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Optimal part matching and joining sequence in non-rigid assemblies for improved geometric quality

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Abstract

For assembly of non-rigid components, given the scanned geometries, a self-compensating assembly line has shown to be capable of steering the assembly process, finding the optimal assembly properties, *e.g.*, joining sequences. However, the computational burden of optimization for each assembly step is still limiting the physical application of this concept. This paper proposes a strategy for identifying the optimal matching of the components and the corresponding joining sequences to reduce the computation time, bypassing repetitive optimization steps. The results show that the proposed method simultaneously provides the optimized component matching and joining sequence leading to a simplified computation process.

Keywords: Matching; Joining Sequence; Optimization, Digital Twin, Geometric Quality

1. Introduction

Assuring the geometric quality of the assemblies has been a challenge for the manufacturing industry and involves a span of activities performed during the product development cycles. Traditionally, the assembly process parameters, namely position, clamping, joining, and releasing from the fixture, are adjusted when problems arise. Therefore, the cost of the adjustments has been relatively high compared to the gained quality improvement. Recently, the concept of individualized processes has gained attention, where a digital twin is steering the manufacturing setup [15, 14]. Adjusting the process parameters based on the individual parts and assembly requirements is the ultimate purpose of such a concept. Several optimization steps take place for each assembly through individualization, requiring time-consuming simulations and computations. In the next section, the challenges associated with the computations in this concept are further addressed.

1.1. Individualized assembly lines

The self-compensating assembly line [15], is designed to adjust the assembly parameters based on the three-dimensional scanned data of each in-going assembly component. In sheet metal assemblies, these parameters include joining sequences and locator adjustments. Furthermore, as each parameters is closely related to the fabricated components deviations, the component combination by which the assembly is composed influences the batch composition.

1.2. Joining sequence analysis

The joining sequence influences the geometric outcome of the assemblies [4]. The aspects around optimization of the sequence for the individual assemblies have been considered comprehensively in the previous research [18, 2]. Furthermore, the choice of the critical joining points to securing the geometric outcome have been studied [9, 22]. Efforts have been dedicated reducing the computation time for optimizing the sequences for each individual assembly [18]. By means of parallel computation and efficient optimization algorithms, the computation time and the number of simulations performed to retrieve the optimal sequences has been reduced by 75% compared to the traditional population-based optimization methods like the genetic algorithms [7, 20, 6]. More time-efficient joining sequence simulation in non-rigid variation simulation has also been introduced bypassing the unnecessary simulation steps [17]. Additionally, a clustering and optimization method

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has been introduced to mitigate the influence of the joining sequence on the batch assembly, and to achieve indistinguishable geometric outcomes by individual joining sequence optimization and batch optimization [16]. However, the interplay between the part matching and the joining sequence has not been considered in the previous research, which will be further elaborated and considered in this paper.

1.3. Part matching

Fitting the produced components in a nominal buck has traditionally been referred to as a matching process in the automotive industry. Adjusting the individual components to fit in this context has been referred to as trimming. Here, part matching is referred to selecting the individual components in a fashion that results in a less need for trimming an assembly. In other words, selecting part instances can be interpreted as a selective assembly process that has been introduced and implemented for rigid components [10, 11]. Efforts have been made introducing this concept for non-rigid components such as sheet metals [21], where a genetic algorithm is implemented to match the parts based on the geometric outcome of the assemblies. For a self-compensating assembly line, the strategies for achieving a higher quality based on part matching and locator adjustment have been studied, and the importance of the locator adjustment have been identified [1]. The effect of the joining sequences in the simulation outcome for part matching has been mostly neglected, or sequence optimization perspectives have not been directly addressed simulating the geometric outcome for the chosen matching strategy in previous research. Additionally, the time consumption of performing such tasks separately in two steps has not been addressed. In this paper, the joining sequence and its optimization perspective have been introduced and integrated into the part matching process for improved geometric quality.

