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Evaluating different strategies to achieve the highest geometric quality in self-adjusting smart assembly lines

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ABSTRACT

Digital twin-driven productions have opened great opportunities to increase the efficiency and quality of production processes. Smart assembly lines are one of these opportunities in which the effects of geometric variations of the mating parts on the assemblies can be minimized. These assembly lines utilize different techniques, including selective assembly and locator adjustments, to improve the geometric quality. This paper signifies that the achievable improvements through these techniques are highly dependent on the utilized fixture layout for the assembly process. Hence, different design methods and productions that can be followed in a smart assembly line are discussed. Furthermore, different scenarios are applied to two industrial sample cases from the automotive industry. The aptest design strategy for each improvement technique is determined. Moreover, the strategy that can result in the highest geometric quality of assemblies through a smart assembly line is defined.

1. Introduction

The availability of enormous amounts of data and automated production lines has opened new opportunities in design and production processes. Utilizing digital twins is one of these opportunities that is receiving significant attention in research topics about manufacturing [1, 2]. There is a shift in most of the industries toward digital twin-driven manufacturing so that it is predicted utilizing digital twins and interactive cyber–physical manufacturing are inevitable requirements of thriving industries in the future [3,4].

The studies regarding digital twins in manufacturing mainly propose utilizing the digital twin for a new application or developing a framework or platform for a previously proposed application. The effects of shifting the manufacturing toward a digital twin driven production on the design have been addressed in fewer publications. Moreover, comparative studies to define which strategy is superior in this type of manufacturing are missing.

Utilizing digital twin are proposed for almost the entire life cycle of products. Schleich et al. [5] presented several models of utilizing digital twins in the design, production, and recycling process of products. Several advantages are highlighted in utilizing digital twins, including self-optimization of production processes and parameters [6], mass personalization [1], production management [7], a higher level of sustainability, and decision-making support [8,9].

Lyu et al. [10] have proposed a smart manufacturing platform practice in which the warehousing is zero. Wang et al. [11] have developed a production control system enabling smart job shop (i.e. high flexibility of rapid changes in the requirement changes). Development of digital twin based frameworks of production is conducted by Cheng et al. [12]. Zhang et al. [13] have developed a cloud base smart manufacturing to address the problem of sequencing the orders when they are placed nearly at the same time. Zheng et al. [14] have defined the research gap in digital twin-driven production as a lack of digital twin reference models for smart manufacturing. Accordingly, they have proposed a generic cyber–physical system architecture to address this gap. Innovative gateway technology is also presented by Zhang et al. [15] in which the objects of a shop-floor are connected through logical connections.

Uncertainties and geometric variations are inevitable issues in mass production that can cause significant loss in manufacturing [16]. Accordingly, the potential of mass personalization and self-optimization can be employed to minimize the effects of geometric variations, and other inherent uncertainties of production [17,18]. For instance, Polini et al. [19] developed a digital twin-driven production process for assembling composite materials. Their study presents great potential in improving the geometric quality of the composites by utilizing a digital twin. Another example is an individualized production process of rear-axle-drives [20].

Individualizing the assembly processes is another potential of digital twin-driven production lines that is proposed by several authors [21, 22]. Assembly lines that enable this individualization are referred to as Smart assembly lines [21].

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A prerequisite of establishing an individualized smart assembly line is to acquire the exact geometry of each produced part before the assembly process. This requirement might be considered a hindrance against the individualization of assembly processes, particularly in the automotive industry. Nevertheless, this issue is solved by emerging new technologies in which the accurate deviations of produced parts can be captured rapidly by different photogrammetry techniques [23].

The geometric deviations can be compensated significantly when the scanned geometry of every produced part before performing the assembly process. This compensation is achievable through different individualization techniques in which the production parameters for each assembly is optimized based on its unique geometry. Wang et al. [24] have proposed a digital twin driven assembly system in which positioning of the part on each other is optimized by utilizing the scanned data of the produced parts. This framework is, however, limited to rigid assemblies without welding or other types of joints. Lee et al. [25] have developed an algorithm to predict the assemblies that will fail by utilizing the scanned data of the deformed parts and assembly forces. Among these techniques, selecting the combination of mating parts that results in higher quality in the geometry of the produced assemblies has shown great potential [26,27]. This technique is known as the Selective Assembly (SA). Another promising technique that can be utilized in the individualization of assemblies to achieve minimal geometric variations is Individualized Locator Adjustments (ILA) [28].

Scanning the mating parts before assembly helps in generating a digital twin of each assembly. Crontrath et al. [29] demonstrated that the accuracy of generated digital twins in simulating the assembly process can considerably improve through reinforcement learning. The produced assemblies are also required to be scanned to achieve this goal. Reducing the error between the digital twin simulations and the scanned data of the produced assembly is used as a reward system in this technique.

Fig. 1 illustrates the schematic of a general self-adjusting smart assembly line. The incoming parts can be scanned in their production site before being sent to the assembly workshop or before the assembly process. The assembly process can be simulated if the geometry of the mating parts (including their exact deviations from nominal geometry) and the production parameters, including fixture layout and welding properties, are available. Accordingly, the optimal production parameters of each individual assembly can be determined and applied to the physical assembly. The learning agent can observe the applied parameters, predicted outcomes, and actual outcomes and modifies the determined parameters of the optimization algorithm to minimize the errors.

1.1. Scope of the paper

The previous studies present great potential in employing a self-adjusting smart assembly in production to reduce the effects of geometric variations of mating parts on the assembly. Nevertheless, the sensitivity of assemblies to production parameters are highly dependent on their design parameters. The design is usually performed to have maximum robustness (i.e. minimal sensitivity to uncertainties). These uncertainties are mainly the part variations and locator variations. Having minimal sensitivity to part and locator variations might contradict achieving the highest quality by adjusting these parameters during the production. This contradiction is because if the assembly is not sufficiently sensitive to the variation of locators, adjusting those locators may not significantly modify its geometry.

This study addresses this concern by investigating the effects of the sensitivity of assembly on the achievable improvements through SA and ILA in a smart assembly line. Correspondingly, the design strategies that result in the highest achievable geometric quality for each technique are defined. Furthermore, the superior technique in achieving the highest geometric quality is determined.

Section 2 presents the definition of geometric quality and the method of determining the geometric quality of assemblies by simulations. Section 3 elaborates on the common definition of a robust design and possible strategies that can be utilized to design the assembly fixture layouts. Afterward, two production techniques of SA and ILA are presented, and the method of evaluating the different scenarios in a smart assembly line is described. In Section 4 two industrial sample cases are presented, different design and production strategies are applied to them, and their effects on the geometric qualities evaluated and discussed.

2. Geometric variations

Geometric variation is an inevitable consequence of mass production. The precision and accuracy in which the geometry of a product can be produced are limited. Consequently, the geometry of the produced parts may deviate from their nominal values. These deviations can accumulate in assemblies and result in malfunctions or aesthetic problems. Section 2.1 introduces the criteria used in this paper to quantify and evaluate the geometrical quality. Afterward, the utilized method to simulate the assembly process and determine the geometric quality by digital twins of assemblies is elaborated in Section 2.2.

