Combining selective assembly and individualized locator adjustments techniques in a smart assembly line

(article starts on next page)

Procedia CIRP 97 (2020) 429–434

Contents lists available at ScienceDirect

Procedia CIRP

journal homepage: www.elsevier.com/locate/procir

Combining selective assembly and individualized locator adjustments techniques in a smart assembly line

Abolfazl Rezaei Aderiani*, Kristina Wärmefjord, Rikard Söderberg

Department of Industrial and Materials Science, Chalmers University of Technology, Gothenburg SE-412 96, Sweden

ARTICLE INFO

Article history:
Received 30 September 2019
Revised 23 March 2020
Accepted 25 May 2020

Keywords:
Selective assembly
Locator adjustments
Digital twin
Smart assembly

ABSTRACT

The availability of automated production lines and production data has opened a new opportunity for improving the geometrical quality of assemblies by using a digital twin in the concept of a smart assembly line. In this concept, a digital twin is generated from scanned data of incoming parts for each assembly. The assembly process is then simulated for the digital twin using variation simulation tools. Subsequently, the optimal production parameters are found by utilizing optimization algorithms along with the simulations so that the geometrical qualities of assemblies are maximum. Two effective production parameters that can be optimized in this concept are the combination of parts and adjustments of locators. The techniques to implement optimize these parameters in the production are referred to as selective assembly and individualized locator adjustments, respectively. This paper evaluates the results of optimizing each parameter separately and both parameters together. To attain this goal, the results of applying the optimal parameters on three industrial cases are determined and compared. The results evidence that the potential of individualized locator adjustment in improving geometrical quality is considerably greater than selective assembly.

1. Introduction

Geometrical variation in production is a major issue that can cause both functional and aesthetic problems (Söderberg et al., 2017). Consequently, a large portion of production costs is being spent to cope with reducing these variations and their consequences. New technologies and advances in automation and scanning of parts can be leveraged to mitigate this problem. Taking advantage of this opening, Söderberg et al. (2017) have proposed optimizing the production parameters of assemblies based on the scanned data of mating parts to improve the geometrical quality of the assemblies. This concept is referred to as Smart Assembly 4.0, and it is visualized in Fig. 1.

The deformed shape of produced parts can be obtained by taking several pictures (Bergström et al., 2018) or by utilizing 3D scanning. Based on the concept of a smart assembly line, these data can be utilized in real-time to generate a digital twin for each assembly (Aivaliotis et al., 2019). Thereafter, combinations of parts, adjustments of locators, sequences of welds (Tabar et al., 2019), etc. can be optimized by simulating the production process of the digital twin along with utilizing an optimization algorithm.

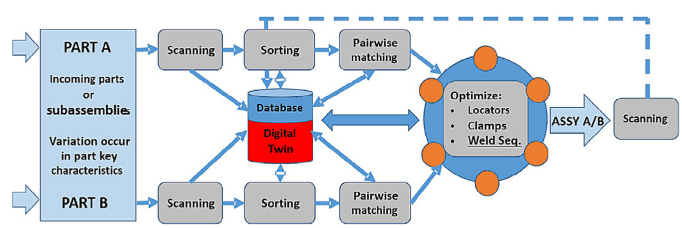

Fig. 1. The proposed concept of Digital Twin for Geometry Assurance by Söderberg et al. (2017).

Optimizing the combination of mating parts to maximize the geometrical quality of assemblies is known as the Selective Assembly technique in the literature. Utilizing this technique has been common in the production of precise assemblies including bearings and engines since 1950th (Mansor, 1961). The early methods of performing selective assembly were based on dividing the mating parts into several groups based on their measured dimensions and matching the groups for assembly (Chan and Linn, 1999; Mansor, 1961). Nevertheless, the number of parts in the matching

* Corresponding author.
E-mail address: aderiani@chalmers.se (A. Rezaei Aderiani).

https://doi.org/10.1016/j.procir.2020.05.263

groups may not be equal. Consequently, some parts would be superfluous. This problem is referred to as mismatching and most of the studies in selective assembly aim to address it (Fang and Zhang, 1995; Mansor, 1961; Xu et al., 2014). Selective assembly techniques are getting more attention in new production lines including cyber factories and smart assembly lines. Aderiani et al. (2019) have developed the application of this technique to sheet metal assemblies, where the deviation of dimensions in the assembly does not have a linear relation with the deviations of mating parts. In this method, the matching is performed for individual parts, instead of dividing the parts into groups and matching the groups.

