FEEDFORWARD CONTROL OF MULTISTAGE ASSEMBLY PROCESSES USING PROGRAMMABLE TOOLING

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ABSTRACT

The combination of feedforward control and programmable tooling has emerged as a promising method to reduce product variation in multistage manufacturing systems. Feedforward control allows compensation of deviations on a part-by-part basis using programmable tooling. This paper addresses the problem of designing an optimal feedforward control law that improves quality. The controller design involves deviations estimation (from in-line measurements), variation propagation modeling and analysis, and process/parts constraints. Therefore, a control law is obtained using constrained optimization. A case study is conducted on a multistage assembly of a vehicle side frame to illustrate the developed methodology.

1. INTRODUCTION

Variation reduction is an important but challenging task in multistage manufacturing processes. As an example, dimensional variation in automobile body may lead to wind noise and water leakage, thus variation should be minimized whenever possible. The autobody assembly process involves up to 150 parts assembled in up to 100 stations, where the sources of variation may come from any parts or assembly operations. Therefore, in such a complex process, determining the deviations and the appropriate correction for variation reduction are always difficult and time consuming tasks.

There are three approaches commonly used in variation reduction in manufacturing: robust design, Statistical Process Control (SPC) and active error compensation. Robust design helps to develop products and processes that are less sensitive to part/process variation and disturbances. However, robustness does not mean complete rejection of errors; therefore, production variation (parts and process variation) may still impact final product quality. SPC has been successfully used to detect changes in product/process caused by mean shift or variation changes, and also to identify some predetermined root causes of variation. However, SPC cannot be used to compensate deviations on a part-by-part basis. This type of compensation can only be achieved using active deviation compensation, which allows the control of product/process deviations through corrections for each assembly.

The enablers of active compensation are:

- Programmable Tooling (PTs): PTs allows the automatic adjustment of locators and clamps used to hold parts. Because of the high precision of the PTs and their capability to perform part-to-part adjustments, they provide the capability to compensate part/tooling deviations. One example of a PT is the Fanuc robot F-200iB (Fanuc, 2006), which was the first robot introduced in assembly to serve as a fixture carrier to allow the assembly of mixed models in the same line.
- In-line dimensional measurement sensors: The development of accurate non-contact sensors that can endure real process conditions has brought the possibility to obtain in-line quality information on the assembly stages (Perceptron, 2006).
- Stream-of-Variation (SoV) modeling tools: SoV tools allow modeling the variation propagation process in multistage assembly processes (Hu 1997; Jin and Shi 1999; Shi 2006). Those models can be used to determine the impact that deviations and control actions have on the final product quality.

Active error compensation in multistage assembly processes can be approached in two ways: feedback control and feedforward control. Feedback control implies that the control actions (corrections) are determined using downstream measurements usually obtained at the end of the process or in certain intermediate stages. On the other hand, feedforward control uses distributed sensors to determine deviations of parts/process, and then apply control actions before the joining takes place. In this way, feedforward control proactively compensates current deviations instead of reacting to past deviations as feedback control does.

Product and process deviations in assembly can be understood as mean shifts and variance changes. Due to the usual absence of auto correlation of the variation sources in multistage assembly systems (Hu and Wu 1990), feedback control can only be used to compensate mean shifts, but not to reduce variability. Thus, feedforward control scheme is preferable in assembly processes to perform corrections prior to the joining by adjusting the position of the PTs. Following this approach deviations are compensated, and quality is improved. Other benefits of using a feedforward control in assembly processes include reducing process ramp-up time (time to market) and improving the disturbance response time. Those advantages not only improve quality, but also enhance process responsiveness and reduce cost.

One of the first attempts to use feedforward control on assembly was done by Svensson (1985). With the help of a vision system, he modified the trajectory of a robot to achieve better fit of doors and windshields in car assembly. Similar applications were reported by Sekine et al. (1991), Wu et al. (1994), and Khorzard et al. (1995), where different techniques were used to determine the appropriate fitting of parts.