2.1. Geometric quality criteria

The quality of a product is usually evaluated by measuring its Key Product Characteristics (KPC). Accordingly, the geometrical quality of products can be determined as the deviation of the actual values of its KPCs from their nominal values. Considering the magnitude of this deviation as d_i for the ith KPC of an assembly, a Root Mean Square of all KPCs in that assembly can be considered as the criterion to evaluate its geometric quality. This criterion is indicated by RMS_d and presented by Eq. (1). The number of KPCs are indicated by n in this equation.

$$RMS_d = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(d_i)^2} \qquad (1)$$

The mean value and variation of deviations of KPCs can be employed to evaluate the geometric quality of all assemblies of a batch together. Eq. (2) presents the mean value of KPC_i among all assemblies for a batch size of N. The index of j represents the assembly number in this equation.

$$\bar{d}_i = \frac{1}{N}\sum_{j=1}^{N}d_{ij} \qquad (2)$$

Variation of a KPC can be quantified as six times its standard deviations as presented in Eq. (3).

$$6s_i = 6\sqrt{\frac{1}{N-1}\sum_{j=1}^{N}(d_{ij}-\bar{d}_i)^2} \qquad (3)$$

The RMS of mean deviations RMS_m, and variations RMS_v of all KPCs in a batch of assemblies are utilized as criteria of evaluating the geometrical quality of a batch of assemblies and presented by Eqs. (4) and (5), respectively.

$$RMS_v = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(6s_i)^2} \qquad (4)$$

$$RMS_m = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\bar{d}_i)^2} \qquad (5)$$

Focusing on improvement in only KPCs may reduce the geometrical quality of other areas. This problem can be avoided by dividing the entire geometry into smaller elements (a finite element mesh) and considering a weighted RMS of all the nodes in the optimization.
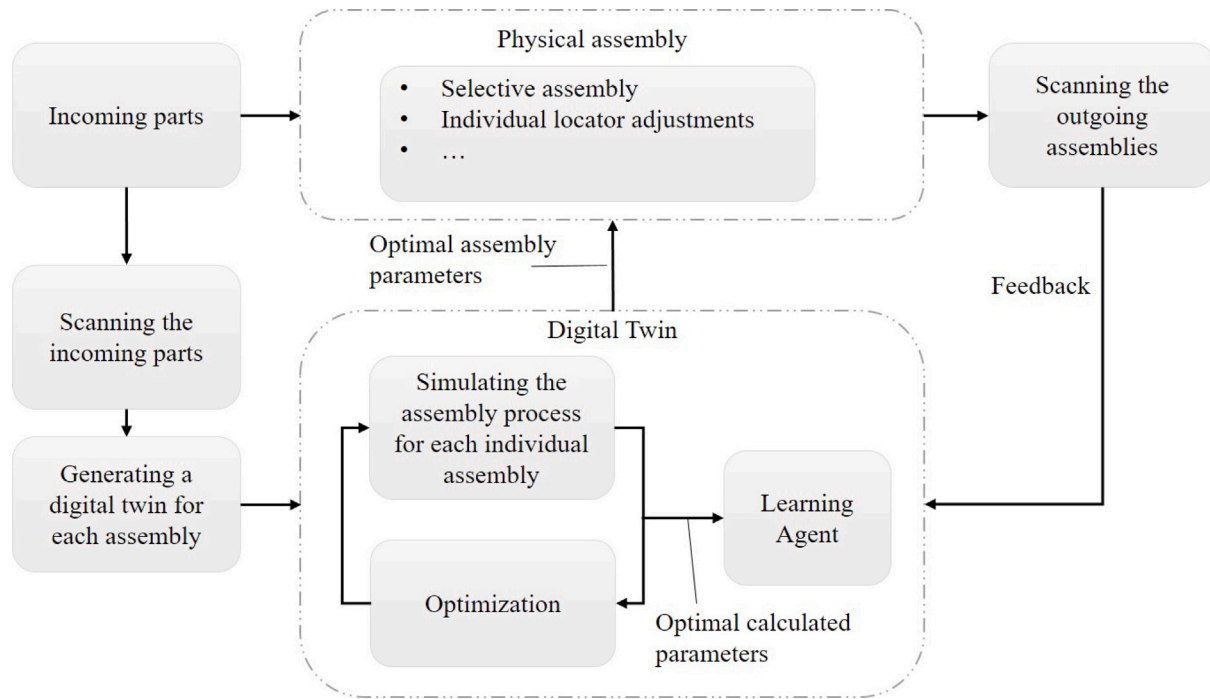
Fig. 1. Schematic of a self-adjusting smart assembly line.

2.2. Variation simulations

Utilizing a digital twin for optimization of assembly parameters requires simulating the assembly process to determine the geometry of each assembly. This process for sheet metal spot-welded assemblies can be divided into the following four stages [30]. The parts are located in fixtures in the first stage. Subsequently, they are clamped to their nominal forms. Afterward, weldings are performed, and the clamps are released in the last stage.

Assuming the deformations during this process are elastic, this process can be simulated using the linear Finite Element Method (FEM). The clamping forces (F_c) can be determined by one linear FE simulation as presented by Eq. (6). In this equation, $[D_1]$ indicates the deformations of parts from their nominal, and $[K_1]$ is the stiffness matrix of the assembly before welding.

$$[F_{c1}] = [K_1][D_1] \tag{6}$$

Assuming the parts are fixated in their nominal forms by fixture locators, welding does not impose any further deformations on the assembly. Hence, the clamping forces before and after welding are equal.

$$[F_{c1}] = [F_{c2}]$$

By connecting the nodes of parts in welding points, the stiffness matrix of the assembly after welding $[K_2]$ can be determined. Subsequently, the deformations of the assembly from the nominal geometry after releasing the clamps can be determined using Eq. (7).

$$[D_2] = [K_2]^{-1}[F_{c2}] \tag{7}$$

The presented procedure of simulating the assembly process for determining the deviations can result in high calculation cost because of the required FEM simulations. Liu and Hu [30] addressed this problem by developing a linear relation between $[D_2]$ and $[D_1]$, known as the Method of Influence Coefficient (MIC). Eq. (8) presents this relation in which $[S]$ the sensitivity matrix of the assembly.

$$[D_2] = [S][D_1] \tag{8}$$

The assembly process of compliant sheet metals can be more complicated than the presented method because of the contacts between sheet metal surfaces during this procedure. Dahlström et al. [31] demonstrated this problem and presented a new method MIC so that by conducting several iterations of MIC, the equilibrium between contact surfaces can be achieved. Furthermore, Wärmfjord et al. [32] developed a method of finding the contact nodes of the assembly. Further improvements are achieved in variation simulations by considering the effects of heat [33] and weld sequence [34].

The assembly process of sheet metals for determining the geometrical deviations can be simulated considering most of the mentioned complexities using commercial programs including 3DCS[1] and RD&T.[2] Nevertheless, contact modeling cannot be simulated by 3DCS. Regarding this issue, RD&T is the leading commercial program.

This study employs the RD&T program to simulate the assembly processes of each digital twin. Accordingly, after scanning the incoming mating parts for assembly, a digital twin of each part is generated containing the information about the deformations of the part from its nominal geometry. Correspondingly, these data are utilized to simulate the assembly process using the RD&T program.

3. Method

The utilized method of evaluating different design and production strategies in a smart assembly line is elaborated in this section. Section 3.1 presents the definition of a robust design for fixture layouts. Subsequently, different strategies that can be followed in designing a fixture layout for a smart assembly line are discussed in Section 3.2. Section 3.3 illustrates two production strategies of SA and ILA and the methods of applying them. After that, the overall procedure of evaluating the different design and production scenarios is presented in Section 3.4.
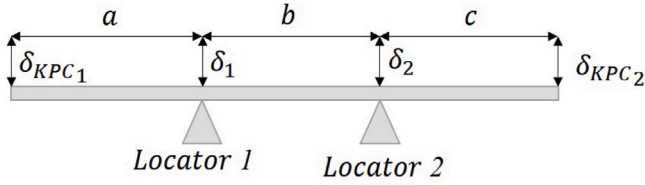
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[1] www.3dcs.com.
[2] www.rdnt.se.

Fig. 2. Simple example of robustness in rigid parts.

3.1. Robust design of fixture layouts

Robust design is usually defined as a design where the quality of the product or its functionality is not sensitive to uncertainties (i.e. noises). In the context of geometric quality, a robust design is defined as a design in which the sensitivity of the geometric quality of the product to the manufacturing uncertainties are minimized [35]. These uncertainties are commonly referred to as variations. The variations in assemblies can be divided into two categories of the input variations and output variations. The input variations are the sources of variation in an assembly. The output variations are the variations in the geometry of the produced assemblies after the fixture clamps are released the spring-back. The input variations can be divided into part variation and tool variation, particularly variation in fixture locators [36]. The manufacturing tolerances of locators are usually tighter than the manufacturing tolerances of parts. They should be roughly 5 to 10 times finer than the production tolerances of the parts [37]. Consequently, the main input variation in sheet metal assemblies is the part variation.

