Development and analysis of a holistic function-driven adaptive assembly strategy applied to micro gears

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ABSTRACT

The precision and functionality of an assembly heavily depend on the dimensions of its components, which can often lead to quality issues. However, increasing precision can be expensive and impractical. Alternative methods, such as adaptive assembly and optimization, can help achieve high-precision assemblies using less precise components. Adaptive assembly involves adjusting the assembly process to account for component variations, which can improve accuracy and reduce errors. Optimization techniques can be used to identify the most efficient and effective assembly strategy for a given set of components, taking into consideration factors such as complexity, volume, cost, and quality. This paper proposes an exclusive adaptive assembly strategy for micro gear pairing by evaluating and comparing different assembly strategies. Manufacturers can determine the best fit for their specific needs and enhance the precision and functionality of their assemblies.

1. Introduction

Production control loops describe model-based production optimization strategies at the organizational level of a production system that are intended to respond to process deviations and improve product quality. These are applicable for production processes where the technological capabilities have been reached and no defect reduction can be achieved by using conventional approaches [1,2]. Component-specific quality data can be recorded thanks to advancements enabled by Industry 4.0 in terms of near-real-time information processing, new sensors for individual component tracking, and sensor technologies for production-integrated measurements of quality data [3–5]. With the quality controller taking process parameters, measurements, control strategies, and a product model into consideration, a variety of control loop concepts for raising product quality can be implemented [6] (see Fig. 1). As production-related reaction measures, different strategies are possible to increase quality despite production deviations. The key concept is the ability to compensate for a second component's deviations from a quality-critical feature through the individual over-fulfillment of another component's feature. Tighter tolerance ranges can be achieved compared to conventionally assembled components by compensating the corresponding components [3,6].

Assembly is an important step in the manufacturing process, as it involves bringing together individual components or subassemblies to create a finished product. It ensures that products are properly put together and functional, while also allowing manufacturers to improve efficiency, quality control, scalability, and cost savings. Also, it is essential for high-precision products in high-tech industries such as aerospace, medical device, and semiconductor manufacturing because it ensures that the final product meets the required specifications and tolerances for the proper functioning of the product and the safety of the user [7]. The high-precision assembly also ensures that the product will perform as intended throughout its intended lifespan, reducing the need for costly repairs or replacements.

Adaptive assembly is an approach to manufacturing that allows the dynamic adjustment of assembly processes based on real-time feedback from sensors and other data sources. It is also known as "smart assembly" or "intelligent assembly" which can be applied in high-tech industries [1,8–10]. One of the main benefits of adaptive assembly is that it allows manufacturers to quickly respond to changes in product design or customer requirements, without the need for extensive retooling or redesign of assembly equipment. This can help to improve the efficiency

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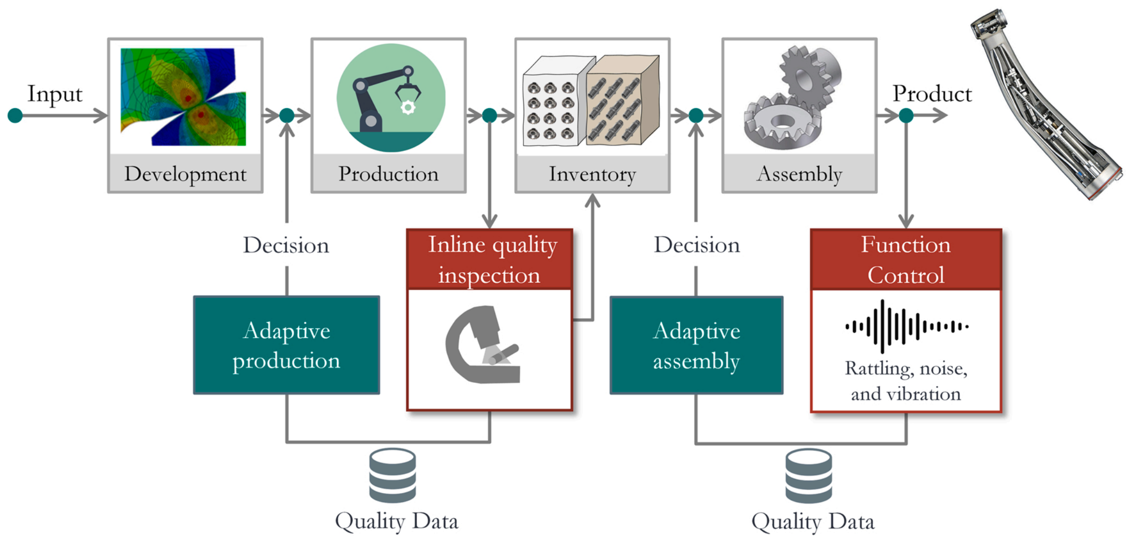


Fig. 1. Production control loops.

and flexibility of the assembly process [11,12]. Therefore, this paper introduces an adaptive assembly strategy that adapts multiple assembly strategies for a specific assembly, appraises the quality response using intelligent systems, and identifies the most suitable strategy. It develops and validates various assemblies' strategies: Random Assembly (RA), Selective Assembly (SA), and Individual Assembly (IA), dealing with micro gear pairs. The adaptive assembly has the potential to benefit high-precision products as it allows for swift modification of the assembly process to optimize for each product's specific requirements.

On these bases, the paper is structured as follows: a brief review of the related research on existing assembly strategies and their application in the domain of tolerance design is brought in Section 2. Section 3 provides a comprehensive detailed framework for gear pairing, including the assembly strategies, associated propositions, and optimization, in which assembly strategies have to fit the assembly structure. In Section 4, the adaptive model is investigated and analyzed for gear pairing use. The last section implies the conclusion and future perspectives of this research.

2. Literature

"Tolerance design" is the investigation of how defect rates can be monitored by controlling variability in the specifications for individual components. Designers prefer tight tolerances to assure product performance; manufacturers prefer loose tolerances making components easier and more economical to produce. Specifying tolerances is therefore a vital key to understanding how the specifications and their variability impact the design requirement and manufacturing performance. However, the specification of design tolerances also affects the number of assembled components and the desired functionality. Therefore, assembly strategies such as selective assembly and individual assembly may represent expedient alternatives as compared to the random assembly of interchangeable components [13–15].

2.1. Assembly strategies

Appropriate partners are chosen in the adaptive assembly quality control loop to compensate for defects [3,16]. Individual and selective assembly strategies are both included under the overarching term of adaptive assembly [1]. Tan and Wu [17] discuss Direct Selective Assembly (DSA) and Fixed Bin Selective Assembly (FBSA) as two pairing optimization methods. By minimizing production defects, FBSA is a selective assembly strategy that provides a method for enhancing product quality while lowering production costs [18,19]. Based on individual deviation from a predetermined set point, single components are grouped into tolerance classes and subsequently paired with corresponding components [20]. Information about the precise geometry is lost when components are grouped into classes. To reduce the information getting lost, a large number of classes and small tolerance margins are required. As a result, the number of tolerance classes is constrained by the number of components, the associated inventory, and overhead expenses. To prevent downtime in case of a bottleneck in terms of component availability, active and passive combinations of non-corresponding classes can be used [20].