A rigid part has six degrees of freedom in space, including three translations in x, y and z and three rotations around these axes. Accordingly, to fixate the part for production processes, including assembly process, these degrees of freedom should be locked by locators. The arrangement of locators to fixating the parts is referred to as a locating scheme. If the part is flexible, additional locators can be employed to resist external forces, including gravity. These additional locators are usually referred to as supports.

Locating schemes are commonly designed based on the nominal geometry of the parts. Nevertheless, the produced parts have some deviations from their nominal geometries. Thus, the locators can be adjusted to compensate for the deviations. This technique is known as locator adjustments. Locator adjustments technique is also referred to as Shimming (Keller and Putz, 2016) and Trimming (Lindkvist et al., 2005) when it is applied to a batch of assemblies. The studies regarding this technique mainly deal with finding the optimal amount of adjustments so that the geometrical variation is minimal in the assembly. Lindkvist et al. (2005) developed a toolbox to find these adjustments for production, based on the available data of the pre-production phase when prototypes are produced. Germer et al. (2014) have developed a metamodel to predict the adjustments based on the data from previously produced assemblies. Keller and Putz (2016) have proposed measuring the locator forces to determine the required adjustments. Aderiani et al. (2019) have proposed individualization of the adjustments based on the scanned geometries of the mating parts using a digital twin. In this method, the amount of adjustments for each assembly is determined by simulating the assembly process of its digital twin. Individualizing the locator adjustments increases the potential geometrical improvements by locator adjustments, three to four times. This is because each produced part has a different geometry. Therefore, it requires different adjustments of locators which is provided by this method.

1.1. Scope of paper

The new availabilities have opened the opportunity to minimize the geometrical variation of assemblies using two techniques of Selective Assembly (SA) and Individualized Locator Adjustments (ILA). The previous studies evidence a substantial improvement in geometrical quality of assemblies when each of these techniques is employed separately. However, the possibility of accumulating these improvements when both techniques are employed in an assembly line is a knowledge gap in this context. Moreover, the potential of each technique in improving the geometrical quality has not been studied compared to the other technique. Therefore, the primary research question of this study is: What will be the results if these two techniques are implemented together in an assembly line? The answer to this question is important because it will clarify whether implementing a technique along with the other technique results in the same improvements as when it is applied separately. The second research question is: Which technique can result in a greater geometrical improvement compared to the other technique? The answers to these questions are essential for establishing a smart assembly line in the industry.

In order to address the gaps presented, different scenarios of applying SA and ILA together and separately to three industrial sample cases are examined. Furthermore, the geometrical qualities of three batches of assemblies are assessed for ten random combinations of parts in the presence and absence of ILA. This assessment can further clarify the effect of performing SA before ILA.

Section 2 of this paper illustrates the utilized methods and tools in this study for applying SA and ILA and obtaining the results. The results of the experiments are presented and discussed in Section 3 and the conclusions are drawn in Section 4.

2. Method

This section illustrates the utilized methods and tools for obtaining the results. Since the goal of each technique is to improve the geometrical quality, definition and quantitative parameters to evaluate the geometrical quality are introduced in Section 2.1. Thereafter, Section 2.2 reviews variation simulation as a tool in predicting the geometrical quality of assemblies. Hence, the methods of applying SA and ILA are presented in Sections 2.3 and 2.4, respectively. Afterward, Section 2.5 demonstrates the utilized sample cases for conducting the experiments. Finally, Section 2.6 describes the designed scenarios and the utilized approach of comparing them.