Although the part variation is the dominant source of variations, in rigid assemblies, robustness is commonly determined by measuring the sensitivity of the KPCs to variation of locators [36]. In rigid parts, it is merely the part variation in the locating points that can amplify or lessen the variation of KPCs. Moreover, the locators do not deform the parts. Correspondingly, the sensitivity of the assembly to the locator variation is identical to the sensitivity of the assembly to part variation.

The concept of robustness for rigid parts and assemblies is demonstrated by a simple example in Fig. 2. In this example a two dimensional rigid part is located by Locator 1 and Locator 2, and the KPCs are defined as the position of the two ends of the part. Variation in the ending points of the part (δ_{KPC_1} and δ_{KPC_2}) are functions of the resultant variations in the locating points (δ_1 and δ_2) regardless of whether the source of δ_1 and δ_2 is part variation, locator variation or a combination of the both. This function is presented in Eq. (9).

$$\begin{bmatrix} \delta_{KPC_1} \\ \delta_{KPC_2} \end{bmatrix} = \begin{bmatrix} \frac{a+b}{b} & \frac{a}{b} \\ \frac{c}{b} & \frac{b+c}{b} \end{bmatrix} \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix} \tag{9}$$

Based on Eq. (9), the amplification of variation in KPCs depends only on the location of the locators (a,b, and c). Considering $a = b = c$ results in amplifying the variation of locators as follows.

$$\begin{bmatrix} \delta_{KPC_1} \\ \delta_{KPC_2} \end{bmatrix} = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix}$$

And considering the $a = c = 0$ does not amplify the variations.

$$\begin{bmatrix} \delta_{KPC_1} \\ \delta_{KPC_2} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix}$$

Söderberg et al. [36] developed a sensitivity index based on this concept in which the designs with indexes of lower or equal to one are considered robust designs. The sensitivity matrix between KPCs and locator variations is extracted by utilizing the transformation and rotation equations of rigid body motions.

Minimizing the sensitivity of assemblies to *locator variations* is the goal in studies that consider the sheet metal assemblies rigid [38–40]. In these cases, the sensitivity matrix [S] can be obtained using rigid body motion equations for a single part and state-space modeling for

assemblies. There are several studies about how to minimize this matrix by deterministic or heuristic algorithms [41]. The design parameters in these studies are the location of different locators and/or slot directions.

Considering the locator variation as the only input variations and minimizing the sensitivity of the output variations to it cannot be used for compliant sheet metal assemblies because of the following reasons. First, in compliant assemblies, the parts can be deformed by the locators. For rigid parts, the input variation can be considered merely locator variations because the entire part follows every transformation or rotation in the locating points. Hence, even though the part variations are dominant, they can be replaced by locator variation for simplicity of simulations because the effects of part variation and locator variation are identical. On the other hand, when the locators might deform the parts, the effects of part variation and locator variation on the output variations are disparate.

Second, other factors, including contact areas and spring-back, may affect the variations and sensitivity of the assembly to the variations. Considering the contacts between parts, the relation between the variation of KPCs and locator variation is no longer linear. In other words, the amplification or reduction of variations is not merely dependent on the fixture layout; and the magnitude of part variation also affects it.

Third, variation magnitudes are not the same in all areas of each part. Depending on the production parameters, some areas of the mating parts might have larger or smaller magnitudes of variations. The pattern of variation in parts affects the sensitivity of the output variations to the input variations in non-rigid assemblies because it affects the part deformation during and after assembly. Therefore, their deformation patterns should be taken into account in the design of the fixture layout.

Several studies have considered the part variation as the source of variations to design the fixture layout for non-rigid assemblies [42–44]. These studies utilize variation simulations to determine the relation between the geometric quality of assemblies and the fixture layout. The design parameters are mainly the location of locators in a specific fixture layout. Aderiani et al. [45] developed a method in which all design parameters of a fixture layout can be optimized simultaneously. These design parameters are the number of additional clamps, the location and type of all locators, and the slot directions. This method is utilized in this study to determine the optimal fixture layout of a design strategy.

3.2. Different design strategies

In a robust design of sheet metal assemblies, the goal is to minimize the output variations by minimizing their sensitivity to the input variations. The main input variations are part variations that can be replaced by locator variations in rigid parts.

On the other hand, in a self-adjusting smart assembly line, the goal is to compensate for the variations by changing the part combinations or locator adjustments. Achieving this goal requires the geometry of the assembly to be controllable by part combinations and locator adjustments. However, minimizing the sensitivity of assemblies to part or locator variations may contradict this goal. This contradiction is because when the geometric quality is not sufficiently sensitive to a parameter, it cannot be controlled by that parameter. Hence, other design strategies rather than minimizing sensitivity to part variations might result in a higher geometrical quality when manufacturing is performed in a smart assembly line. Different possible design strategies are generated, and their effects on final qualities are assessed to address this issue.

To achieve the maximum improvements in a smart assembly line, an alternative design goal can be to maximize the assembly sensitivity to input variations instead of minimizing it. The input variations also can be part variations, locator variations, or both part and locator variations simultaneously. Accordingly, six different alternatives of design strategies can be followed. Table 1 presents a list of these strategies.

Table 1
Possible strategies to design the fixture layouts.

Strategy	Input variations			Sensitivity	
	Parts	Locators	Both	Minimum	Maximum
1	✓			✓	
2		✓		✓	
3			✓	✓	
4	✓				✓
5		✓			✓
6			✓		✓

3.3. Different production strategies

Different assembly techniques for improving the geometrical quality can be employed in a self-adjusting smart assembly line. In each technique, some production parameters are controlled to reduce the effects of uncertainties or utilize them to achieve a higher geometrical quality in the assemblies. Two common techniques that their implementations are developed in the literature are studied in this paper. These techniques are selective assembly and individualized locator adjustments.

Selective assembly is a technique in which the combination of the mating parts of assemblies is controlled so that relatively higher geometric qualities of assemblies are achieved. This technique has been used in the assembly of highly precise products, including piston–cylinder and bearings from 1940th [46].

Selective assembly can be performed by two different means of fixed-bins and individualized assemblies [26]. In the fixed-bin selective assembly, the incoming parts are divided into several groups based on their measured dimensions. Then, the matching groups will be defined and assembled together. This method is common in the production of bearings, engines, and hard disks. The main advantage of this method is its lower logistic costs. The main disadvantage is that the number of parts in the matching groups may not be equal. Consequently, some parts will be superfluous.

Several studies in the context of selective assembly have focused on defining the bins so that the number of superfluous parts is minimal [47,48]. Other studies have focused on finding the optimum combination of the bins so that the variations and superfluous parts are minimal [49–51].

Utilizing a selective assembly in assemblies that do not require high precision has not been reasonable because of the additional costs of scanning and logistics that this technique implies to the production. However, digital twin-driven productions and smart assembly lines have opened a new opportunity to develop the applications of this technique to a broader range of assemblies [52]. The fixed-bin selective assembly cannot be applied to sheet metal assemblies because the incoming parts cannot be categorized based on one or two criteria [27]. Hence, individualize selective assembly can be used in which the matching is conducted for each individual part instead of classifying the parts into different bins.

Selective assembly can be employed in a smart assembly line by utilizing variation simulation tools and optimization algorithms. The geometry of each assembly can be determined by simulating the assembly process for each digital twin when different combinations of mating parts are selected. Accordingly, the optimal combination can be determined for the digital twins. Appropriately, this combination will be used in the assembly line to select the mating parts and assemble them [53].

To apply selective assembly in this study, variation simulations of assemblies are conducted by RD&T. In this process, an interactive connection between a Genetic Algorithm (GA) and RD&T is developed. In each function evaluation, RD&T provides the RMS_v and RMS_m of the batch of assemblies for the generated combination of parts by GA [27,54]. To convert the multi-objective optimization problem

to single-objective optimization summations of RMS_v and RMS_m is considered as the objective of the problem.

Locators adjustment (shimming) is commonly utilized in the assembly of sheet metals in body in white [55]. Locators adjustment is a great technique to compensate for the unpredicted variations of incoming parts or fine-tuning the locators of fixtures [56].