1.4. Scope of the paper

In a self-compensating assembly line, parts are being matched, locators are adjusted and joining sequences are optimized to improve the geometric outcome of the assembly and compensate for the in-going geometric variation. Aspects surrounding joining sequences and part matching have been studied separately. The joining sequences and the part matching are a function of the existing deviation in the fabricated components, yet the interplay of two and their influence on the final assembly outcome for a batch of assemblies have not been discussed. In this paper, an efficient integrated part matching and joining procedure is introduced requiring reduced computation time.

2. Proposed part matching and joining sequence optimization method

To simulate the geometric outcome of the assemblies, given the part deviation or variation, non-rigid variation simulation [8, 3, 5] is deployed. The following section introduces the applied non-rigid variation simulation approach.

2.1. Non-rigid variation simulation

The method initially strives to establish a sensitivity matrix of the assembly between the part deviation and assembly deviation. This sensitivity is also used to model the contact behavior of the components during all the assembly steps including:

- positioning and clamping in the fixture,

$$\boldsymbol{K}\boldsymbol{u} = \boldsymbol{f}, \tag{1}$$

  where $\boldsymbol{K}$ is the global stiffness matrix of the assembly and $\boldsymbol{u}$ is the assembly displacements in the fixture, and $\boldsymbol{f}$ is the corresponding force vector associated with the displacements.
- Joining:

$$\boldsymbol{K_w}\boldsymbol{u} = \boldsymbol{f_w}, \tag{2}$$

  where $\boldsymbol{K_w}$ is the modified stiffness matrix and $\boldsymbol{f_w}$ is the derived forces on the weld point.
- Removing the parts from the fixture and springback.

$$\boldsymbol{u} = \boldsymbol{S}\boldsymbol{f}, \tag{3}$$

  where $\boldsymbol{S}$ is the sensitivity matrix derived from the modified stiffness matrix.

The contact response of the assembly is calculated by the quadratic programming of the contact forces. This program based on the minimization of the potential energy [19] is represented by:

$$\begin{aligned} \underset{f}{\text{minimize}} \quad & \frac{1}{2}\boldsymbol{f}^T\boldsymbol{S}\boldsymbol{f} + \boldsymbol{f}^T\boldsymbol{u} \\ \text{subject to} \quad & -\boldsymbol{S}\boldsymbol{f} \leq \boldsymbol{u} \\ & \boldsymbol{f} \geq \boldsymbol{0}, \end{aligned} \tag{4}$$

where $\boldsymbol{f}$ is a vector of contact forces, $\boldsymbol{S}$ is the assembly sensitivity matrix, and $\boldsymbol{u}$ is a vector of the initial penetration in the contact nodes. This step is performed to avoid the penetration of parts in the adjacent areas in each of the steps above.

2.2. Part matching for batch analysis

It has been shown that capturing the relative displacement in the weld points with the given sequence can reveal the behavior of the assembly after joining [17]. The principle for part matching in this paper is based on identifying the pair of parts with an optimal initial weld relative displacement prior to welding. To this end, the part combinations are generated for each component and the initial weld displacements are derived. Alternatively, for large batch numbers and large number of components a clustering and optimization approach can be applied to the problem [16]. Since the nature of the part matching problem is combinatorial, greedy search algorithms [12] can be applied to generate proximal solutions. Here, for simplicity, we consider that the part combination can be generated, and the memory issues will not occur. Each part combination is thus associated with a feature vector of the relative weld displacements. The feature vector is sorted in ascending order, and the first instance of the part with the lowest weld relative displacement is chosen to be included in the batch. The process then iterates until the batch is filled. The diagram describing the workflow for generating the batch and sequence optimization is shown in Fig. 1.