The aforementioned feedforward control strategies were related to the variation in one particular stage, without considering down stream processes. This single stage approach is only effective on reducing variation in multistage assembly processes if the stage involved is the last one, or the Key Product Characteristics (KPC) of the product controlled in the stage will not be affected by later processes. However, if none of those conditions hold, the single stage control is not appropriate because it does not consider the impact of deviations and control actions on the downstream part dimension. Therefore, the control actions obtained for the single stage scheme may not be optimal to improve final product quality.

A feedforward control in a multistage process needs a model to determine the impact that control actions at one intermediate stage have on the final product. Mantripragada and Whitney (1999) proposed a multistage model and the use of optimal control theory to determine control actions during the assembly. Using measurements of the parts before assembly, they were able to calculate the control actions that minimize the final product variation. They assumed that parts are the only source of variation in the process. More recently, Djurdjanovic and Zhu (2005) proposed the use feedback and feedforward control using the state space model to control deviations in multistage machining applications by modifying the position of the fixtures and tool path. However, those papers do not address the feedforward control of the multistage assembly process including parts/process requirements and specific engineering constraints on the derivation of the control actions.

This paper presents a methodology to design an optimal feedforward control that improves product quality by considering process/parts characteristics, multistage variation propagation, and constraints in process and control actions due to actuator characteristics, interference with other components and other factors. Thus, the determination of the control actions can be formulated as a constrained optimization problem, where the requirements to determine the optimal actions are:

- Obtaining an expression of the final product deviations (objective function) as a function of the control actions and the estimated parts deviations obtained from distributed measurements.
- Defining the search space for the control actions considering the PT's constraints and parts/processes characteristics.
- Determining the control actions that minimize the effects that the estimated deviations have on final product quality without violating the constraints, by using a suitable optimization method.

The remainder of the paper is organized as follows: Section 2 presents the multistage process model and the control estimation problem. Section 3 addresses the part/process deviations estimation problem and the development of the optimal feedforward control law in details. A case study is presented in Section 4, and the conclusions are given in Section 5.

2. FEEDFORWARD CONTROL OF MULTISTAGE ASSEMBLY

This section formulates the optimal feedforward control problem for multistage assembly processes that includes part and process constraints. First, the SoV model is presented, which is used to determine the impact that the control actions have on the final product quality. Second, it is addressed the determination of the control action as a constrained optimization problem using estimated deviations.

2.1 SoV Model

The model used here to describe the variation propagation in multistage assembly of rigid parts is the state space model developed by Jin and Shi (1999).

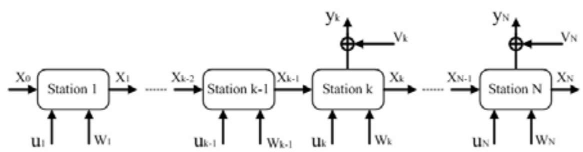

FIGURE 1. MULTISTAGE MANUFACTURING PROCESS.

Figure 1 presents a schematic of a multistage assembly process. As the subassemblies are moved from one stage to the next stage, they sequentially accumulate errors (Shiu et al. 1996). This process can be modeled as,

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

$$\mathbf{y}_k = \mathbf{C}_k\mathbf{x}_k + \mathbf{v}_k;\quad k = 1 \cdots N, \qquad (2)$$

where Eq. (1) is the state equation, variable $\mathbf{x}_k \in \Re^n$ represents the state of the system in stage k (part deviations from nominal). Variables $\mathbf{u}_k \in \Re^p$ and $\mathbf{w}_k \in \Re^n$ represent the fixture deviations and the disturbances respectively. Matrix $\mathbf{A}_k \in \Re^{n \times n}$ stands for the reorientation matrix, which relates the fixture layout of two adjacent stages (*k-1* and *k*). The effects of fixture deviations into the state of the system are determined by matrix $\mathbf{B}_k \in \Re^{n \times p}$. The observation equation, Eq. (2), is used to determine the deviations of the measurement points $\mathbf{y}_k \in \Re^m$, which usually corresponds to the KPCs of the product. Their deviations are obtained from the state using the observation matrix $\mathbf{C}_k \in \Re^{m \times n}$ and adding the measurement noise $\mathbf{v}_k \in \Re^m$. For details on how to derive each matrix please refer to Jin and Shi (1999), Ding et al. (2000), and Shi (2006).