Individualized locators adjustment is developed for self-adjusting smart assembly lines based on the conventional locator adjustments, also known as shimming [28]. The geometry of assemblies in this technique is controlled by adjustable locators of fixtures based on the individual geometry of each assembly [55]. Fixtures and locators are designed based on the nominal geometry of the parts. Individualization fine-tunes the fixture based on the unique geometry of each produced part. In ILA, the geometric quality of each assembly will improve while in general locators adjustment (shimming) the geometric quality of some assemblies might be reduced [28]. Accordingly, there is a great potential for geometric quality improvements of assemblies by utilizing this technique.

The procedure of defining the optimal adjustments of locators is similar to defining the optimal combination of parts. In this procedure, a real-coded GA is utilized along with RD&T to determine the adjustments that result in the highest geometric quality of the assemblies [28].

Combining both SA and ILA is another possible strategy of manufacturing in a smart assembly line. However, the effects of part combinations on the geometry of assemblies will reduce significantly when ILA is utilized [57]. Accordingly, employing both techniques will not result in a higher geometric quality than applying only ILA [57]. Hence, the following three strategies are studied for the production phase.

1. The production is performed without implementing a smart assembly line.
2. The production is performed with ILA in a smart assembly line.
3. The production is carried out with SA in a smart assembly line.

3.4. Evaluation method

The effects of different design and production strategies on the geometric quality of assemblies are evaluated. This evaluation is conducted by following each design strategy of the sample cases, firstly. After that, the production of the assemblies is simulated in a smart assembly line. The manufacturing simulations are conducted by implementing individualized locator adjustments, selective assembly, and without any improvement technique. Fig. 3 presents the overall process of the evaluation.

In each step of this method, an optimization algorithm is utilized along with simulation variation tools to define the optimal parameters of the design or the production. Accordingly, a proper interaction between the optimization algorithm and the variation simulation tool is developed.

Figs. 4 and 5 illustrate the established interactions in SA and ILA. The optimization for SA and ILA will be conducted for the scanned parts (digital twins). Accordingly, an optimal combination of parts for each batch of digital twins and a set of optimal adjustments for each individual digital twin will be determined in SA and ILA, respectively. The utilized GA to obtain the optimal combination of the parts, Fig. 4, is a sequencing GA in which each solution contains several sequences of integers, each representing a produced part. On the other hand, a locator adjustment can be a real number between the adjustment bounds. Hence, a real-coded GA, Fig. 5, is used in which each solution contains several real numbers, each indicating the adjustment value of each locator in its locking direction.

The utilized genetic operators in the sequencing GA differs from the real-coded GA. The crossover operation of the sequencing GA is a random key crossover [58] where the sequences are encoded to several
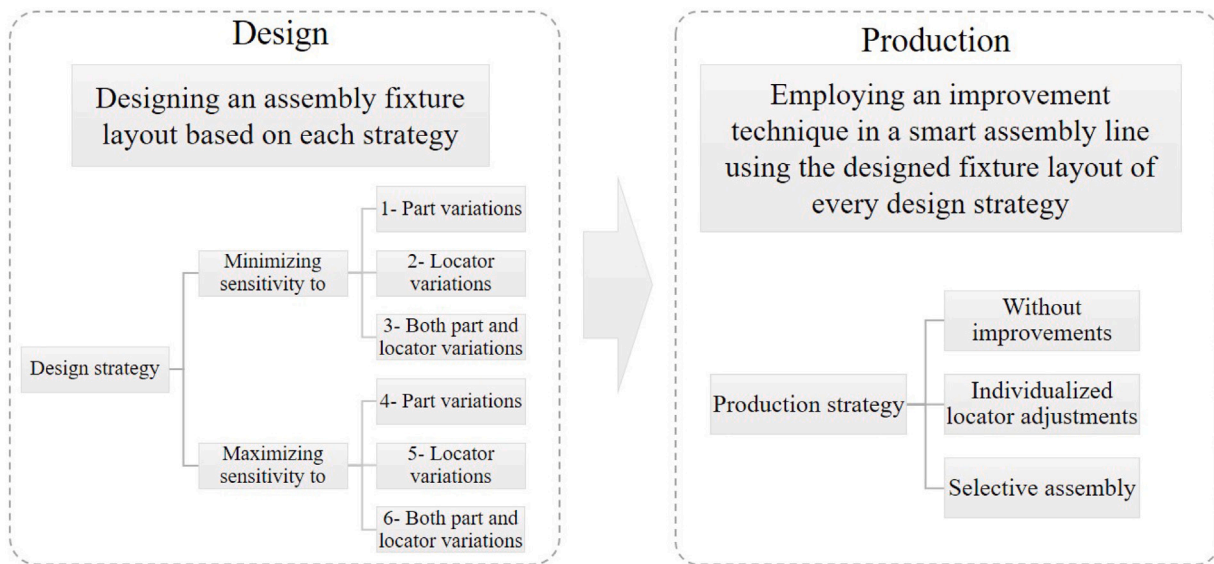
Fig. 3. The overall procedure of evaluating different possible strategies.

random numbers, the crossover applies to them, and then they are decoded to sequences again. Using this type of crossover is because each solution should represent a complete sequence of the integers. If a one-point crossover is applied, one of the new solutions may miss some integers while the other has them twice. The crossover for the real-coded GA is an arithmetic combination of the real numbers selected for this operation.

The mutation in sequencing GA is conducted by randomly selecting an integer in the sequence and swapping its position in the sequence with the previous integer. The mutation in real-coded GA is performed by adding or subtracting a random fraction of the real number to it so that it is still inside the boundaries of the feasible solutions.

Fig. 6 displays the type of interaction in the fixture layout design. In the design of the fixture layout based on each design strategy, the GA provides a fixture layout for the assembly. The variation simulation tool determines the geometric quality for 1000 Monte-Carlo simulations of the input variations. This procedure continues until the optimal fixture layout based on the defined strategy is determined. Each fixture layout is encoded to a combination of integers, binaries, and real numbers. Consequently, in the crossover operation, the integer and binary sections of the new solutions are generated by conducting a one-point crossover between the selected solutions. The real parts of the new solutions are generated by obtaining a random arithmetic combination of the real parts of the selected solutions. To apply the mutation in the combined GA, a random number of the solution is chosen. Depending on whether that number is a binary, integer, or real number, the correspondence mutation operation is applied. If the parameter is the real part of the solution (slot directions), the same mutation as the real-coded mutation is applied. If it is a binary parameter and its value is zero, it will change to one and vise versa. For the integer values, another random integer value inside the bounds replaces the previous value.

The utilized parameters and operator in each optimization procedure are based on [28] and [54]. Roulette wheel selection [54] is utilized in all GAs to select the crossover operation solutions. The crossover and mutation rates are considered 0.7 and 0.3, respectively. The population size is defined as 100, and the maximum number of iteration is considered 200. Another convergence criterion utilized is to stop the optimization if the best solution does not improve after 50 iterations.
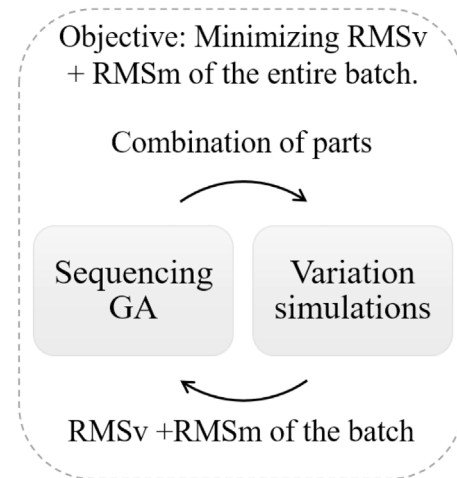

Fig. 4. The utilized interactions between GA and the variation simulation tool in SA.

4. Results and discussions

Different design and production scenarios are evaluated by implementing them in the design and production of two sample cases from the automotive industry. The first sample case is a batch of ten assemblies consisting of three sheet metal parts welded together with seven spot welds. Fig. 7 displays this sample case and its simulation model. The second sample case is also a spot-welded sheet metal assembly of two parts. Fig. 8 indicates an image from this assembly and its simulation model.

A batch of ten assemblies is considered for the analysis of each sample case. Accordingly, ten deformed parts for each mating part are generated based on the scanned data of the produced parts. After that, six fixture layouts are designed for each sample case based on the six design strategies. Subsequently, the three production strategies are simulated for each design strategy by utilizing the digital twin of each assembly. Moreover, the sensitivity of assemblies to part combinations and locator adjustments are evaluated for each design strategy.