Let us consider a part matching problem for a batch of N assemblies of two parts, for each there are also N components available. The solution space is $N! \times N!$, creating the possible batch compositions. The greedy approach includes selecting the best part combination among the possible alternatives. For the first part combination, there are $N \times N$ available alternatives. The part combination with the lowest weld relative displacements is chosen. Next, there are $(N-1)\times(N-1)$ available part combinations, where the alternative with the lowest weld displacements is chosen. These steps are continued until there is one choice and one alternative is available. In the next section, this method is applied to a reference assembly.

2.3. Joining sequence optimization

To retrieve the geometric outcome of the assembly equation 2-4 above is iterated on the applied sequence, modifying the generated sensitivity matrix [17]. The optimization of the sequences for the geometric outcome can be formulated as below.

$$\begin{aligned} \underset{s_i}{\text{minimize}} \quad & \boldsymbol{u}(s_i) \\ \text{subject to} \quad & s_i : \{1, \ldots, p\} \to \{p, \ldots, 1\}, \;\; p \in \mathbb{N}. \end{aligned} \tag{5}$$

Here $\boldsymbol{u}$ is the final assembly displacement after joining with a sequence, s_i. The sequence s_i belongs to a permutation set of 1 to p elements, which are the ordered weld points. To solve this combinatorial optimization problem efficiently, a stepwise algorithm presented in [18] has been employed to the problem. The algorithm identifies the optimal sequence, element-wise and thereby minimizing the geometric deviation of the assembly.

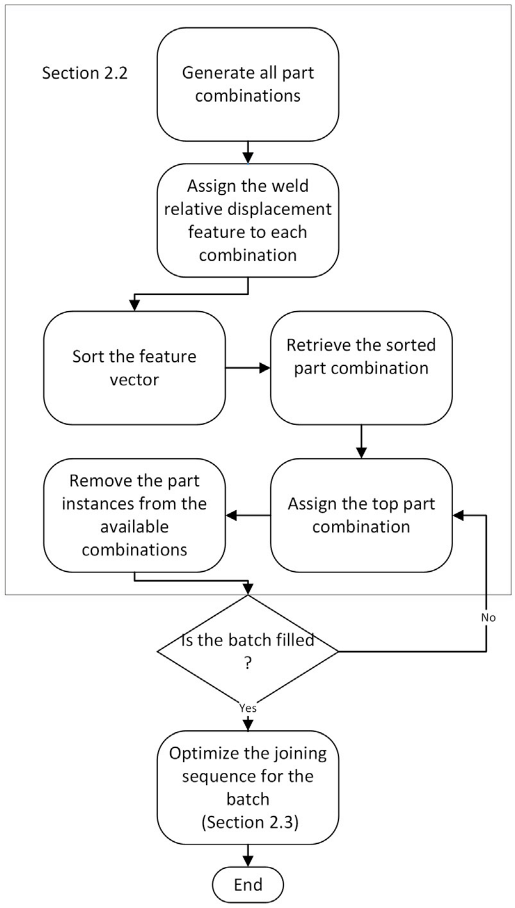

Fig. 1. Part matching and sequence optimization steps

3. Proposed method evaluation

The proposed part matching and joining sequence optimization is applied to a reference assembly, and the results are compared with individualized sequence optimization.

3.1. Reference assembly

The assembly consists of two sheet metal parts, for each 10 instances are available. Both parts have elasticity of 210 GPa, while the thickness of the upper part is 1.2 mm and the lower part's thickness is 1.6 mm. The aim is to find the optimal part matching and joining sequences for a batch of 10 assemblies. There are seven weld points on this assembly, all are welded in a single station with a balanced welding gun. The positioning points and weld points are shown by arrows and spheres accordingly, in Fig. 2. The assembly is modeled in the CAT-tool RD&T [13]. The assembly model includes 159 contact points. Each full FEM run takes 7.28 seconds, while each contact calculation takes approximately 0.06 seconds.