The state transition matrix $\mathbf{\Phi}_{k,i}$ describes the deviation transmission between stages i and k (Ding et al. 2000), and it is calculated as $\mathbf{\Phi}_{k,i} \equiv \mathbf{A}_{k-1}\mathbf{A}_{k-2}\cdots\mathbf{A}_{i+1}\mathbf{A}_i$, $k>i$; $\mathbf{\Phi}_{i,i} \equiv \mathbf{I}$ (**I** is the identity matrix). Then, Eq. (2) can be written as,

$$\mathbf{y}_N = \mathbf{\Gamma}_0\mathbf{x}_0 + \sum_{k=1}^{N}\mathbf{\Gamma}_k\mathbf{u}_k + \sum_{k=1}^{N}\mathbf{\Psi}_k\mathbf{w}_k + \mathbf{v}_N , \quad (3)$$

where $\mathbf{x}_0$ represents the deviation of the incoming parts, $\mathbf{\Gamma}_k = \mathbf{C}_k\mathbf{\Phi}_{N,k}\mathbf{B}_k$, $\mathbf{\Gamma}_0 = \mathbf{C}_N\mathbf{\Phi}_{N,0}$ and $\mathbf{\Psi}_k = \mathbf{C}_k\mathbf{\Phi}_{N,k}$.

The deviations of the incoming parts, fixtures deviations, disturbances and noise are considered as random variables with mean of zero and covariances of $\Sigma_{x_0}, \Sigma_u, \Sigma_w$ and Σ_v respectively. They are also considered to be independent among them (e.g. $Cov(\mathbf{u}_k, \mathbf{v}_k) = 0$) and to be independent between different stages (e.g. $Cov(\mathbf{w}_i, \mathbf{w}_j) = 0,\ \forall i \neq j$).

In assembly, in-line measurements are usually obtained using OCMM sensors (Optical Coordinate Measurement Machine), which provide information on the displacement of the measurement points in 1D or 2D. The measurement points are usually selected to coincide with the KPCs. Therefore, they correspond to features that are important for the functionality, cost and safety of the product.

2.2 Feedforward Control Problem Formulation

The feedforward control formulation is based on compensating deviations of parts/ subassemblies and process before the joining process takes place as presented in Fig. 3.

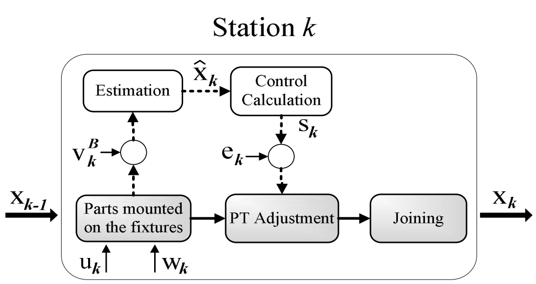

FIGURE 3. PROCEDURE TO CORRECT DEVIATIONS.

After the parts/subassemblies are mounted on the fixtures, measurements are performed to determine the deviations of the parts. Since the measurements are corrupted with noise ($\mathbf{v}_k^B$), then, the true state of the system can only be estimated. Using the estimation, it is possible to determine the control action vector $\mathbf{s}_k$, which will be applied by the PTs. Since the PT are not perfect, there is going to be an error $\mathbf{e}_k$ on the applied control actions. Finally the state of the system at stage k can obtained as,

$$\mathbf{x}_k = \mathbf{A}_{k-1}\mathbf{x}_{k-1} + \mathbf{B}_k(\mathbf{u}_k + \mathbf{s}_k + \mathbf{e}_k) + \mathbf{w}_k . \quad (4)$$

Using the state space model is possible to determine the effect that the estimated deviations and control actions have on the estimated final product deviations $\tilde{\mathbf{y}}_{N/k}$, given the information available in stage k (the derivation of $\tilde{\mathbf{y}}_{N/k}$ is presented in detail in section 3.2). By doing so, the control action determination can be formulated as a constrained optimization problem, where the objective function is the weighted sum of the squares of $\tilde{\mathbf{y}}_{N/k}$ as presented in Eq. (5).