DSA, on the other hand, is an algorithm that determines an optimal combination of available components, and each component is assigned to exactly one other component, making it part of individual assembly strategies. Components are not grouped into tolerance classes for individual assembly. Since each component ID is connected to a specific measurement, no information is lost. Thus, individual assembly methods outperform selective assembly strategies in terms of product quality but are also more expensive due to the need of securing individual component traceability and storage in the production process [21].

2.2. Tolerance design and assembly strategies

Random assembly involves obtaining a product where its components are chosen randomly. This approach has been the research topic of several studies in the manufacturing area, with researchers exploring its potential benefits such as cost savings. Therefore, by using a random sampling method to select components, manufacturers can take advantage of economies of scale and reduce their costs [2]. The random assembly allows manufacturers to use a larger pool of components than the SA and IA methods, which ensures reducing the costs associated with sourcing, tracking, and stocking specialized components. However, random assembly also has some challenges. One challenge is the quality control. Because the components to be assembled are chosen randomly, it can be difficult to ensure that the final product meets the required quality standards. This is particularly true in industries such as automotive, where the quality of individual components can have a significant impact on the overall performance of the product [22]. Therefore, SA and IA methods could be proposed to improve the overall performance while keeping tolerance specifications the same or even lower them.

The selective assembly has been used in manufacturing for years and has been focused on several key aspects [23–25]. Selective assembly is a

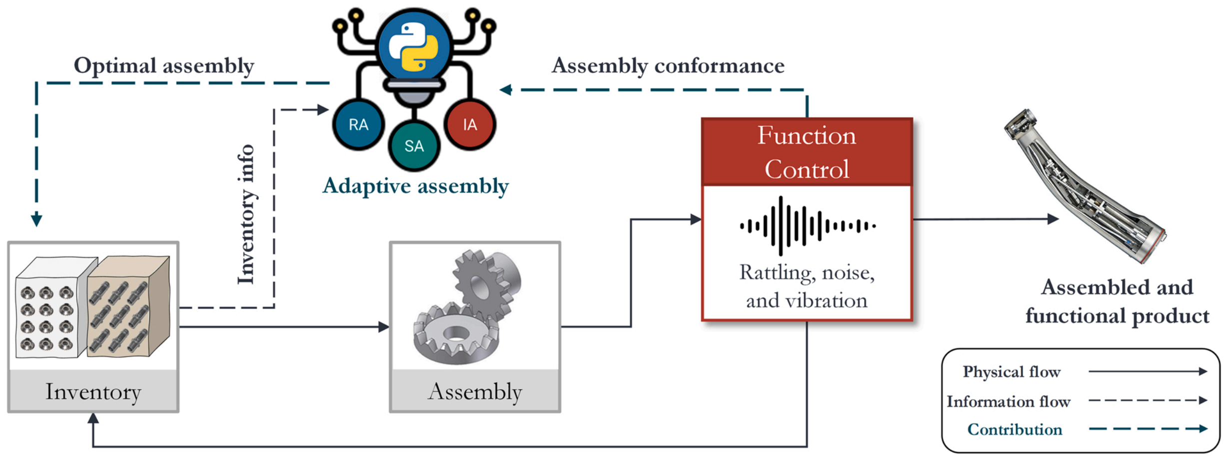
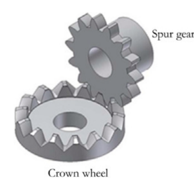


Fig. 2. Proposed adaptive assembly scheme.

technique to preserve functional requirements between two mating components which may be obtained from relatively low-precision components. In SA, the mating components are manufactured with wide tolerances, therefore, it is required to 100% inspect all the manufactured components, then they are partitioned into dimensional bins. Afterward, the components are then randomly selected from within bins for assembly with minimum clearance. As far as SA is concerned, the existing studies can be categorized into two main streams: (1) pairing methodologies and (2) binning strategies.

The pairing methodologies are more objected to proposing an efficient bin combination method that satisfies the performance requirement [26–29]. This stream also studies criterion to properly combine bins according to components' variability degree, such as selecting binning strategies and tolerances allocation between components to be paired. A variety of assembly criterion such as matching ratio maximization [30,31], surplus components minimization [15,23], assembly variation minimization [32,33], and assembly cost minimization [23, 34] can be found in the literature. The second stream in SA studies discusses the binning strategies that are focused on the optimization of the components' binning strategies to minimize variations and surplus components. In the literature, the classical partitioning methods are classified as (a) equal width (variance) partitioning [35,36] and (b) equal area (probability) partitioning [37,38] aimed at minimizing assembly variation or scrap. Moreover, recent binning strategies are focused on concerning the difference in mating component size distribution. In this case, optimized partitioning helps to minimize surplus components and quality loss [2,38–40]. On these bases, the goal of the adaptive assembly strategy in this paper is to determine the best strategy for gear pairing, based on the quality of the output produced by each strategy. By assessing the quality response related to each assembly strategy, the adaptive assembly strategy helps identify the strategy that is most suitable for a particular assembly situation.

In reality, as the number of components, interdependencies among them, and levels of complexity increase, the assembly process becomes more intricate and cannot be generalized. To address this issue, one potential solution is to approach the assembly of a product with multiple components by breaking it down into several subassemblies, then assembling the final product. The primary objective of this paper is to initiate an adaptive assembly for the high-precision pairing problem, specifically in the dental instrument industry, where gear pairing is a vital concern. This model enables the use of tolerance analysis model of the assembly and assesses multiple assembly strategies to recommend the most suitable one. The subsequent section provides detailed information on the matter.



Parameter	Spur gear	Crown wheel
Module m	0.280 mm	0.280 mm
Number of teeth z	13	19
Profile shift factor x	0.4	-

Fig. 3. Use case.

3. Proposed adaptive assembly strategy for micro gears pairing problem in high-precision industry

This section introduces an adaptive assembly method that adapts and assesses different assembly strategies tailored for gear pairing, including random assembly, selective assembly, and individual assembly.

3.1. Approach description

An adaptive assembly is an approach in manufacturing that allows for the dynamic adjustment of assembly processes based on real-time feedback from sensors and other data sources. It is also known as "smart assembly" or "intelligent assembly" which can be applied in high-tech industries [8,41]. One of the main benefits of adaptive assembly is to let a quick answer to changes in product design or customer requirements, without the need for extensive retooling or redesign of assembly equipment. This can help to improve the efficiency and flexibility of the assembly process [11]. This paper proposes a novel adaptive assembly strategy that can be adapted to each type of assembly product and returns the fittest assembly strategy. The application of the approach has a strong dependency on the tolerance analysis model which evaluates the quality response of the assembly. However, in this paper, the focus is on the micro gear pairing problem which is used in dental instruments. The approach is detailed in Fig. 2.

Gears are used in a variety of industries in power transmission systems. Durability, a constant transmission ratio, reduced size, excellent efficiency, and suitability for a wide range of powers are just a few of the benefits. On the other hand, they have several drawbacks, such as the vibration of the gear meshing system, which causes unwanted noises. The main source of such noises is Kinematic Transmission Error (KTE), which is caused by gear misalignment, tooth profile inaccuracies, and tooth deflections [42]. As a result, the KTE value reduces the quality level of paired gears due to geometric deviations. This paper analyses the pairing of gears with explicit specifications (Fig. 3).

