in a four station SUV side panel assembly process. To apply the simulated annealing algorithm, the initial temperature $\boldsymbol{T}$, and cooling ratio (K_b) were carefully selected. The experimental result presented in Chapter 5 shows that the best optimal design of fixture layout was found when we use a simulated annealing algorithm with cooling ratio(k_B) = 0.9. Simulated annealing yields the optimal fixture design whose maximal sensitivity level is only 70.7% of the currently used fixture layout design. The resulting optimal fixture layout is more robust with regard to environmental noise – the reduction of 29.3% in sensitivity implies the same amount of reduction in product variation levels under the same variation inputs according to the definition of sensitivity. The improvement in product quality will lead to a remarkable cost reduction in manufacturing systems.

For a design optimization problem such as this multi-station fixture-layout design, it may be too costly, sometimes even impossible, to find the global optimum. Simulated annealing is a good trade-off between optimality and algorithm efficiency. Although the algorithm is discussed in the specific context of fixture layout design in a automotive panel assembly process, we feel that the variation propagation model, the selection of design criterion, and the resulting simulated annealing algorithm are fairly flexible and can be applied to a variety of other engineering system designs.

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