$$\begin{aligned} J = \min_{\mathbf{s}_k} \ & \tilde{\mathbf{y}}_{N/k}^T\mathbf{Q}_k\tilde{\mathbf{y}}_{N/k} \\ \text{s.t. } & \mathbf{g}(\tilde{\mathbf{y}}_{N/k}^T, \mathbf{s}_k) \leq \mathbf{0} \end{aligned} , \quad (5)$$

where matrix $\mathbf{Q}_k \in \Re^{m\times m}$ is the weight matrix, $\mathbf{Q}_k$ is a diagonal and positive definite matrix. The values of the weighting coefficients account for the relative importance of the KPCs. The set of constraints $\mathbf{g}(.,.)$ include the design and manufacturing requirements for the location of the KPCs and stage/PT characteristics.

3. DETERMINATION OF THE CONTROL ACTIONS

This section presents the procedures to determine the optimal control actions using the estimated parts deviations.

3.1 Deviation Estimation

Being in stage k, the system equations before the control actions are applied can be described as:

$$\mathbf{x}_k^B = \mathbf{A}_{k-1}\mathbf{x}_{k-1} + \mathbf{B}_k\mathbf{u}_k + \mathbf{w}_k \quad (6)$$

$$\mathbf{y}_k^B = \mathbf{C}_k\mathbf{x}_k + \mathbf{v}_k^B; \quad k = 1\cdots N , \quad (7)$$

where the super index ^{B} stands for the condition *before* applying the control. Using Eq. (7), it is possible to estimate the state of the system $\hat{\mathbf{x}}_k$ using the Weighted Least Squares (WLS) estimation method as,

$$\hat{\mathbf{x}}_k = \mathbf{C}_k^{\dagger}\mathbf{y}_k^B, \quad (8)$$

where, $\mathbf{C}_k^{\dagger}$ is the pseudoinverse of matrix $\mathbf{C}_k$, and it is calculated as $\mathbf{C}_k^{\dagger} = (\mathbf{C}_k^T\mathbf{R}_k\mathbf{C}_k)^{-1}\mathbf{C}_k^T\mathbf{R}_k$. Here matrix $\mathbf{R}_k \in \Re^{m\times m}$ is a weighting coefficient matrix, which accounts for differences in the importance and characteristics of the measured points (KPC or non-KPC points, sensor noise level, measurement point importance, etc.), and it is a positive definite diagonal matrix. If matrix $\mathbf{R}_k$ contains on its diagonal the inverses of the sensors noise variances, then, according to Franklin et al. (1998), $\hat{\mathbf{x}}_k$ is the best linear unbiased estimator of $\mathbf{x}_k^B$.

3.2 Control Action Determination

At stage *k*, it is possible to write down the effects that the different variation sources and the control actions have on the final product deviations $\tilde{\mathbf{y}}_N$ as presented in Eq. (9).

$$\tilde{\mathbf{y}}_N = \mathbf{\Psi}_k\mathbf{x}_k^B + \mathbf{\Gamma}_k(\mathbf{s}_k + \mathbf{e}_k) + \mathbf{v}_N. \quad (9)$$

The PTs error vector $\mathbf{e}_k$ is assumed to be a random variable with mean of zero and covariance Σ_e, where the value of the covariance depends on the precision (repeatability) of the PTs utilized.

The expected deviations of the final product measurements, given the information available up to stage *k*, can be obtained by calculating the expectation of Eq. (9) as,

$$\tilde{\mathbf{y}}_{N/k} = \mathbf{\Psi}_k\hat{\mathbf{x}}_k + \mathbf{\Gamma}_k^C\mathbf{s}_k. \quad (10)$$