Many mathematical theories have been developed in order to calculate the kinematic transmission error [43,44], however, in this paper, an exclusive data-driven model in literature is employed to assess

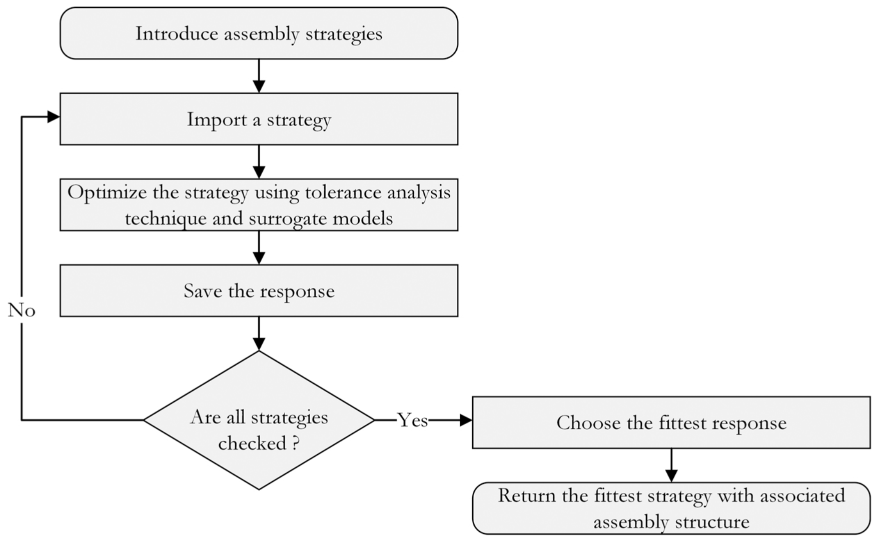
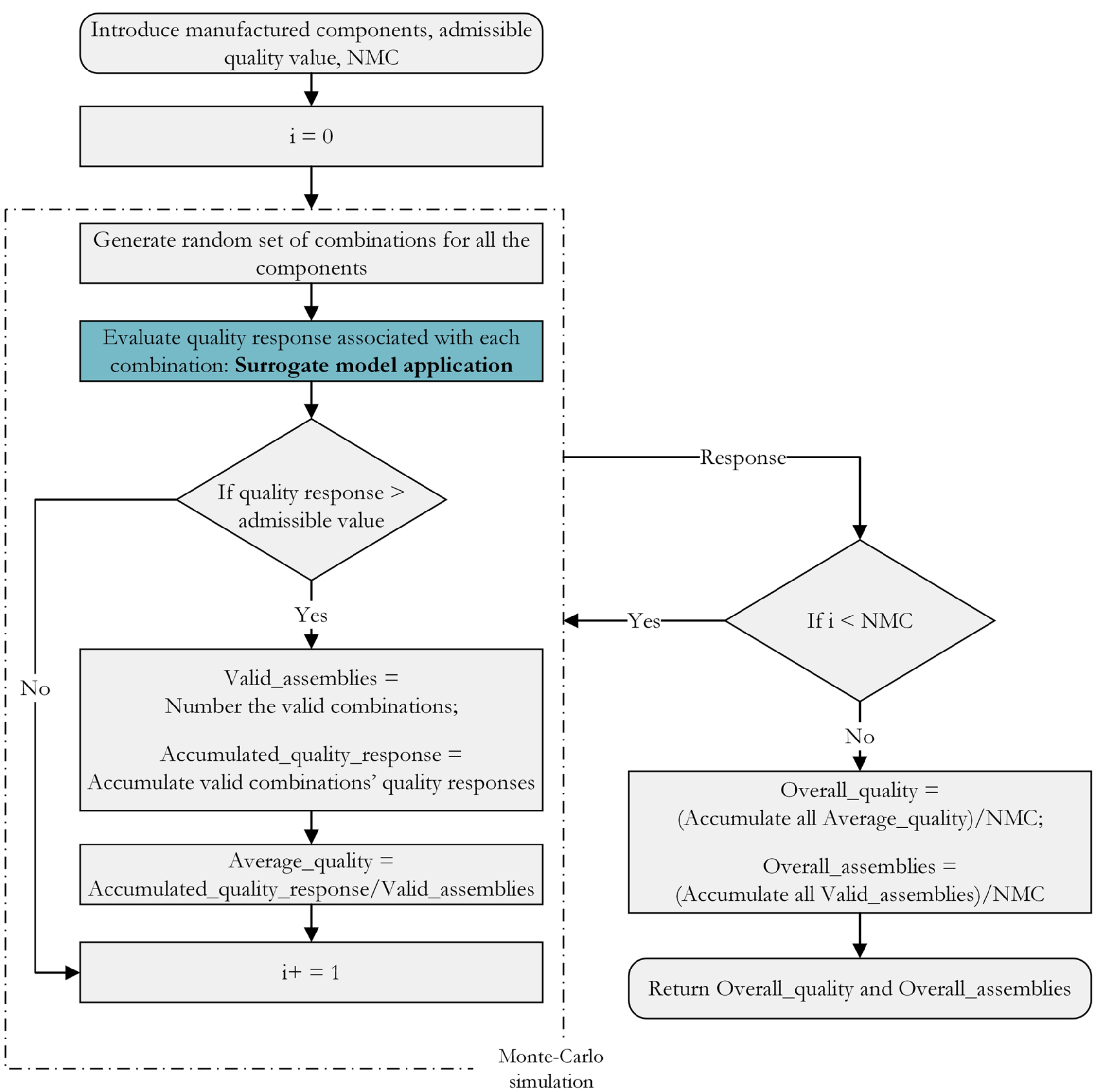


Fig. 4. Adaptive assembly strategy procedure.



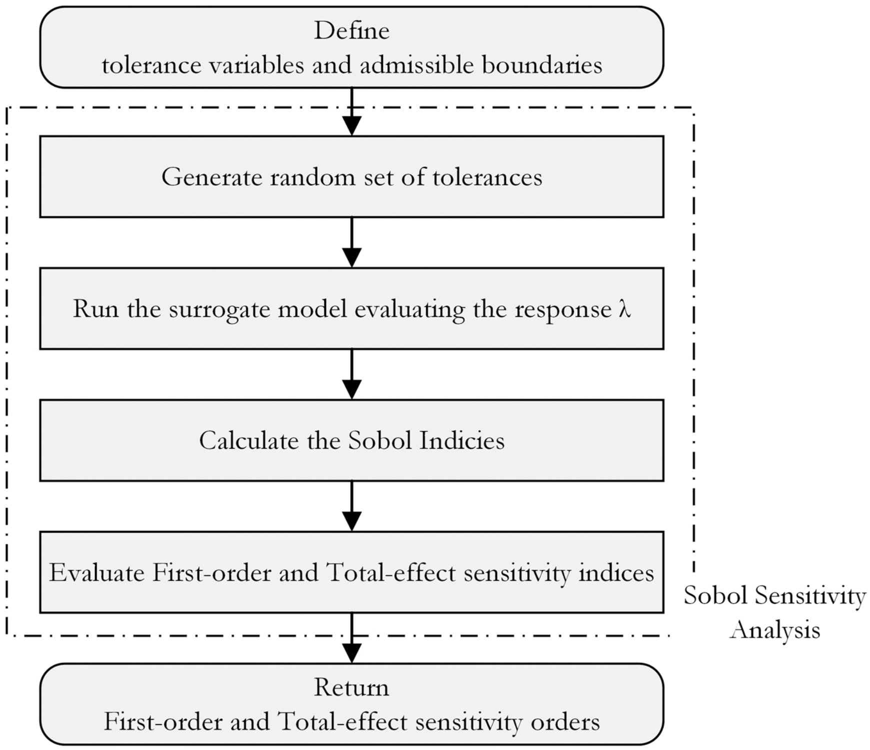


Fig. 6. Sobol sensitivity analysis.

the KTE value function of a set of geometrical deviations and our work is heavily reliant on the existing surrogate model [45]. The authors [45] proposed a neural network-based model which receives paired gears' geometrical deviations and returns the KTE value which indicates the quality of the pair.