Section 4.1 presents the effects of each design strategy on the geometric quality with and without utilizing ILA. The effects of each design strategy on the achievable improvements by SA are demonstrated in
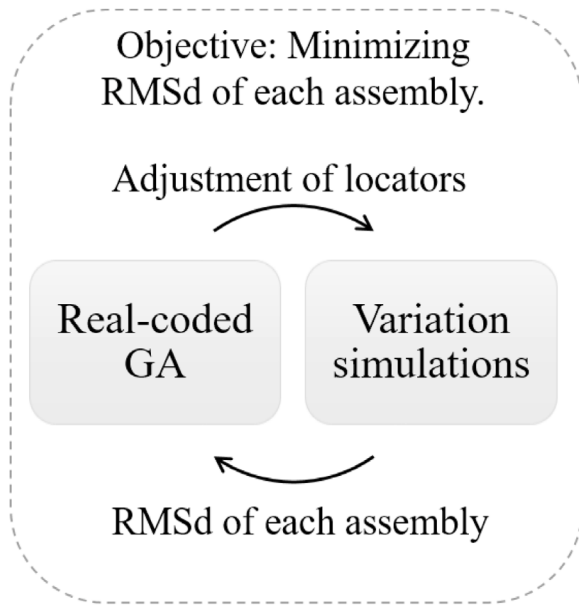
Fig. 5. The utilized interactions between GA and the variation simulation tool in ILA.
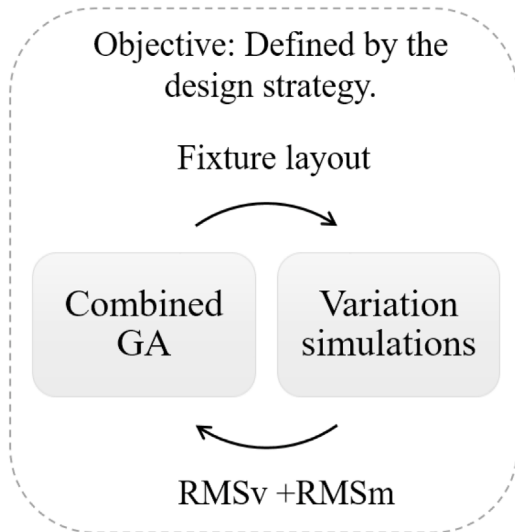

Fig. 6. The utilized interactions between GA and the variation simulation tool in designing the optimal fixture layout based on each design strategy.

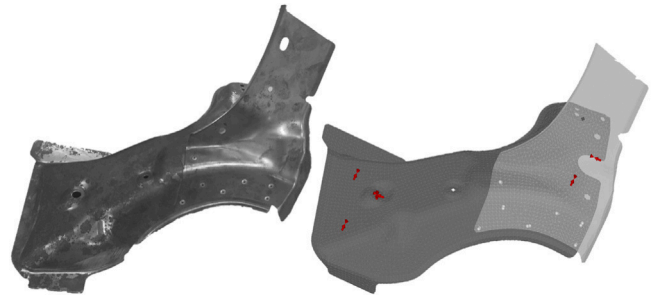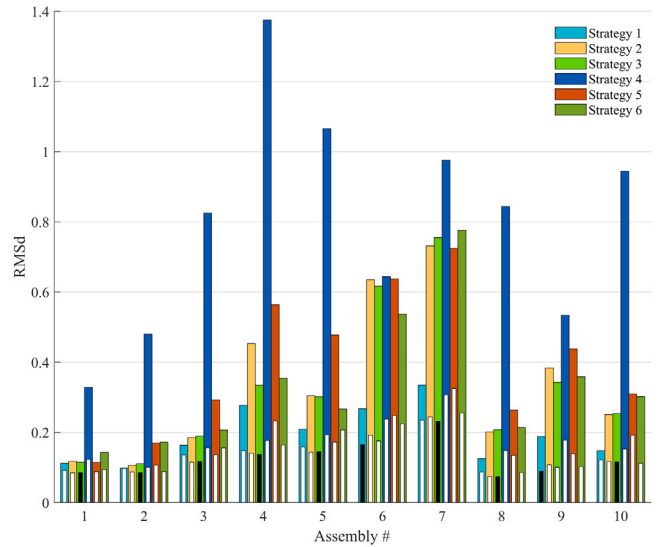**Fig. 7.** The fist sample case and its simulation model.

Fig. 8. The second sample case its simulation model.

Fig. 9. RMS_d of each assembly of sample case 1 without ILA (color bars), with ILA (white bars), and the lowest RMS_d (black bars) for different design strategies. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Section 4.2. Section 4.3 illustrates a comparison of the highest achievable improvements from ILA, SA, and without ILA/SA. Section 4.4 elaborates on verification of the results, and several potential subjects for further developments of this study are suggested in Section 4.5.

4.1. Production by ILA

The goal of utilizing ILA in an assembly line is to control the geometric variation of assemblies by adjusting the locators. Nevertheless, the achievable improvements through this technique are dependent on the utilized fixture layout for the assembly procedure. This section evaluates the effects of all design strategies on the achievable improvements. Then, the strategy that results in the maximum achievable improvements by ILA is determined. To evaluate the improvements, the geometric quality of the produced assemblies without utilizing a smart assembly line is also presented for each design strategy.

Figs. 9 and 10 present RMS_d of each individual assembly with and without applying ILA for the first and second sample cases, respectively. In these figures, RMS_d of each assembly without applying ILA is indicated by a color bar. Each color in these charts represents a fixture layout design strategy. The RMS_d of the same design strategy when ILA is applied is indicated by a white bar inside the corresponding color bar. However, the minimal RMS_d of each assembly with ILA (i.e. the superior design strategy) is indicated by black color to make it distinguishable among the other strategies.
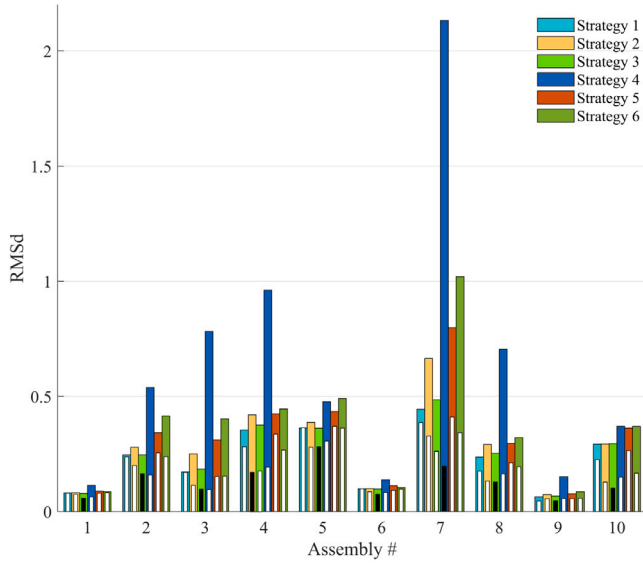
Fig. 10. RMS_d of each assembly of sample case 2 without ILA (color bars), with ILA (white bars), and the lowest RMS_d (black bars) for different design strategies. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

As expected, for production without ILA, the first design strategy leads to the minimal RMS_d for each assembly. In production without ILA or SA, the design strategies that are carried out to maximize the sensitivity will not result in low deviations. Therefore, design strategies 4, 5, and 6 cannot be the superior design strategies for production without a smart assembly line. Among strategies 1, 2, and 3, the input variation of the design strategy 1 (i.e. only part variation) is identical to the input variation in production. Hence, this design strategy is superior for production without employing smart assembly lines.

The minimal RMS_d of each assembly with ILA suggests the third design strategy as the superior strategy for ILA. Nevertheless, in the assembly numbers 6 and 9 for sample case 1, the first strategy results in a slightly better improvement than the third strategy. The assembly numbers 4 and 7 in the second sample case also have slightly lower deviations with strategies 2 and 4, respectively. However, considering the overall improvements, the superiority of the third design strategy is clear.