2.1. Geometrical quality

Geometrical quality of products can be assessed based on the deviation of their geometry from their nominal geometry. Nevertheless, the criteria for assessing geometrical quality of an individual assembly differ from a batch of assemblies. For a single assembly, deviation of dimensions from their nominal values can be combined to a single criterion. This combination is commonly performed by employing Root Mean Square (RMS) of the deviations. In this study, the geometry is divided into small elements and RMS of the deviation of these elements is considered as the criterion to evaluate the improvements in geometrical quality. This criterion is presented by RMS_{dj} and represents RMS of deviations of all nodes of the assembly j. Eq. (1) presents the formulation of this criterion. In this equation, d_{ij} represents the magnitude of deviation of node i in assembly j and n indicates the number of all nodes.

$$RMS_{dj} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(d_{ij})^2} \tag{1}$$

To evaluate the geometrical quality of a batch of assemblies, variation and mean deviations are employed. The mean deviation of a node is the average deviation of it among all assemblies of the batch. Geometrical variation is considered as six times the standard deviation. Eq. (2) presents the formulation of this parameter. In this equation, d_i represents the deviation of each node and $\bar{d}_i$ indicates the mean deviation in node j of the assembly. The variable N is the number of assemblies in the batch which is referred to as the batch size.

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

The RMS of variation and mean deviation of all nodes of the assemblies are considered as criteria for evaluating geometrical quality of a batch of assemblies. The former is presented by RMS_v and the latter is indicated by RMS_m.

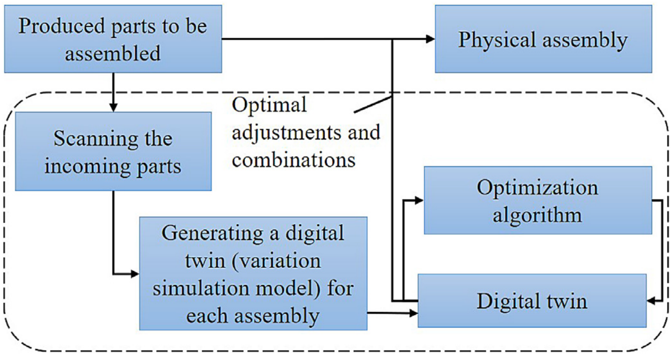

Fig. 2. Generating a digital twin from the scanned data of each produced part.

2.2. Digital twin

Variation is inevitable in producing the mating parts of the assemblies. Therefore, each produced part has a unique shape that requires unique production properties including locator adjustments and combinations of parts. Accordingly, the assembly process should be simulated for each individual assembly to determine the optimal production parameters for that assembly. Having the scanned data of all incoming parts, a variation simulation model of each assembly can be generated, which is referred to as the digital twin of that assembly. This procedure is visualized in Fig. 2.

Variation simulations aim at predicting the variation of a product by considering different sources of variations including part variations and fixture variations. These inputs can be generated using Monte Carlo simulations or scanned data of the produced parts.

The assembly process, particularly spot welded sheet metal assemblies, can also be simulated using variation simulations. To attain this goal, Finite Element (FE) simulations can be utilized to determine the deviations of the product after the assembly process. Moreover, utilizing the Method of Influence Coefficient (MIC) results in less calculation cost for obtaining the same results (Liu and Hu, 1997). Considering contact elements in variation simulations leads to obtaining more realistic results and improves the accuracy (Dahlström and Lindkvist, 2007).

The aforementioned capabilities in variation simulation of assembly process are gathered in a Robust Design and Tolerancing (RD&T) program with the capability of conducting variation simulations for both rigid and non-rigid parts and considering contact modeling in the simulation which is utilized in this study.

To simulate the assembly process, FE model of the assembly is generated from the CAD parts of the nominal geometries. Thereafter, for each individual assembly, a deviation is allocated to each node of the model based on the scanned data of the produced parts. Accordingly, the geometrical outcome of each individual assembly can be determined by simulating the process for its digital twin that is the simulation variation model generated from scanned data.

2.3. Selective assembly

There is a variety of methods for performing selective assembly technique. Nevertheless, most of these methods are limited to rigid assemblies where the relation between dimensional deviations of the assembly and mating parts are linear. Since the method presented by Aderiani et al. (2019) does not have this limitation and it is applicable to sheet metal assemblies, this method is utilized in this research.

In this method, a multi-objective optimization problem with two objectives of RMS_v and RMS_m is presented and solved. To attain this goal, firstly the deviations of assemblies are obtained using variation simulation tools. Thereafter, a mixed-integer nonlinear programming optimization problem is generated and solved using the GAMS program for these types of problems. The multi-objective optimization problem is converted to a single objective optimization by considering the summation of both RMS_v and RMS_m as the objective of the optimization.