Furthermore, Fig. 4 demonstrates the focus of this paper on proposing a decision tool to illustrate the adaptive assembly scheme where several exclusive strategies including random, selective, and individual assembly strategies are proposed and examined to improve assembly quality using a tolerance analysis model. Therefore, the following section explains in detail the assembly approaches and associated issues.

3.2. Random assembly

Random assembly combines components or subassemblies in a random or unordered sort, rather than following a specific sequence or blueprint. This approach can be simulated using the Monte-Carlo technique. The method's flow chart is outlined in Fig. 5. Moreover, it is assumed that components are manufactured and labeled. Each label contains a component specification. Afterward, the simulation method uses labels along with the associated specifications to assess the random assembly efficiency. Therefore, each iteration of the simulation involves randomly generating a pair for each component and then evaluating the quality response using the tolerance analysis\surrogate model checking to see if they fit together in a way that satisfies admissible criterion.

In Fig. 4, the application of the surrogate model is highlighted in the evaluation step which assesses the quality response of the randomly generated combinations. The generation of random combinations in practice reduces assembly costs. However, it doesn't minimize the risk of errors and defects in the final product. Random assembly requires that the operators or workers have a good understanding of the assembly process and the used components.

3.3. Selective assembly (SA)

Selective assembly is a cost-effective solution for achieving high precision. It involves inspecting components during production, grouping them into categories based on specific quality characteristics, and then only pairing components within those categories according to a pre-determined criterion. This approach transforms a product quality issue into a problem of system design and operation. The development of optimal selection strategies for high-quality products is a complex task. As aforementioned in the literature, we can characterize the nature of the optimal solutions by studying two main streams: (1) Key Characteristics (KCs) identification (Sections 3.3.1), (2) binning methods (Section 3.3.2), (3) bins combination criterion (Section 3.3.3), and mixed strategy solutions (Section 3.3.4). The ladders are realized in this section.

3.3.1. KCs identification

Selective assembly applies to assemblies with components possessing one KC. Since a complex assembly may be assembled of components with multiple characteristics, a solution to this challenge is to identify the KC. The identification of the KC is recognized using sensitivity analysis to determine how the functionality of the assembly is affected by variations in input characteristics. Therefore, the surrogate model helps to estimate the assembly response corresponding to geometrical deviation on each characteristic. The identification of KCs can be investigated using sensitivity analysis. In this research, a probabilistic sensitivity analysis method so-called Sobol method is employed to identify the KCs on the components of the assembly. This method expresses relative sensitivities as the fraction of the variance of the assembly response that can be attributed to each uncertain characteristic [46]. The steps of Sobol sensitivity analysis are detailed in Fig. 6.

In this method, to build a picture of the importance of each characteristic in determining the assembly response variance, first-order sensitivity index (S1) and total-effect Sensitivity Orders (ST) are measured [46]. A higher sensitivity index means higher importance of

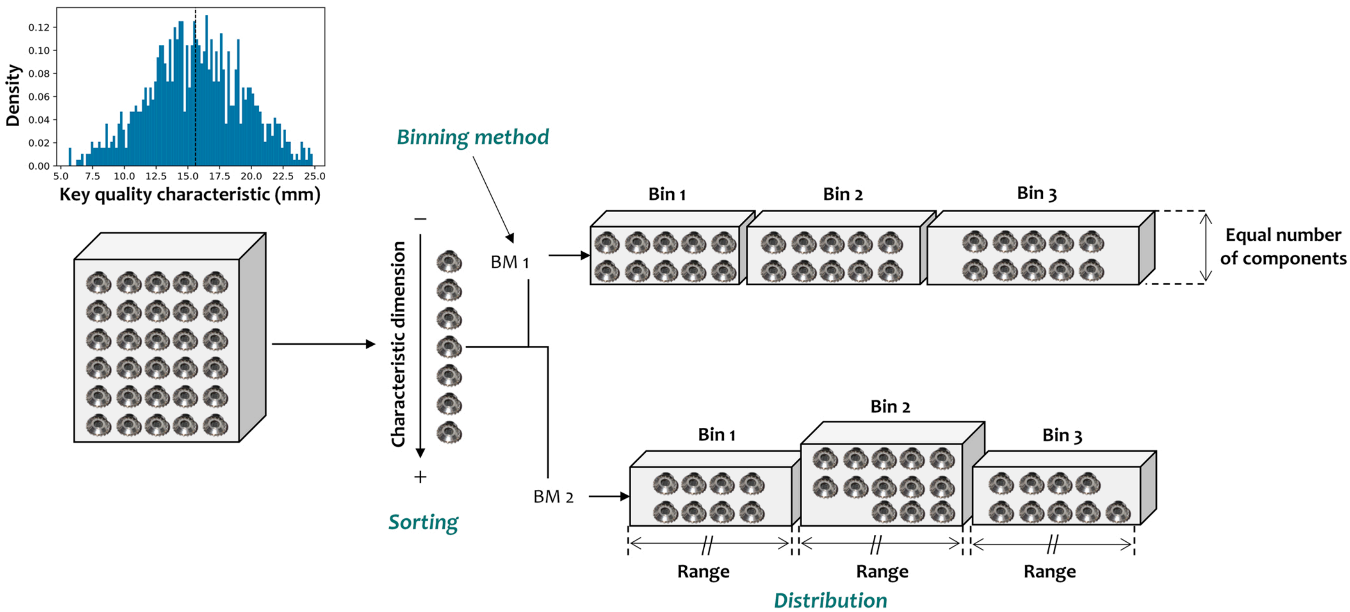


Fig. 7. Binning methodology schemes.

the characteristic. Once, the KCs are identified, the components can be categorized and distributed among the bins.

3.3.2. *Binning methods*

Binning methods in selective assembly involve grouping components into clusters, or "bins", based on their similarity. Different binning methods can be used to classify and separate components based on their characteristics. Some common methods include [2,35,47].

- Feature-based binning: This method uses geometric features, such as edges, corners, and points, to classify and group components.
- Dimensional binning: This method classifies, and groups components based on their dimensional characteristics, such as size, length, width, and height.
- Statistical binning: This method uses statistical techniques, such as principal component analysis (PCA) and linear discriminant analysis (LDA) to classify and group components based on their characteristics.