As presented in section 2.2 the control actions are obtained based on the constrained optimization of Eq. (5). Writing down the constraints, the control problem can be formulated as follows,

$$\begin{aligned} J = \min_{\mathbf{s}_k} \quad & \tilde{\mathbf{y}}_{N/k}^T\mathbf{Q}_k\tilde{\mathbf{y}}_{N/k} \\ \text{s.t. } & \tilde{\mathbf{y}}_{N/k} \in \left[LSL_{\tilde{\mathbf{y}}_{N/k}}, USL_{\tilde{\mathbf{y}}_{N/k}}\right] \\ & \mathbf{s}_{\min} \le \mathbf{s}_k \le \mathbf{s}_{\max} \\ & \mathbf{s}_k = \begin{cases} \mathbf{s}_k & \text{if } |\mathbf{s}_k| \ge \mathbf{\Delta}_s \\ \mathbf{0} & \text{otherwise.} \end{cases} \end{aligned} \quad (11)$$

This general formulation includes the existence of constraints on the position of the KPCs and the control actions. The first constraint ensures that the final product KPCs are going to be within the Upper and Lower Specification Limits (USL and LSL). The second constraint restricts the control actions to be within the upper and lower PT actuation limits ($\mathbf{s}_{\min}$ and $\mathbf{s}_{\max}$) that can be applied on each part/subassembly. The control action limits consider PTs workspace limitations and interferences with other stage components. Finally, the third constraint is an or-type one, where there are two possibilities for $\mathbf{s}_k$: it is either bigger than or equal to a threshold $\mathbf{\Delta}_s$ ($\mathbf{\Delta}_s > \mathbf{0}$), or it is zero. This type of threshold is used to avoid obtaining control actions that cannot be performed by the PTs. The value of the threshold can be obtained according to the accuracy of the PTs.

Varying $\mathbf{\Delta}_s$ in Eq. (11) can be understood as using different types of PTs. Therefore, such study can lead to identify the appropriate PTs to be used based on an effectiveness analysis.

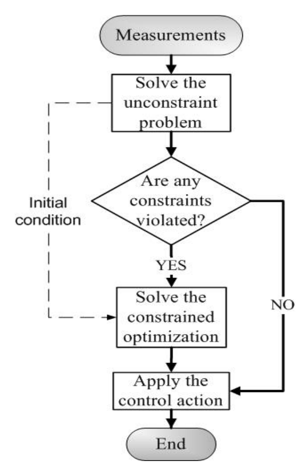

FIGURE 4. PROCEDURE TO DETERMINE THE CONTROL ACTION.

Figure 4 presents the procedure proposed to determine the control actions, which is based on determining first the unconstrained optimal solution of Eq. (11). If this solution does not violate any constraints, then control action can be directly applied. If one or more constraints are violated, then, the constrained optimization problem has to be solved.

The unconstrained solution ($\mathbf{s}_k^{*Unc}$) of problem (11) can be obtained by replacing Eq. (10) into Eq. (11) and solving it as a WLS problem (similar to the one in Section 3.1). Following this approach, the control action can be written down in terms of the measurements before control as,

$$\mathbf{s}_k^{*Unc} = -\mathbf{K}_k \mathbf{y}_k^B , \quad (12)$$

where the control gain matrix $\mathbf{K}_k$ is obtained as,

$$\mathbf{K}_k = \left[(\mathbf{\Gamma}_k^C)^T \mathbf{Q}_k \mathbf{\Gamma}_k^C \right]^{-1} (\mathbf{\Gamma}_k^C)^T \mathbf{Q}_k \mathbf{\Psi}_k \mathbf{C}_k^{\dagger} . \quad (13)$$

To solve the constrained optimization problem, we used the sequential quadratic programming algorithm coded in Matlab (fmincon), due to its flexibility to handle different types of constraints.

The first constraint in Eq. (11) may cause the nonexistence of an optimal solution. This happens when the incoming parts and subassemblies at stage k are so severely deviated from their nominal that it is impossible to satisfy the first constraint. Therefore, there is no control action capable to adjust the KPCs to make them be within their specification limits. If that is the case, the control action should be set to zero.

4. CASE STUDY

The case study simulates the assembly of a Sport Utility Vehicle (SUV) side frame (Fig. 5), proposed by Ding et al. (2002). The side frame is formed by four parts, which are assumed to be rigid and free to move in the x-z plane only (3 dof per part).