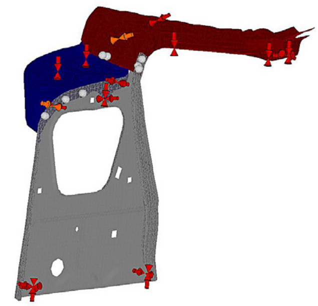

Fig. 3. Sample case 1.

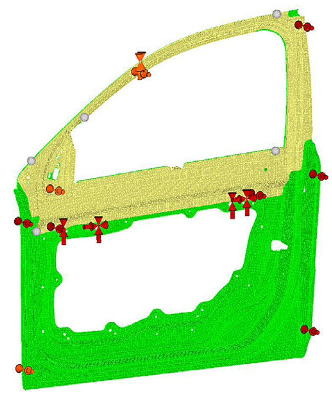

Fig. 4. Sample case 2.

2.4. Individualized locator adjustments

In order to adjust the locators of assemblies individually, an optimization problem of finding optimal adjustments for each individual assembly should be solved. However, in contrast to the selective assembly problem, the objective of the optimization is improving the geometrical quality of each individual assembly, not the entire batch together. Accordingly, RMS_d of each assembly is considered as the objective of each optimization. The generated residual stresses and maximum stress during the assembly process are also determined and limited by adding two penalty functions to the objective function.

This optimization problem is solved using a real-coded Genetic Algorithm (GA) (Eshelman and Schaffer, 1993). The optimization algorithm is developed in MATLAB and an interactive connection between MATLAB and RD&T is generated. For each function evaluation, MATLAB gives RD&T a set of locator adjustments as input and RD&T calculates RMS_d and stresses for the provided adjustments.

2.5. Sample cases

Different scenarios of applying the two techniques are evaluated by conducting experiments on three industrial sample cases. These cases are sheet metal assemblies from the automotive industry. The cases are modeled in RD&T program by considering contact elements between different components, the locating schemes, and spot welds. Figs. 3, 4 and 5 illustrate the generated model for

Fig. 5. Sample case 3.

Table 1
RMS_v and RMS_m before and after applying different scenarios.

Case	Criteria	Without improvements	Different scenarios					
			1	2	3	1 [%]	2 [%]	3 [%]
1	RMS_v	1.68	0.85	0.29	0.3	49	83	83
	RMS_m	0.39	0.24	0.08	0.08	38	77	77
2	RMS_v	1.07	0.78	0.57	0.50	27	46	53
	RMS_m	0.30	0.25	0.17	0.16	18	43	46
3	RMS_v	1.12	0.76	0.47	0.44	32	58	61
	RMS_m	0.26	0.21	0.12	0.11	19	53	57

the first, second and third sample cases, respectively. These figures illustrate the models with the utilized locating schemes for welding.

To simulate a smart assembly line, 25 deformed parts for each component of every sample case is generated based on the scanned data of produced parts. Accordingly, 25 assemblies should be generated for each sample case. The assembly process of producing these assemblies are simulated by following different scenarios of applying the techniques presented.

2.6. Comparisons approach

To compare the acquired improvements from each technique and combination of them, three different scenarios of improvements are designed and experimented. Fig. 6 visualizes the flowchart of each scenario. The first scenario is to apply only SA and the second scenario is to apply only ILA. The third scenario is then to examine the combination of these two techniques together. The selected mating parts for each assembly influences the optimal adjustments of locators. Consequently, the adjustments of locators that are optimal on a combination of parts are not optimal for other combinations. As a result, SA should be applied before determining the optimal adjustments of locators. In other words, to combine the two techniques in a smart assembly line, the optimal adjustment of locators cannot be determined before determining the optimal combination of the mating parts. Accordingly, the third scenario is to find the optimal combination of the mating parts firstly. Thereafter, finding the optimal adjustments of locators for individual assemblies resulting from the optimal combination.

To calculate the resulting improvements from each scenario, the geometrical quality of the batches when none of the improvement techniques is applied should also be available. Therefore, the average RMS_v and RMS_m of 1000 assemblies with random combinations of parts are also provided and the improvements are calculated based on them.