Each method has its advantages and disadvantages, and the choice of which method to use will depend on the specific application and the characteristics of the components. Since complex assemblies possess multiple characteristics, the statistical method is investigated using the KC identification method discussed. Afterward, the binning method is divided into two approaches (see Fig. 7): An equivalent number of components or predefined tolerance boundaries.

a) BM1: Equivalent number of components The first binning method BM1 is based on the equal area (probability) that distributes the components in equal numbers among the existing bins. This method is a quantitative-based method in which an equivalent number of components can be found in all bins for each type of component. This method helps decrease the number of scraps and residuals in the inventory.
b) BM2: Define tolerance boundaries This method is a qualitative-based method which is originated from the equal width (variance) partitioning method; however, the width of the bins can be adapted. The modification of the width is purposed to improve the assembly quality. Since the number of the distributed components in the bins may differ, the number of residual components may increase.

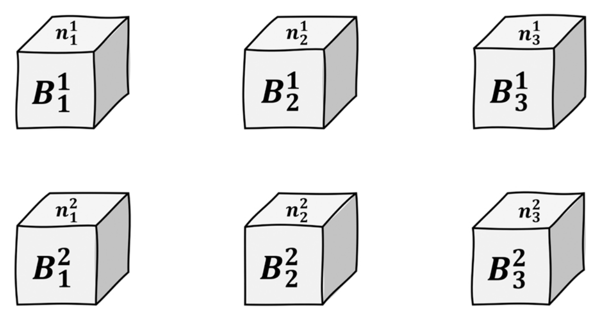


Fig. 8. Exemplary assembly of two components.

Therefore, the residual components will be stored in the inventory to be assembled for the next production cycle.

3.3.3. *Bins combination criterions*

In selective assembly, bin combination is the process of selecting the appropriate storage bin for a given component. This is typically done after the component has been classified and grouped based on its characteristics. The bin combination process is important for ensuring that the correct bins are combined, which can improve the efficiency and accuracy of the assembly process. Bin combination also helps to reduce the risk of errors and maximize the assembly's precision. The combination of several bins is referenced to criterion such as yielding the maximum number of assemblies or maximizing the quality of the assemblies required to be achieved.

Parameters:	
S	Set of possible combinations of bins
B_i^{co}	Associated bin i to component co
n_i^{co}	Number of components co in bin i
co	Number of the variety of components
$QE_{i,i'}$	Evaluated quality value of combination s
$N_{i,i'}$	Number of the possible assemblies from combination s
$x_{i,i'}$	1 if bin i associated with component 1 is combined with bin i' associated with component 2

Let us assume a product assembled of two distinct components which are distributed among three existing bins (Fig. 8).

MS1: Customer–manufacturer satisfaction		MS2: Manufacturer – customer satisfaction
Leader level: Customer satisfaction		*Leader level*: Manufacturer satisfaction
Maximize the assembly quality	VS.	Maximize the number of the pairs
Subject to:		*Subject to:*
Follower level: Manufacturer satisfaction		*Follower level*: Customer satisfaction
Maximize the number of pairs		Maximize the assembly quality

Fig. 9. Mixed strategy approaches comparison.

Each bin stores n number of specific types of components which can vary. For instance, bin B_3^2 which is indicated as the third bin, stores n_3^2 number of component 2 inside. The set of possible combination S for the exemplary can be given as follow:

$$S = \{ \{B_1^1, B_1^2\}, \{B_1^1, B_2^2\}, \{B_1^1, B_3^2\}, \{B_2^1, B_1^2\}, \{B_2^1, B_2^2\}, \{B_2^1, B_3^2\}, \{B_3^1, B_1^2\}, \{B_3^1, B_2^2\}, \{B_3^1, B_3^2\} \}$$

Consequently, the set $\{B_2^1, B_2^2\}$ means that bins B_2^1 and B_2^2 are combined and the number of the assemblies for this combination is equal to the minimum number of the components in the bins $N_{2,2} = \min\{n_2^1, n_2^2\}$. This indicates the assumption that the redundant number of the other type of component will be stored. The mathematical optimization model of the combination problem can be formulated as follows:

$$mix\backslash\max \quad criterion \tag{1}$$

Subject to,

$$\sum_{i=1}^{3} \sum_{i'=1}^{3} x_{i,i'} = number \quad of \quad bins \tag{2}$$

$$\sum_{i'=1}^{number \quad of \quad bins} x_{i,i'} = 1 \forall i \in [1, number \quad of \quad bins] \tag{3}$$

$$\sum_{i=1}^{number \quad of \quad bins} x_{i,i'} = 1 \forall i' \in [1, number \quad of \quad bins] \tag{4}$$

where Eq. (1) represents the objective of the assembly optimization where the model is constrained to Eq. (2) which indicates the cumulative combination should be equal to the number of bins; and Eq. (3) and Eq. (4) illustrate that each bin corresponding to each component can be combined with one bin of the other component. Thus, the problem is defined, a variety of optimization criterion can be defined. In this case, the proposed criterion are defined as follows:

a) Quality criterion mean maximization (QCMM)

QCMM is an expected value that evaluates the quality of conformed assembled components within the selected bins. This criterion manages to maximize the quality of the assemblies; therefore, it represents the potential quality of an assembly that targets customer satisfaction. The increase in quality increases customers' satisfaction. Eq. (5) depicts the mathematic representation of the criterion:

$$Mean \quad Quality = \sum_{i=1}^{3} \sum_{i'=1}^{3} \frac{QE_{i,i'}}{N_{i,i'}} \times x_{i,i'} \tag{5}$$

where QE_s indicates the evaluated quality value of the possible assemblies which is divided by the number of the possible pairs N_s. The summands of the value upon all paired bins depict the total mean value of the assemblies which is divided by 3 (the number of bins for each type of component) to estimate the expected quality value overall.

b) Paired number maximization (PNM)

PNM indicates the expected number of conformed assemblies. This criterion illustrates the manufacturer's expectation of the production plan, which means maximizing the number of assemblies subject to quality constraint. In Eq. (6) the criterion is formulated:

$$Pairs = \sum_{i=1}^{3} \sum_{i'=1}^{3} N_{i,i'} \times x_{i,i'} \tag{6}$$

c) Quality criterion inertia minimization (QCIM)

QCIM is the inertia of the quality value which measures spread around the mean value. It aims at improving the mean quality while minimizing the standard deviation and is formulated as below: [1,3].

$$Inertia = \sum_{i=1}^{3} \sum_{i'=1}^{3} (mean_s + deviation_s) \times x_{i,i'} \tag{7}$$

Subject to,

$$mean_{i,i'} = \frac{QE_{i,i'}}{N_{i,i'}}, \forall i, i' \in \tag{8}$$

$$deviation_{i,i'} = \sqrt{\frac{\sum_{j \in s} \left(QE_{i,i'} - mean_{i,i'}\right)^2}{N_{i,i'}}}, \forall i, i' \in \tag{9}$$

3.3.4. Mixed strategy (MS) solutions

In the previous section, QCMM, PNM, and QCIM are presented as indicators that present the customer's satisfaction value, the manufacturer's expectation, and a general indicator, respectively. Contrary to QCIM which provides the assembly structure while minimizing the variation of the assembly from the mean value of the quality criterion, QCMM and PNM target the value which satisfies the customer and manufacturer, exclusively. A mixed strategy is an approach to this type of problem that optimizes the assembly while satisfying customers' and manufacture's expectations. In this approach, the manufacturer and customer call as players whose satisfaction criterion differ. Therefore, an appropriate approach to solve this problem is to define two levels of optimization such as leader level (upper-level) and follower level (lower-level). Each level represents the criterion of each player that is required to be satisfied.