The assembly is performed in three stages with final measurement taken in a final inspection stage. The assembly sequence is summarized as follows: in the first stage the fender is attached to the A-pillar, then the B-pillar is added in the second stage, and in the third stage the rear quarter is attached. Afterwards, the complete assembly is moved to stage four for final inspection. The locators sequence used are: $\{(P_1, P_2), (P_3, P_4)\}_{StageI}$, $\{(P_1, P_4), (P_5, P_6)\}_{StageII}$, $\{(P_1, P_6), (P_7, P_8)\}_{StageIII}$ and $\{(P_1, P_8)\}_{StageIV}$. It is assumed that (i) all the required measurement points (marked in Figure 5b) are available at each station, (ii) PTs are used to hold all the parts in stages I and III, and (iii) there are not fixture errors and disturbances in the measurement stage. The parts are assumed to be rigid and the variation happens only in the x-z plane

The control performance using the algorithm derived in Sec. 3.2 are presented through (a) calculating the Quality Index (*QI*) defined in Eq. (14) as the reduction of the 2-norm of the final measurement standard deviation (σ) with and without using control actions. (b) checking if some KPC's deviations exceed the 2 mm/6σ limit, which is the standard in the automobile industry.

$$QI = \frac{\left\| \sigma_{y_{N/k}}^{w/o\ Control} \right\|_2 - \left\| \sigma_{y_{N/k}}^{Control} \right\|_2}{\left\| \sigma_{y_{N/k}}^{w/o\ Control} \right\|_2} \times 100 . \quad (14)$$

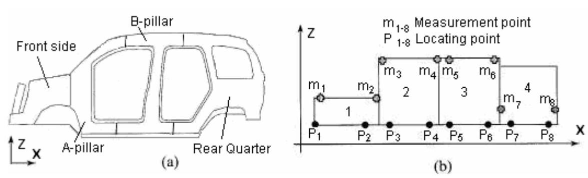

FIGURE 5. SCHEMATICS OF AN SUV SIDE FRAME AND ITS SIMPLIFICATION (Ding *et al.* 2002).

TABLE 1. EFFECT OF THE CONTROL AND THE CONSTRAINTS ON THE MEASUREMENT POINTS QUALITY (Units: mm).

Meas. point	W/o control		Control w/o const.		Control with const.	
	Std in x	Std in z	Std in x	Std in z	Std in x	Std in z
M_1	0.16	0.06	0.06	0.04	0.07	0.04
M_2	0.16	0.32	0.06	0.10	0.07	0.12
M_3	0.34	0.24	0.11	0.11	0.13	0.13
M_4	0.34	0.27	0.17	0.16	0.13	0.17
M_5	0.24	0.22	0.23	0.15	0.23	0.16
M_6	0.28	0.24	0.28	0.15	0.28	0.15
M_7	0.22	0.25	0.08	0.10	0.12	0.12
M_8	0.22	0.07	0.08	0.04	0.12	0.05

The parameters used in the simulations are $\Sigma_{x_0} = 0.04 \cdot \mathbf{I}$, $\Sigma_u = 0.0017 \cdot I$, $\Sigma_w = 0.0001 \cdot \mathbf{I}$, $\Sigma_e = 0.0017 \cdot \mathbf{I}$, and $\Sigma_v = 0.0009 \cdot \mathbf{I}$, where the units are mm^2, and **I** stands for the identity matrix with appropriate dimensions. The USL and the LSL were set to 0.8 mm and -0.8 mm respectively for all the KPCs. The values of s_{min} and s_{max} were set to -5 mm and 5 mm respectively to all the PTs, and the value of the threshold $\boldsymbol{\Delta}_s$ was set to 0.1 mm for all the PTs. The weighting coefficients matrices $\mathbf{Q}_k$ and $\mathbf{R}_k$ (k=1, 2 and 3) were set equal to the identity matrix. The results reported are based on the simulation of 1500 assemblies.

Table 1 and Fig. 6 present the standard deviation of the KPCs in the x and z directions for the cases with and without control. In the with-control case, both with and without constraints scenarios are included.