Conducting SA means assembling the parts with the combination that results in maximum geometrical quality. Accordingly, the assumption is that geometrical quality of assemblies is dependent on the combination of mating parts. This assumption is valid when ILA is not applied. However, the validity of this assumption can be questioned for assemblies that are produced by employing ILA. Therefore, to clarify the dependency of the geometrical quality when ILA is employed, RMS_v and RMS_m of a batch of assemblies is determined for ten random combinations of the mating parts. Thereafter, these parameters are obtained again after applying ILA for the same combination of parts and compared with their previous amounts.

3. Results and discussions

The three different scenarios are applied to the three sample cases and the results are determined. Table 1 lists the obtained results from these scenarios and the average results of random combinations. The results of applying different scenarios are presented by both the value and the percentage of improvement for each criterion.

The obtained results for the first sample case demonstrate considerably larger improvements for the second scenario (applying only ILA) than the first scenario (applying only SA). Moreover, the same improvement is achieved for the second and third scenarios. The results for the second and third sample cases evidence improvements of roughly two times larger for ILA compared to SA in both RMS_v and RMS_m. In these sample cases, combining SA and ILA results in improvements of maximum 4% larger than improvements of ILA alone. Based on the obtained results of Table 1 performing selective assembly before ILA has a very low impact on the resulting improvements from ILA.

To clarify this issue further, the effects of part combinations on the potential improvements from ILA are investigated. This investigation is conducted by comparing RMS_v and RMS_m of 10 random combinations of parts for the sample cases with a batch size of 10. Fig. 7 visualizes fluctuations of RMS_v before and after applying ILA for different combinations. Fig. 8 demonstrates the same results for RMS_m.

The dependency of RMS_v and RMS_m on the combination of the mating parts reduces considerably when ILA is utilized in production. The ranges of fluctuations of RMS_v are 1.45, 0.37, and 0.25 for the first, second and third sample cases, respectively, before applying ILA. These ranges reduce to 0.25, 0.06, and 0.035, respectively, after applying ILA. The same reductions are evident in RMS_m. The results evidence that the effects of applying SA will be reduced substantially when it is employed along ILA. The reason for this reduction is the lower dependency of RMS_v and RMS_m on the combination of parts when ILA is applied.

The Spearman Rank Correlation coefficients between geometrical qualities before and after ILA are obtained for all cases. These coefficients are 0.67, 0.75, and 0.8 between RMS_v for the first, second and third sample cases, respectively. The coefficient values between RMS_m of different combinations before and after applying are 0.45, 0.39 and 0.67, for the first, second and third sample cases, respectively. These correlation coefficients indicate that the combination of parts that results in the lowest geometrical variation before applying ILA is the combination that results in the lowest geometrical variation after applying ILA with a high probability. Nevertheless, the combination of parts that results in a lower RMS_m without ILA may not be the same as the combination of parts that results in lower RMS_m when ILA is conducted.

3.1. Future work

Another important factor in the achievable improvements by ILA is the fixture layout of the assembly. The effects of this factor will be investigated in future studies. Moreover, another important research question for future work is whether it is better to have a sensitive fixture layout to be able to control the quality by ILA or it is better to have a fixture layout that is not sensitive.