To further assess the effects of each design strategy, fluctuations of RMS_v and RMS_m of each sample case are evaluated for 100 random adjustments. Different random adjustments between [−2 2] are generated for all locators and applied to each assembly. Figs. 11 and 12 illustrate these fluctuations for RMS_v and RMS_m of sample case 1, respectively. The fluctuations of RMS_v and RMS_m in the second sample case are presented by Figs. 13 and 14, respectively.

The results exhibit that the strategies in which the sensitivity is maximized lead to extremely large deviations in the assemblies. Consequently, when design strategies 4, 5, and 6 are utilized, ILA cannot compensate for the deviations, although the sensitivity is increased.

Comparing the results of strategies 1, 2, and 3, evidence that reducing the sensitivity to locator variations (strategies 2 and 3) leads to greater improvements than strategy 1 in which the sensitivity is minimized only to part variations. Hence, minimizing the sensitivity to locator variations results in higher geometric quality than not considering locator variations at all.

4.2. Production by SA

In SA, the effects of part variations are minimized by selecting the optimal combination of the parts. Changing the combination of parts alters the geometric quality of all assemblies of the batch, despite ILA that
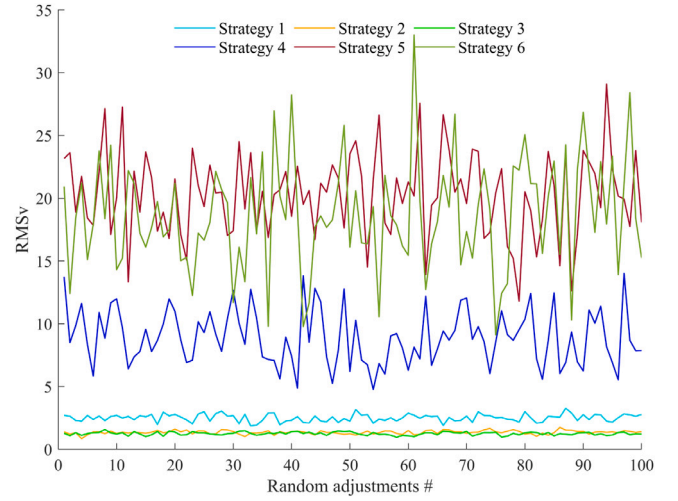

Fig. 11. Fluctuations of RMS_v of the first sample case for random adjustments of locators between [−2 2].
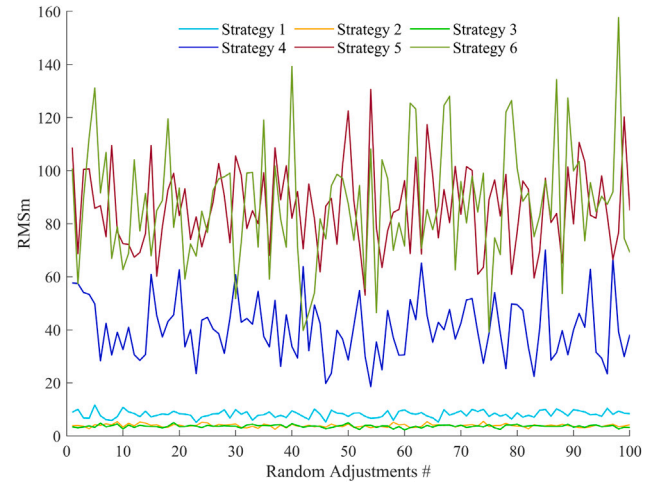

Fig. 12. Fluctuations of RMS_m of the first sample case for random adjustments of locators between [−2 2].
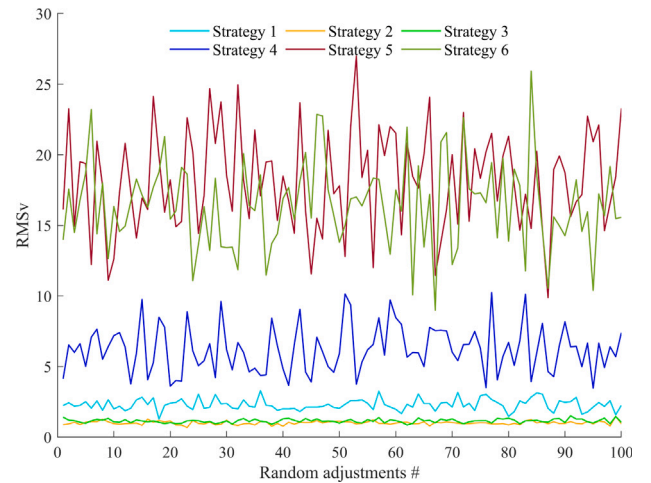

Fig. 13. Fluctuations of RMS_v of the second sample case for random adjustments of locators between [−2 2].
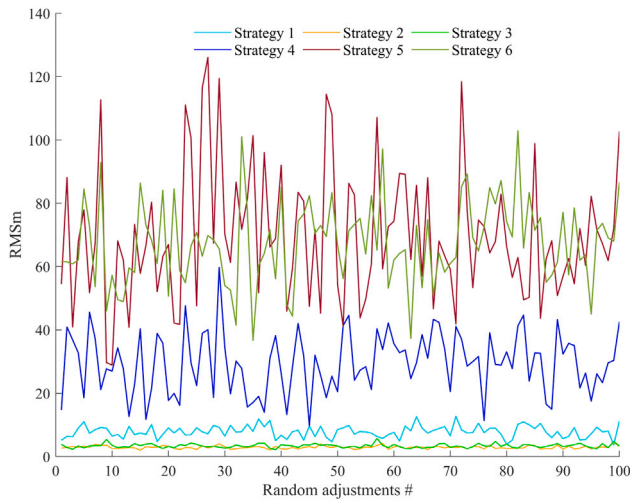
Fig. 14. Fluctuations of RMS_m of the second sample case for random adjustments of locators between $[-2\ 2]$.
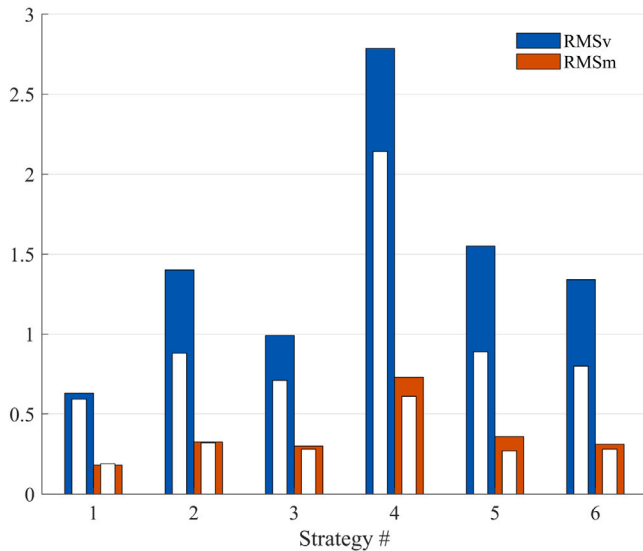

Fig. 15. Geometric quality of the assemblies without (color bars) and with applying SA (white bars) for sample case 1 with different design strategies. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 16. Geometric quality of the assemblies without (color bars) and with applying SA (white bars) for sample case 2 with different design strategies. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 17. RMS_v of assemblies of the sample case 1 for 100 random combination of mating parts.

the geometric quality of each individual assembly can be controlled separately. Therefore, to evaluate the achieved improvements by SA, RMS_v and RMS_m of the entire batch should be considered instead of RMS_d of each assembly.

The utilized strategy in the design of fixture layout affects the sensitivity of the assemblies to the combination of mating parts. Consequently, the achievable improvements by SA depend on the strategy that is utilized to design the fixture layout. Accordingly, the RMS_v and RMS_m of the batch when produced with and without applying SA are compared for each strategy. Figs. 15 and 16 illustrate these results for the first and second sample cases, respectively.

The RMS_v and RMS_m of the assemblies without applying SA are indicated by color bars in these figures. The improved values of RMS_v and RMS_m by SA are indicated by white bars inside the corresponding color bar of each strategy.