3.2. Individualized assembly process outcome

In an individualized assembly line, for each combination of the parts the joining sequence is optimized separately. In this

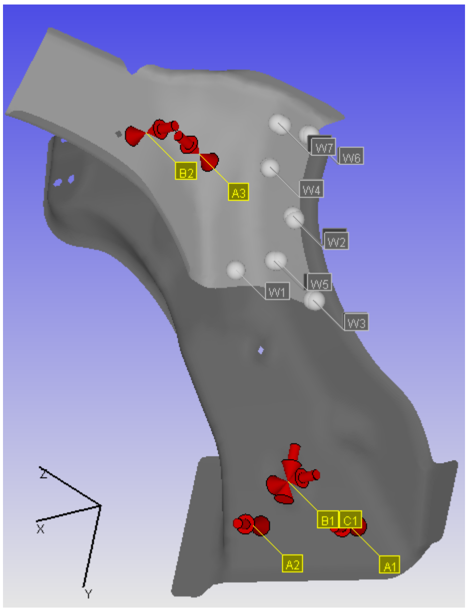

Fig. 2. Reference Assembly

Table 1. Individualized Optimization

Individualized Optimization	Batch variation range (mm)	Batch Mean (mm)
Opt. Sequences & Matched	0.1212	0.3757
Opt. Sequence & Not Matched	0.4298	0.4089
Unideal Sequences & Matched	0.3583	0.6711
Unideal Sequence & Not Matched	0.4742	0.7368

case, there are 10 instances available for each part, thereby an optimal joining sequence, Section 2.3, is put forward for each of the 100 possible combinations. Here the part combinations are $(1, 1), (1, 2), ..., (5, 10), ..., (10, 10)$. The optimal part matching based on the outcome of the joining sequence optimization for each combinations is derived. This is performed to compare the achieved results with the proposed approach. Fig. 3 (A) depicts the result of the batch root mean square of the displacements in the normal direction of all the including mesh nodes of the assembly. This measure is chosen due to its generic nature, while any other key characteristic points can also be applied to the method. Table 1 presents the retrieved range and mean of the achieved displacements for four scenarios. Firstly, when optimized joining sequence and optimized part matching are considered, secondly, part matching is not performed, but the joining sequences are optimized; thirdly, when part matching is performed and unideal joining sequences are applied to the assemblies. Finally, when neither part matching of sequence optimization is performed on the batch. As clearly can be seen, applying the joining sequence optimization and part matching can improve the range of the displacements by 74% and the batch mean deviation by 49%. Table 2 presents the computation time associated with this individualized part matching setup, which will be compared against the batch process in the following section.

Table 2. Computation time

Computation Time Results	Numebr of full FEA Runs	Number of Contact calculations	Time (s)
Individualized	5600	50400	40768
Batch Process	56	504	245

Table 3. Batch Optimization

Batch Optimization	Batch variation range (mm)	Batch Mean (mm)
Opt. Sequences & Matched	0.3090	0.4418
Opt. Sequence & Not Matched	0.4342	0.4820
Unideal Sequences & Matched	0.36	0.6493
Unideal Sequence & Not Matched	0.4807	0.7102

3.3. Batch process outcome

The proposed part matching and joining sequence optimization, Section 2.2 and 2.3, is applied to the assembly, and the optimal batch is composed. The sequence optimization is then applied to the selected batch of assemblies, generating one optimal joining sequence for the batch. Notice that here only one full FEA run is performed for each joining sequence on the batch, helping to reduce the computation time. In this approach, the combination of parts that is put forward by the proposed approach, Section 2.2, is evaluated by the extended MIC and contact modeling approach presented in Section 2.1. Fig. 3 (B) presents each assembly displacement in the batch for similar scenarios as in Section 3.2. With this method, an improvement of 35% is achieved in the range of displacements applying part matching and optimal sequence. This improvement has been 38% for the mean deviation of the selected batch of assemblies. The details of displacement range and mean deviation of the batch is presented in Table 3 for the four scenarios. The total computation time with the proposed approach is presented in Table 2. The computation time required for the batch process optimization is considerably lower than the individualized process, due to the reduced number of full FEA runs and contact calculations. Considering that the achieved improvement for the batch geometric quality has been obtained with substantially lower computation time indicates the adequacy of the chosen batch of parts and joining sequence optimization approach.