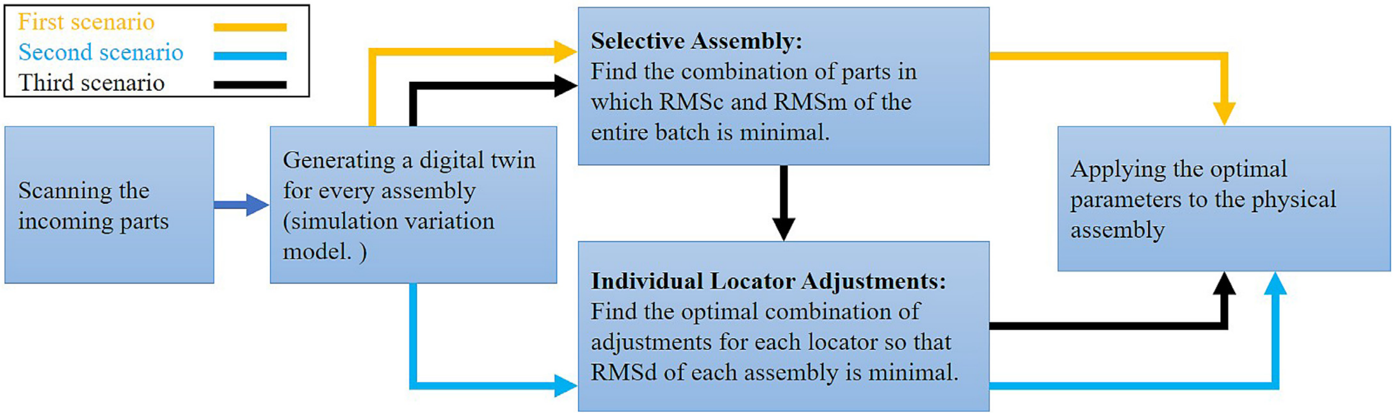

Fig. 6. Three different scenarios of applying SA and ILA using a digital twin in a smart assembly line.

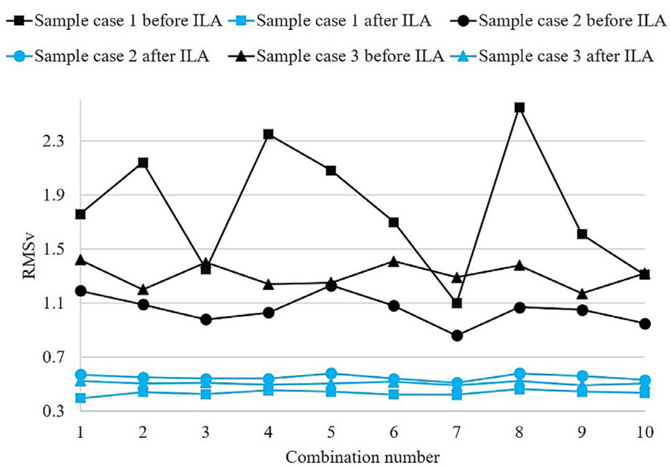

Fig. 7. Fluctuation of RMS_v for different combination of parts before and after applying individualized locator adjustments.

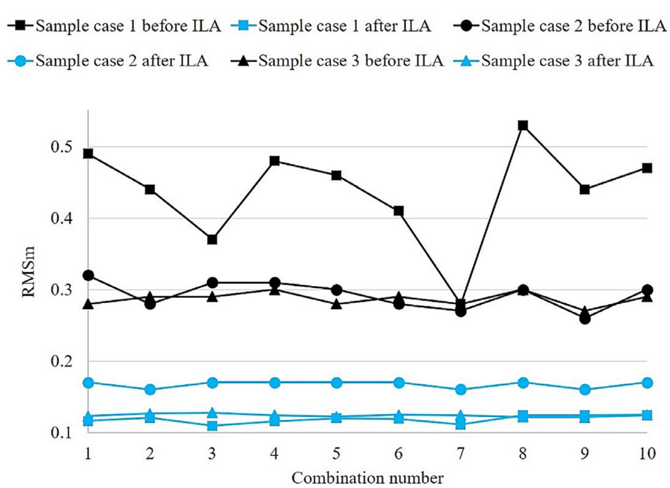

Fig. 8. Fluctuation of RMS_m for different combination of parts before and after applying individualized locator adjustments.

4. Conclusion

This paper investigated the possibility of accumulating geometrical improvements from selective assembly and individualized locator adjustments techniques in a smart assembly line for compliant sheet metal assemblies. Besides, the potential of these techniques in improving the geometrical quality was compared against each other. Three different scenarios of applying these techniques were tested on three industrial sample cases and the results were evaluated. In two scenarios, selective assembly and individualized locator adjustments were applied separately and in one scenario selective assembly was employed along with individualized locator adjustments. The obtained improvements in the geometrical quality were compared to each other and a scenario when a random combination of parts without any adjustments is applied. The following conclusions can be drawn from the obtained results.

- The resulting geometrical quality improvement from individualized locator adjustments is substantially greater than selective assembly when only one of these techniques is employed.
- Performing both of these techniques does not result in a great change from applying only individualized locator adjustments.
- The dependency of geometrical quality on the combination of mating parts reduces considerably when individualized locator adjustments are utilized.
- The combination of mating parts that results in a minimal geometrical quality is almost the same when individualized locator adjustment is applied compared to when it is not applied.