The approach initiates with satisfying the lower-level criterion, so-called the superior player, and optimizing the criterion associated with each binning method. At this level, the optimum criterion, and the optimum assembly structure, as well as the payoff (corresponding criterion) for the upper-level player is obtained. Next, the approach satisfies the upper-level criterion and locates the solution among the lower-level solutions which satisfy the upper-level the most. In this regard, the first step to locate the optimal solution is to set up a payoff matrix. The payoff matrix is a table in which binning methods are listed in rows and the criterion objectives (i.e. QCMM and PNM) are in the columns. The cells show the payoffs to each binning method and the optimal value of the objectives including the assembly structure and the value of the other objectives corresponding to the assembly structure. Once the matrix is set up, two decision rules can be taken as follows:

1) MS1: Customer–manufacturer satisfaction
   In this strategy, the customer comes in the upper-level of the optimization and the manufacturer comes in the lower-level. Therefore, the lower-level obtains the assembly structure which obtains the maximum number of pairs; then, on the upper-level, the assembly structure which causes the maximum assembly quality will be selected.
2) MS2: Manufacturer – customer satisfaction

Contrary to MS1, the manufacturer leads the optimization approach and the customer follows the leader. It means that in the lower-lever, the approach locates the optimum solutions which maximize the assembly quality corresponding to each binning method. Afterward, the manufacturer takes the next step and selects the solution which maximizes the number of pairs the most. In Fig. 9, the two approaches are compared.

On these bases, in this section, the selective assembly and relevant subjects are discussed. In this method, components are distributed among existing bins, afterward, the bins are paired in a way that satisfies the requirements of the assembly. This method improves the assembly quality and number of the conformed assembly compared to random assembly, however, it may cause an increase in the number of residuals in the inventory department in one production time. An alternative to this method is to assemble components individually in a manner that maximizes the overall quality of the assemblies. This approach is proposed in the coming section.

3.4. Individual assembly

Individual assembly is often used for high-precision or high-value products where quality and accuracy are crucial. It is also commonly used for low-volume or one-of-a-kind products, where mass production methods are not cost-effective. Individual assembly may take more time and resources than batch or mass production, but it allows for a higher degree of control over the production process and can produce higher-quality products. For individual assembly, each component is assigned to another one to optimize at least one target variable. In this context, three algorithms are developed and presented. The considered target variables are the number of usable parts, which should be maximized, and a characteristic feature (i.e. KTE) that describes the quality of the pairing. In general, characteristics are considered which describe the deviation from the target value and are to be minimized for higher quality and are therefore referred to as quality criterion (QC) in the following.

3.4.1. Optimum quality criterion (OQC) algorithm

The OQC algorithm is used to find a solution for the assignment problem that contains minimal QCs in the pairings. This approach is inspired by Sedgewick [48] who proposes a quick sorting algorithm that works by partitioning an array or list of elements into two sub-arrays, according to a chosen pivot element, and then recursively sorting the sub-arrays. Quick sort has an average-case time complexity of $O(n\log n)$, which makes it one of the fastest general-purpose sorting algorithms in practice. However, its worst-case time complexity is $O(n^2)$ if the pivot selection strategy is not well-designed. On these bases, in this process, pairings with a very small QC are preferred over pairings with a larger QC. The procedure is as follows and is also shown as a pseudo-code below.

All QCs for all pairings are determined and stored in a list. Then, this list is sorted by QC. In Python, this is implemented with a quicksort algorithm. Starting with the pairing with the lowest QC, the algorithm iterates through this list. At the same time, the pairing objects already used are stored in another list. If a pairing is found where both pairing objects are not yet used, this pairing is selected and the then newly used pairing objects are stored in the second list. This process is continued until all pairing objects are assigned.

3.4.2. Maximum part usage algorithm (MPU)

The maximum part usage algorithm (MPU) is proposed to maximize the number of individual pairs. In addition to all QCs of the pairings, also a threshold value for the QC above which a pairing in productive use would cause two rejects. This algorithm aims to assemble parts exclusively in such a way that only permissible pairs (pairs below the QC threshold) are formed. The procedure is shown as a pseudo-code as follows:

OQC algorithm

OQC pseudo-code

```
Create List: List of Pairs
For all possible pairing combinations with (QC, Spur_ID, Crown_ID):
    Create List: L1
    Add to L1: QC, Spur_ID, Crown_ID
    Add to List of Pairs: L1
Sort List of Pairs with respect to QC
Create List: Used_Gears, Pairing_Instruction
For all elements e in List of Pairs:
    If e. Spur_ID and e. Crown_ID not in Used_Gears:
        Add to Pairing_Instruction: e
        Add to Used_Gears: e. Spur_ID, e. Crown_ID
Return Pairing_Instruction
```

MPU algorithm

MPU pseudo-code

```
Create List: List of Pairs
For all possible pairing combinations with (QC, Spur_ID, Crown_ID):
    Create List: L1
    If QC bigger threshold:
        Add to L1: QC, Spur_ID, Crown_ID
        Add to List of Pairs: L1
Create List: Pairing_Possibilities_ID_1, Pairing_Possibilities_ID_2
For all ID_1, ID_2 in All_IDs:
    Add to Pairing_Possibilities_ID_1: create list: ID_1
    Add to Pairing_Possibilities_ID_1: create list: ID_2
For Elements e in List of Pairs:
    Add to Pairing_Possibilities_ID_1[ID]: e. Spur_ID, e. Crown_ID
    Add to Pairing_Possibilities_ID_2[ID]: e. Crown_ID, e. Spur_ID
Sort Pairing_Possibilities_ID_1 with respect to length of sub-lists
Sort Pairing_Possibilities_ID_2 with respect to length of sub-lists
Create List: Used_Gears, Pairing_Instruction
For all Elements e in min_length(Pairing_Possibilities_ID_1, Pairing_Possibilities_ID_2)
    If e. Spur_ID and e. Crown_ID not in Used_Gears:
        Add to Pairing_Instruction: e
        Add to Used_Gears: e. Spur_ID, e. Crown_ID
Return Pairing_Instruction
```

First, all QCs for the pairings are determined and stored in a list. All QCs that exceed the threshold are deleted from the list. Then a list is created in which for each pairing object still permissible pairings are listed. These are now sorted by number, called "list 1" in the following. The pairing object that has the fewest pairing possibilities is used initially. Analogous to OQC, a second "list 2" is created, in which all pairing objects that have already been used are listed. If a pairing is found from list 1 where the pairing object to be used is not yet in list 2, this pairing is selected. Then additionally used pairing objects are added to list 2. This process is continued until pairing objects are assigned subject to quality constraints.