The results suggest the first design strategy as the superior design strategy when SA is employed in the production. The difference between the geometrical quality without and with applying SA is
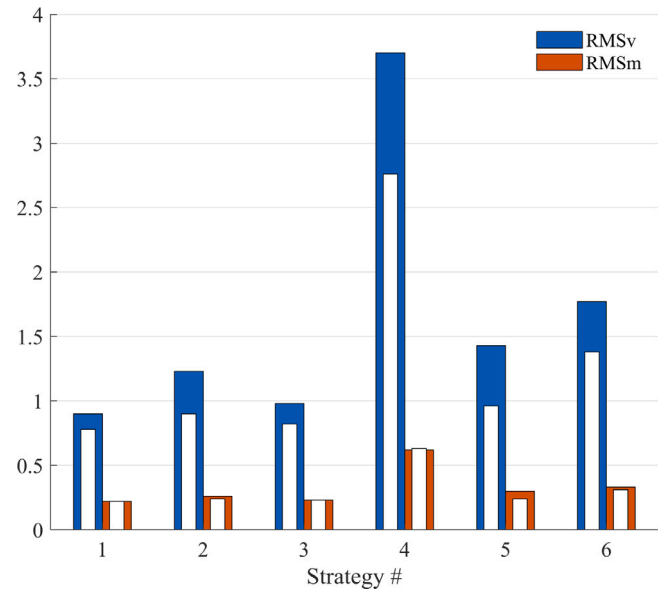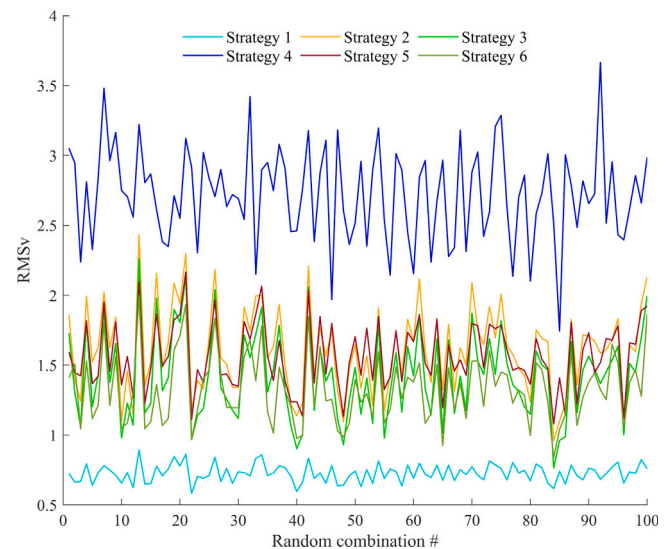
not significant for the design strategy 1. However, even though the variations for other strategies are significantly improved by SA, they still have larger variations than strategy 1.

The effects of design strategy on the sensitivity of assemblies to part combinations are further evaluated. Hence, the RMS_v and RMS_m of each assembly are determined for 100 random combinations of mating parts and different design strategies. The RMS_v and RMS_m of the batch of assemblies in the first sample case are illustrated by Figs. 17 and 18, respectively. Figs. 19 and 20 demonstrate the fluctuations of RMS_v and RMS_m of the second sample case, respectively.

The results approve the same conclusions obtained from the optimal combination of parts (i.e. SA. The strategies that result in lower sensitivity to part combinations) also result in a better average geometrical quality. Accordingly, although the sensitivity of assemblies to part combinations has significantly increased by strategies 2 to 6, the average
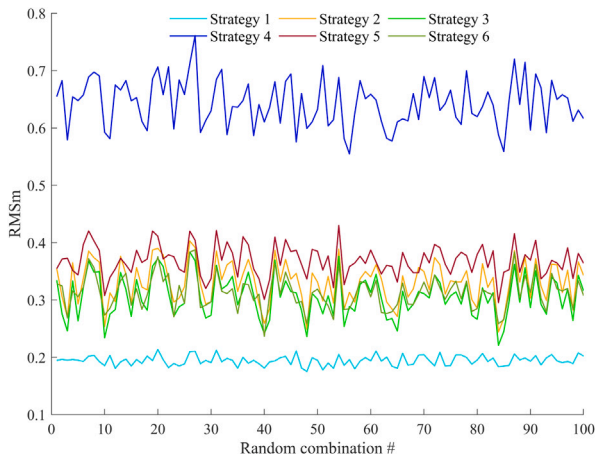
Fig. 18. RMS_m of assemblies of the sample case 1 for 100 random combination of mating parts.
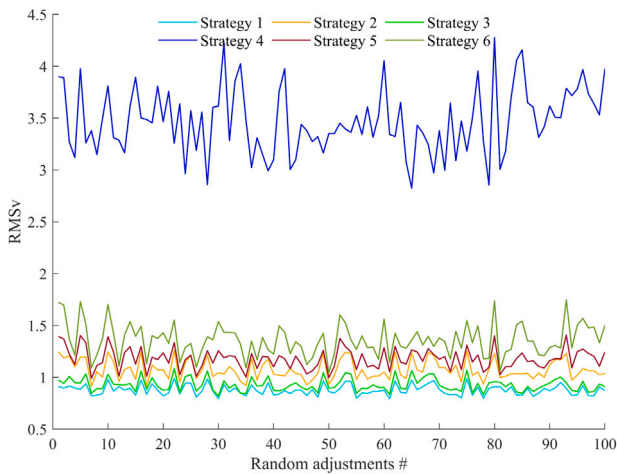

Fig. 19. RMS_v of assemblies of the sample case 2 for 100 random combination of mating parts.

Fig. 20. RMS_m of assemblies of the sample case 2 for 100 random combination of mating parts.

loss of geometric quality has also significantly increased, which cannot be compensated for by applying SA.
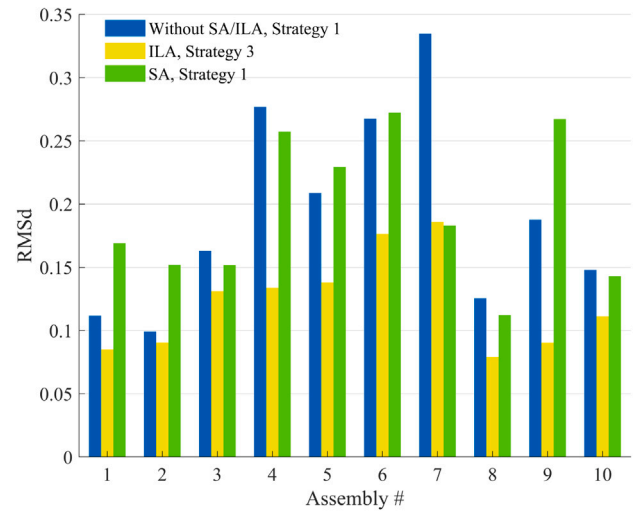

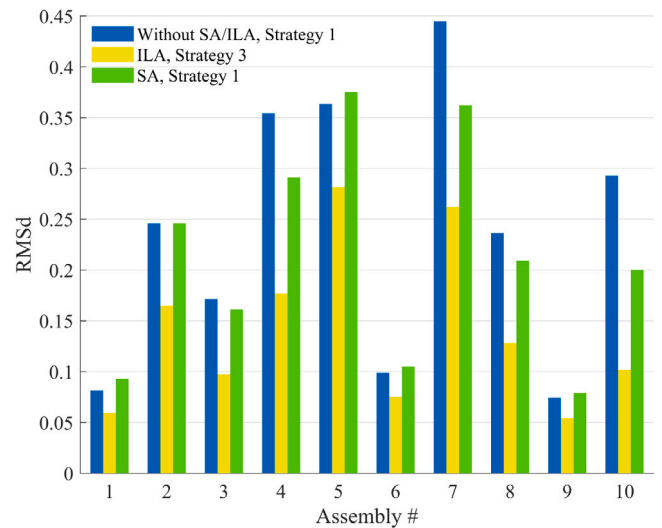**Fig. 21.** RMS_d of assemblies of the sample case 1 for the best design strategy of each production strategy.

Fig. 22. RMS_d of assemblies of the sample case 2 for the best design strategy of each production strategy.