4. Conclusion

The self-compensating individualized assembly line for non-rigid components is based on part matching and joining sequence optimization requiring no physical, technological additions to the assembly steps. The interplay of the two tasks have not been addressed previously. In this paper, an approach has been proposed for direct part matching and joining sequence optimization for a batch of assemblies. The proposed approach has been applied to a batch of assemblies, and the achieved range and mean deviation of the batch are compared to the indi-

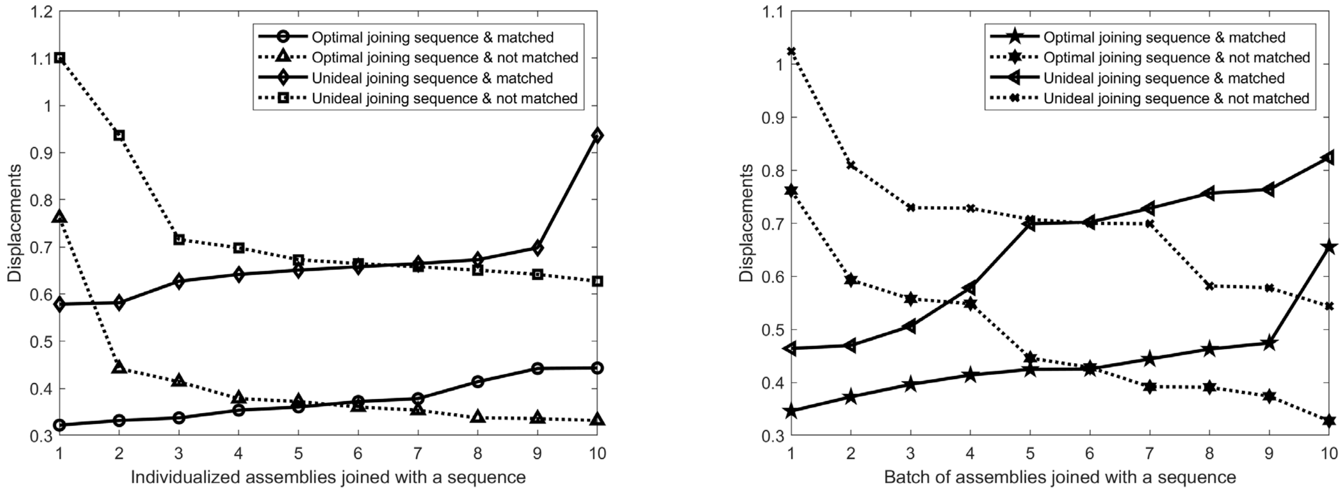

Fig. 3. (A) Individualized assembly outcome (B) Batch assembly outcome

vidualized setup. The results show that the proposed method is capable of identifying the suitable part matching for improved geometrical quality both in an individualized setup and in batch processes. Additionally, the joining sequence impact on the analyzed assembly has been higher than the part matching impact. This applies both to individualized optimization and batch process optimization. This is due to the limited solution space for the part combinations compared to the joining sequence. Furthermore, it has been shown that combining the two tasks leads to a higher improvement impact compared to deploying one task. Finally, the computation time invested in the batch process optimization has been considerably lower than of the individualized optimization, making the method suitable for handling larger problem sizes.

The impact of the part matching and joining sequences for batch processes where larger bath sizes and assembly components are available can be further studied for a better understating of a suitable applicable method. Future studies on an approximation of the impact of each task, addressed in this paper, on the overall quality of the assembly helps the smooth transition towards a physical implementation of a digital twin for an assembly setup.

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