3.4.3. Global optimum quality criterion (GOQC)

GOQC is an individual assembly scheme that evaluates all the combinations of the components and selects the pairs with the maximum quality level. This method is adapted from the Kuhn–Munkres (or Hungarian) algorithm [49], a combinatorial optimization algorithm, to solve the One-to-One (O-O) assignment problem. In this problem, one task is matched to one, and the time complexity is O(n^3), where n is the number of rows or columns in the quality matrix being optimized. Therefore, the model is adapted to match component-to-component and maximize the quality of the overall assemblies while satisfying the pre-defined quality level. The mathematical representation of the model can be expressed as follows:

$$\max Quality = \sum_{i\in A}\sum_{j\in B} QE_{ij} \times x_{ij} \tag{10}$$

Subject to,

$$\sum_{i\in S} x_{ij} = 1 j \in C \tag{11}$$

Table 1
Evaluated KTE for all the possible combinations of the spur gears and crown wheels.

Crown wheel label Spur gear label	C1	C2	C3	C4	C5	C6	C7	C8	…	C1000
S1	25.3	21.4	25.9	23.5	21.9	18.1	30.1	25.0	…	20.0
S2	24.9	16.8	25.2	24.3	20.2	14.4	27.2	23.0	…	15.2
S3	20.1	18.0	21.2	19.5	17.7	13.0	13.8	18.6	…	10.6
S4	22.1	21.6	22.5	23.8	17.2	17.9	25.2	23.0	…	12.6
S5	21.2	18.7	23.2	22.2	20.9	15.0	28.8	19.8	…	11.8
S6	24.4	16.3	25.7	23.2	19.2	17.5	25.6	20.7	…	15.0
S7	19.7	21.2	17.5	18.0	16.8	12.7	24.2	19.6	…	11.6
S8	21.2	17.7	20.8	20.0	18.2	13.9	21.9	15.4	…	7.4
…	…	…	…	…	…	…	…	…	…	…
S1000	19.6	16.3	22.1	17.9	19.3	12.7	25.2	20.4	…	11.4

$$\sum_{j\in C} x_{ij} = 1 i \in S \quad (12)$$

$$QE_{ij} \times x_{ij} \geq addmissible \quad quality \quad i \in S, j \in C \quad (13)$$

In this method, the quality response QE of an individualized assembly can be assessed by the application of a model. Therefore, in this example, this model is embedded into the assembly problem which assesses the assembly response of each assembly as well as the overall assembly response. In the following section, the application of the proposed adaptive assembly is studied and analyzed for the gear pairing problem.

4. The approach implementation analysis

Therefore, let us assume that the manufacturing department has produced 1000 conformed parts of each gear type which associate with different geometric deviations due to manufacturing imperfections. Therefore, the possible ways to pair two gears are equal to $\underbrace{\binom{1000}{1}}_{Spur\ gear} * \underbrace{\binom{1000}{1}}_{Crown\ \ wheel} = 1000 * 1000 = 10^6$ And, the number of possible combinations in random assembly is equal to $\left(\underbrace{\binom{1000}{1}}_{spur\ gear} * \underbrace{\binom{1000}{1}}_{Crown\ \ wheel}\right) + \left(\underbrace{\binom{999}{1}}_{spur\ gear} * \underbrace{\binom{999}{1}}_{Crown\ \ wheel}\right)$ - $+\left(\underbrace{\binom{998}{1}}_{spur\ gear} * \underbrace{\binom{998}{1}}_{Crown\ \ wheel}\right) + \cdots + \left(\underbrace{\binom{1}{1}}_{spur\ gear} * \underbrace{\binom{1}{1}}_{Crown\ \ wheel}\right) = 1000^2 + 999^2$ - $+998^2 + \cdots + 1^2 = \sum_{i=1}^{1000} i^2 = \frac{1000*1001*2001}{6} = 333833500$. Consequently, Table 1 details a brief example of all combinations and their associate evaluated KTE.

Crown wheels are labeled with "**C**" and spur gears are marked with "**S**". For instance, if spur gear S4 and crown wheel C3 are paired, the estimated KTE value is equal to 22.5 (μm). The admissible KTE value for the pairing strategy is assumed to be 23 (μm). It means that if the associated KTE with two paired gears exceeds the admissible value the pairing is not acceptable. A simple and common solution in practice is to assemble the gears randomly. A Monte-Carlo simulation for 10^6 random assemblies is employed which means each iteration pairs 1000 of each gear randomly and reports the number of feasible pairs and average KTE value of all the pairs. Finally, the simulation reported a 609 average number of pairs with a 22.7 (μm) average KTE value. Subsequently, selective assembly and individual assembly are applied to pair the gears efficiently while satisfying the quality requirements. Once Table 1 is arranged, the first step in the selective assembly is to identify the KC on each type of gear. To do so, the employed surrogate model and Sobol analysis are engaged to identify the KC.

Fig. 10 depicts the Sobol results using the surrogate model which identifies $T^{Spur\ gear}_{Pitch\quad error}$ and $T^{Crown\ wheel}_{Pitch\quad error}$ as the most vital characteristics having the most impact on the KTE value. Once the KC is identified, the next step in selective assembly is to distribute the gears between the bins regarding their $T_{Pitch\ error}$. In Section 3.3.2, several binning methods are proposed, and the associated bins are detailed in Table 2. For instance, if the distribution of the spur gears is applied using BM2, the first bin SB1

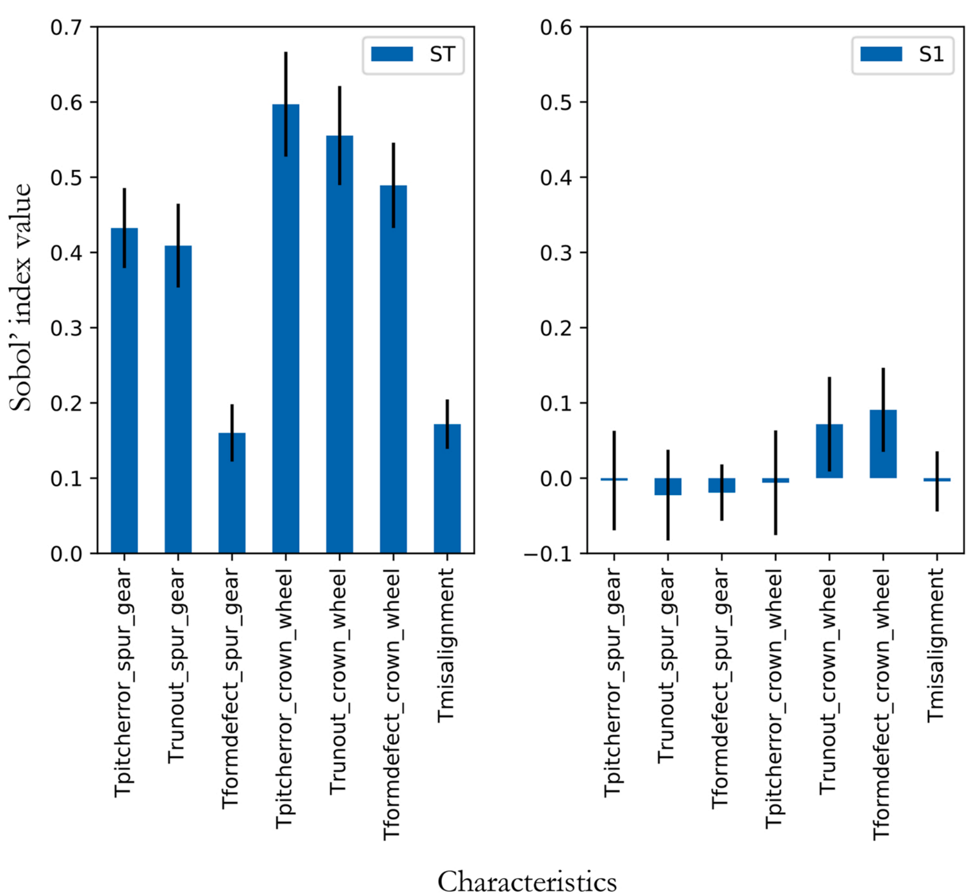


Fig. 10. Gears KC identification using Sobol indices.