4.3. Comparing production strategies

Sections 4.1 and 4.2 presented the effects of utilizing different design strategies on each production strategy. Based on these results, design strategy 1 is superior for production without SA/ILA and production with SA. Moreover, design strategy 3 is superior for production with ILA. This section compares these three scenarios together to determine the superior scenario in achieving the highest geometric quality.

Figs. 21 and 22 illustrate the geometric quality of each individual assembly, RMS_d, for the aforementioned scenarios for the first and second samples cases, respectively. Based on the results, the maximum quality can be achieved by utilizing Strategy 3 in designing the fixture layout and employing ILA in the assembly process.

The parts of each assembly are the same in production without SA/ILA and production with ILA. However, applying SA results in a completely different combination of the mating parts. Hence, the assembly numbers presented in Figs. 21 and 22 do not present the same assemblies when SA is applied compared to the two first scenarios. Consequently, the RMS_d of each assembly can be compared for the

Table 2
Summary of achieved improvements by SA and ILA compared to assemblies without ILA/SA but with optimized fixture layout.

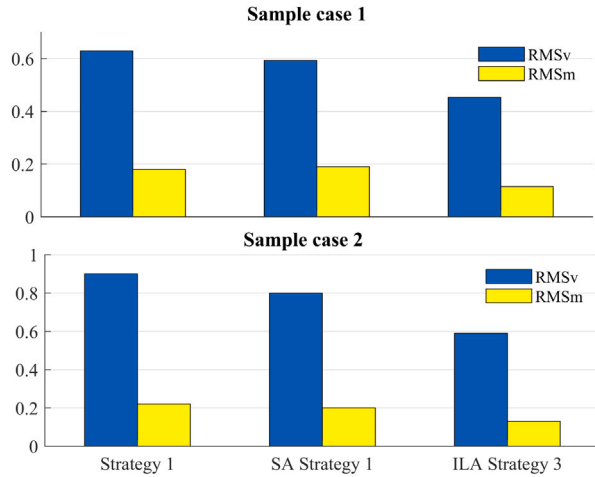|	SA [%]		ILA [%]	
	RMS_v	RMS_m	RMS_v	RMS_m
Sample case 1	5	1	30	40
Sample case 2	9	4	33	35

Fig. 23. Geometric quality of the entire batch of each sample case for the best design strategy of each production strategy.

first and second scenarios individually but not with the third scenario. Accordingly, RMS_ds of all individual assemblies together when SA is applied can be compared with all RMS_ds of the other two scenarios.

Considering the maximum and minimum RMS_ds of individual assemblies, the results evidence that utilizing SA can reduce the deviations of the assemblies with maximum deviations. However, this improvement is conducted at the cost of increasing the deviations of assemblies with minimal deviations. This may not be an issue because the problematic assemblies are usually those with the highest deviations.

Fig. 23 presents a comparison of RMS_v and RMS_m of the entire batch for the different scenarios. These results evidence that the greatest improvements in both variations and the means deviations can be achieved by applying ILA in production and utilizing Strategy 3 in the design. Nevertheless, utilizing SA and using Strategy 1 results in lower variations relative to production without SA/ILA, but almost the same mean deviations of the assemblies.

A summary of achieved improvements is listed in Table 2. These improvements are determined relative to assemblies that their fixture layout is optimized based on strategy 1 but are not assembled in a smart assembly line. The first two columns represent the improvements by SA with design strategy 1. The second two columns present the achieved improvements by utilizing ILA with design strategy 3.

4.4. Verification of the results

Several parameters might have affected the obtained results. Therefore, a verification of the results is conducted by varying these parameters and evaluating their effects on the findings. These parameters are the magnitudes of the locator variations in the design phase, the allowable range of adjustments, and the accuracy of the locator adjustments.

The input variations in the design phase can be either part variations, locator variations, or both. The part variations can be defined based on the measured deviations of the similar parts that are previously produced or by experience. However, it is supposed that the actual variations of locators in production are negligible. On the other

hand, in several design strategies, including strategy 3, locator variations should be included in the input variations, in addition to the part variations. However, it is not clear how large variations should be applied in these strategies, and based on what references, the magnitude of these variations should be defined.

To address this issue, the sensitivity of the design to the magnitude of these variations is evaluated by applying different magnitudes of locator variation and determining the fixture layouts for design strategies 2, 3, 5, and 6 of each sample. The applied magnitudes are 1, 2, 3, and 4 mm. However, the determined fixture layout for different magnitudes of locator variations is nearly the same for all ranges. Accordingly, the range of the applied locator variation does not play an important role in the obtained fixture layout in design strategies 2, 3, 5, and 6.

The second parameter that changing its value may affect the findings is the accuracy of the applied locator adjustments in ILA. The value of the minimum adjustment that can be applied to a locator is limited in practice because of the limits in the accuracy of the locator geometry and control system. The findings in this study are determined by assuming that the accuracy of the locator adjustments in ILA is 0.1 mm (i.e., in ILA, adjustments of less than 0.1 mm cannot be applied). However, to examine the effects of this assumption on the results, the accuracy is increased to 0.01 and 0.001 mm. Nevertheless, the obtained results from these accuracies do not present noteworthy changes.

The third parameter that its value can affect the achievable improvements is the allowable range of locator adjustments. Each locator can be adjusted in a defined range in its locking direction to an extent. Adjustments in larger values may result in large locating forces, contact forces, and plastic deformations of the parts. Hence, a maximum range of allowable adjustments should be defined. This maximum range can be a subjective matter, depending on the assembly properties. Consequently, the effects of different ranges of maximum allowable adjustments on the findings are evaluated. For this aim, four intervals of [−0.5 0.5], [−1 1], [−2 2], and [−4 4] are tried as allowable intervals for adjustments in ILA. The results indicate that in all cases for both samples, the optimal adjustments lay in the interval of [−1 1] even when the allowable adjustments are in the interval of [−4 4]. Limiting the allowable adjustments to [−0.5 0.5] results in relatively lower improvements than [−1 1].

4.5. Future work

This paper was mainly focused on SA and ILA as two main techniques that can be utilized in a smart assembly line to improve geometric quality. Assessments of other potential techniques can be conducted in future studies. These potential techniques are assembling sequence optimization, welding sequence optimization, and clamping sequence optimization. Moreover, there can be design parameters, including the number and location of welds, that affect the achievable improvements in a smart assembly line. The effects of these parameters can be studied in future studies. The same study can be conducted for other products rather than assemblies, including machining and bending. Future studies can also be continued by applying the presented techniques in a production line of sheet metal assemblies to validate the results further.

5. Conclusions

Smart assembly lines can be utilized to improve the geometric quality of assemblies by individualizing the assembly process. The individualization can be performed by measuring the input uncertainties and controlling them through different techniques. Selective assembly and individualized locator adjustments are two established methods that are focused on in this study. The former reduced the effects of variations by controlling the combinations of mating parts. The latter controls the variations by adjusting the fixture locators in small scales.

The utilized fixture layout for production is the primary factor in the achievable improvements through these techniques. Based on that, six different design strategies are defined that can be followed to minimize or maximize the sensitivity to part variations, locator variations, or both variations. Accordingly, different design and production strategies are utilized for two industrial sample cases from the automotive industry, and the results are evaluated.

Based on the results, the design strategy in which the sensitivity to only part variations are minimized results in the highest quality for production without utilizing an improvement technique and production by the selective assembly. For production by individualized adjustments, the strategy in which sensitivity is minimized for both locator and part variations results in the highest improvements.

Moreover, the results evidence that individualized locator adjustment is superior in improving the geometric quality compared with selective assembly or not using an improvement technique. The main conclusions can be summarized as follows.

- Individual locator adjustment is the superior technique in compensating the variations in a smart assembly line relative to SA.
- To achieve the maximum geometric improvements by ILA, the fixture layout should be designed so that the sensitivity of assemblies to both part and locator variations is minimized.
- To achieve the most significant improvements through SA, the sensitivity should be minimized only to part variations.

CRediT authorship contribution statement

Abolfazl Rezaei Aderiani: Conceptualization, Software, Formal analysis, Investigation, Writing - original draft, Visualization. **Kristina Wärmefjord:** Conceptualization, Writing - review & editing, Supervision, Project administration. **Rikard Söderberg:** Conceptualization, Writing - review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

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