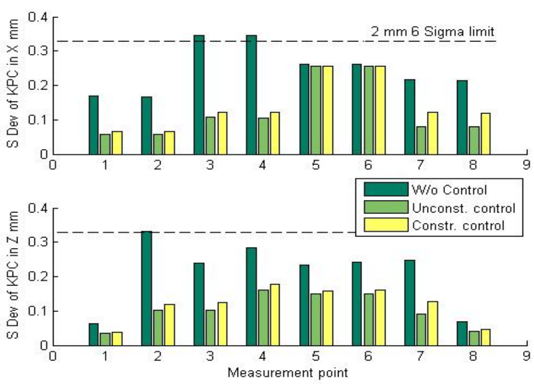

FIGURE 6. STANDARD DEVIATIONS OF THE MEASUREMENTS POINTS (KPCs).

The effect of using control significantly improves quality. The values of *QI* are 46.2% and 41.2% for the unconstrained and constrained control respectively. As can be expected, the constrained control improvement is less than the unconstrained one. However, the drop is not too big, and it reflects a more realistic process. By analyzing the figure, it is possible to observe that only the uncontrolled case exceeded the 2mm 6σ (σ=0.33 mm) threshold. Due to the lack of actuators in stage **II**, the effects of both controls do not significantly improve the position of KPCs M_5 and M_6 in the x direction. However, both controllers help in the z direction. The reason is that if part 3 is joined in stage **II** in the wrong position, the deviations that this part has in the x direction can not be corrected by relocating the subassembly formed by parts 1, 2 and 3 in stage **III** (the subassembly can not be stretched or compressed to correct the errors). However, a significant portion of the deviations in the z direction (~30%) can be corrected by relocating the subassembly in stage **III**.

In the case with control and with constraints, different scenarios are analyzed to study the impact of the threshold $\boldsymbol{\Delta}_s$ has on the quality improvement. This analysis may help to select the appropriate PT for a given process. Table 3 and Fig. 7 present the results using different values of the threshold. The effect on the improvement has a sigmoid shape, where for small thresholds, equivalent to using an accurate PT, there is a small drop in the *QI*. However as the threshold increases (greater than 0.1 mm) the *QI* tends to decay asymptotically to zero.

TABLE 3. EFFECT OF THE THRESHOLD $\boldsymbol{\Delta}_s$ ON THE QUALITY IMPROVEMENT.

$\boldsymbol{\Delta}_s$ mm	*QI* %	Exceed 2 mm (6σ) ?
0	44.5	No
0.05	44.0	No
0.075	42.6	No
0.7	40.2	No
0.15	33.7	No
0.2	23.8	No
0.25	14.8	No
0.3	9.3	No
0.35	4.8	No
0.4	1.2	Yes

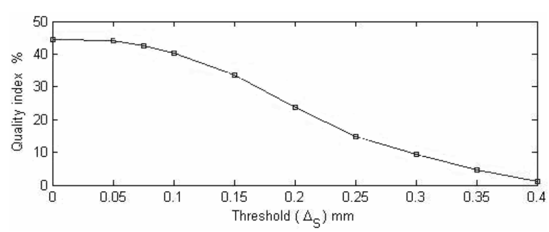

FIGURE 7. EFFECT OF THE THRESHOLD $\boldsymbol{\Delta}_s$ ON THE QUALITY IMPROVEMENT.

5. CONCLUSIONS

This paper proposes a new approach to improving product quality in multistage assembly processes by deviation compensation using feedforward control. The proposed method makes uses of distributed sensing and programmable fixturing technologies in determining and correcting deviations on a part-by-part basis. The problem of determining the optimal control action is formulated as a constrained optimization by considering design specifications and actuator/process characteristics. A method is proposed to obtain the solutions to the constrained problem by first solving the unconstrained one and then searching the constraint boundaries to find a global optimal solution. A case study that considers the assembly of a SUV side frame in three stages is presented considering the existence of PTs in only two stages. The results proved that feedforward control reduces the variation of the final product KPCs by more than 40%. The effect of PTs accuracy on the resulting quality improvement is also analyzed. From this analysis it can be concluded that for high PT accuracy the effect is almost constant. However, as the PT accuracy diminishes, there is a significant decrease in the amount of variation that can be reduced.

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