Acknowledgments

This work was carried out in collaboration within Wingquist Laboratory and the Area of Advance Production at Chalmers within the project Smart Assembly 4.0, financed by The Swedish Foundation for Strategic Research. Their support is gratefully acknowledged.

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.

CRediT authorship contribution statement

Abolfazl Rezaei Aderiani: Conceptualization, Methodology, Software, Writing - original draft, Data curation, Visualization. **Kristina Wärmefjord:** Supervision, Writing - review & editing, Conceptualization. **Rikard Söderberg:** Supervision, Writing - review & editing, Conceptualization.

References

Aderiani, A.R., Wärmefjord, K., Söderberg, R., Lindkvist, L., 2019. Developing a selective assembly technique for sheet metal assemblies. Int. J. Prod. Res. 57 (22), 7174–7188. doi:10.1080/00207543.2019.1581387.

Aderiani, A.R., Wärmefjord, K., Söderberg, R., Lindkvist, L., 2019. Individualizing locator adjustments of assembly fixtures using a digital twin. J. Comput. Inf. Sci. Eng. 19 (4), 041019. doi:10.1115/1.4043529.

Aivaliotis, P., Georgoulias, K., Chryssolouris, G., 2019. The use of digital twin for predictive maintenance in manufacturing. Int. J. Comput. Integr. Manuf. 32 (11), 1067–1080. doi:10.1080/0951192X.2019.1686173.

Bergström, P., Fergusson, M., Sjödahl, M., 2018. Virtual projective shape matching in targetless cad-based close-range photogrammetry for efficient estimation of specific deviations. Opt. Eng. 57, 57–68. doi:10.1117/1.OE.57.5.053110.

Chan, K.C., Linn, R.J., 1999. A grouping method for selective assembly of parts of dissimilar distributions. J. Qual. Eng. 11 (2), 221–234.

Dahlström, S., Lindkvist, L., 2007. Variation simulation of sheet metal assemblies using the method of influence coefficients with contact modeling. J. Manuf. Sci. Eng. 129 (3), 615–622.

Eshelman, L.J., Schaffer, J.D., 1993. Real-coded genetic algorithms and interval-schemata. Elsevier, pp. 187–202.

Fang, X., Zhang, Y., 1995. A new algorithm for minimizing the surplus parts in selective assembly. Comput. Ind. Eng. 28 (2), 341–350.

Germer, C., Nagat, M., Klenk, T., 2014. Die virtuelle Messdatenanalyse bei Volkswagen. Konstruktion 66 (10), 94–98.

Keller, C., Putz, M., 2016. Force-controlled adjustment of car body fixtures - verification and performance of the new approach. Procedia CIRP 44, 359–364. doi:10.1016/j.procir.2016.02.162.

Lindkvist, L., Carlson, J.S., Söderberg, R., 2005. Virtual locator trimming in preproduction: rigid and non-rigid analysis. In: Proceedings of the International Mechanical Engineering Congress and Exposition. ASME, pp. 561–568. doi:10.1115/IMECE2005-81266.

Liu, S.C., Hu, S.J., 1997. Variation simulation for deformable sheet metal assemblies using finite element methods. J. Manuf. Sci. Eng. Trans. ASME 119 (3).

Mansor, E., 1961. Selective assembly-its analysis and applications. Int. J. Prod. Res. 1 (1), 13–24.

Söderberg, R., Wärmefjord, K., Carlson, J.S., Lindkvist, L., 2017. Toward a digital twin for real-time geometry assurance in individualized production. CIRP Ann. 66, 137–140. doi:10.1016/j.cirp.2017.04.038.

Tabar, R.S., Wrmefjord, K., Sderberg, R., Lindkvist, L., 2019. A method for identification and sequence optimisation of geometry spot welds in a digital twin context. Proc. Inst. Mech. Eng. Part C: J. Mech. Eng. Sci. 0 (0). doi:10.1177/0954406219854466. 0954406219854466

Xu, H.Y., Kuo, S.H., Tsai, J.W.H., 2014. A selective assembly strategy to improve the components utilization rate with an application to hard disk drives. Int. J. Adv. Manuf. Technol. 75, 247–255. doi:10.1007/s00170-014-6106-y.