Table 2
Binning methods comparison for the gear pairing.

Binning methods	The number of the gears			The variation range of the KC (μm)		
	Bin 1	Bin 2	Bin 3	Bin 1	Bin 2	Bin 3
$BM1^{Spur\ gear}$	334	333	333	[1.0, 5.8)	[5.8, 10.2)	[10.2, 15.1]
$BM2^{Spur\ gear}$	257	334	409	[1.0, 4.7)	[4.7, 9.4)	[9.4, 15.1]
$BM1^{Crown\ wheel}$	334	333	333	[1.0, 9.3)	[9.3, 17.2)	[17.3, 25.1]
$BM2^{Crown\ wheel}$	264	362	374	[1.0, 8.0)	[8.0, 16.0)	[16.1, 25.1]

contains 257 spur gears with a variation in the range of [1.0, 4.7) (μm) on $T^{Spur\ gear}_{Pitch\ error}$, the second bin SB2 stores 334 spur gear in range of [4.7, 9.4) (μm), and the last bin SB3 holds 409 gear in the range of [9.4, 15.1] (μm). Consequently, the gears are distributed into the bins respecting the proposed binning methods. Next, based on the assembly criterion in Section 3.3.3, the bins are combined, and the criterion are assessed.

Table 3 details the assessment of the criterion corresponding to each binning method, including the bins' pairing structure. More in detail, if the enterprise prefers to improve the quality by minimizing the KTE value, the optimal decision is to distribute the gears among the existing bins based on method BM1, and the bins' combination is structured as follows: SB1 is paired with CB2, SB2 is paired with CB1, and SB3 is paired with CB 3. By this structure, on average 710 gears will be paired and the average KTE value of 19.6 (μm) is yielded. Fig. 11 depicts evaluations of the KTE attained by deploying selective assembly approaches, encompassing all conceivable combinations. Each illustration in the figure displays the random pairing distribution based on the optimal combining structure achieved for each approach.

The comparison of the overall KTE values of two mixed solutions MS1 and MS2 can be found in Fig. 11(b) and Fig. 11(d). In the case of dedicated gears pairing, taking solution MS1 to combine the bins optimally results in 728 conformed pairs with a mean KTE value of 20.11 (μm). However, if the decision is on improving the quality in the first place, afterward improving the number of the pairs, taking solution MS2 improves the KTE value slightly to 20.1 (μm) but decreases the number of the pairs to 710 pairs. Since solution MS1 doesn't show a great impact on improving the pairing strategy quality, solution MS2 could be a practical decision that maintains a fair quality as well as an optimal number of pairs owing to the mapping of the two solutions MS2 and PNM. Additionally, a comparison of the variety of assembly strategies is illustrated in Fig. 13.

As the results illustrate, selective assembly improves the gear pairs' quality as well as the number of pairs efficiently. However, it doesn't provide a global structure for each gear to guarantee the quality of the pairs sufficiently. On the other hand, individual assembly is more of a dedicated assembly that can promise better performance. To apply the proposed individual assembly strategies, first, the GOQC algorithm is exercised to find the optimal pairs which result in the minimum KTE for all the pairs. Contrary to the selective assembly which combines the bins, GOQC is proposed to apply an exhaustive exploration that evaluate all the possible combinations and find the optimal for all gears.

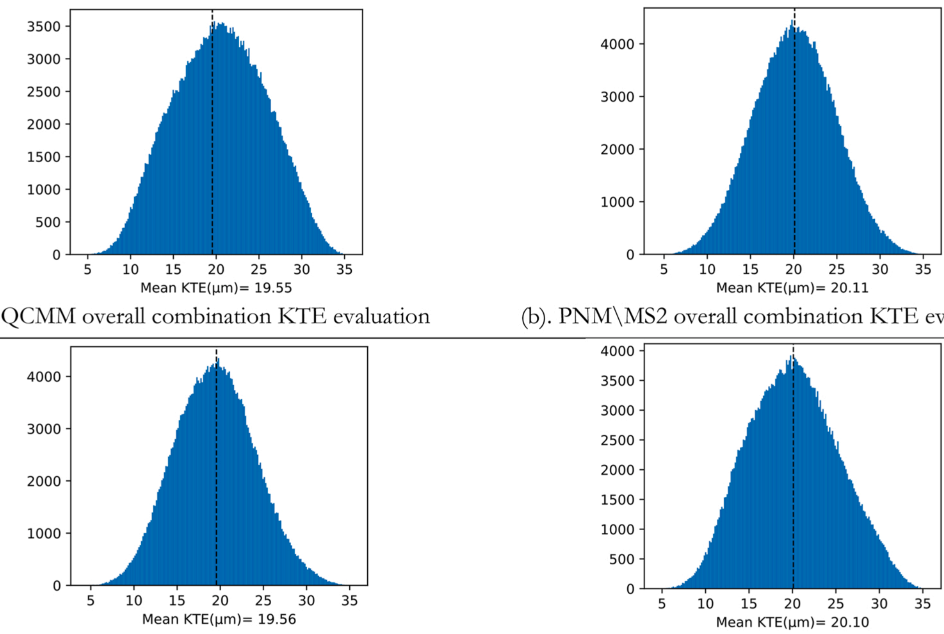
Table 4 details an example of how the GOQC algorithm structured optimal gear paring. For instance, the spur gear S3 is paired with crown wheel C893 and the predicted KTE is equal to 16.0 (μm). The optimal overall KTE value for all the pairs is equal to 15.3 (μm) and 984 gears are paired, optimally. Second, the MPU algorithm is run to pair gears individually in a way that a maximum number of pairs are yielded while the requirements are satisfied. In this method, 982 optimal pairs are matched individually with an average KTE value of 18.7 (μm). The last, the OQC algorithm is applied to obtain minimal QCs in the pairings. In this algorithm, compared to the other two algorithms the number of pairs and quality drop, however, it pairs the gears more efficiently when it comes to the computation complexity. An optimal number of 904 pairs is obtained with an average KTE value of 14.8 (μm). Fig. 12 (a) shows the result of the MPU algorithm, where the pairing has the highest number of pairs compared to OQC, which prioritizes the overall quality of all pairs. On the other hand, GOQC provides the complete solution (pairing structure) that results in the optimal global KTE for all pairings and the greatest number of pairs that are guaranteed.

Additionally, Fig. 12 (d) demonstrates the optimization time of each strategy to reach the optimum solutions associated with each strategy.

Table 3
SA binning methods and combination criterion assessment.

	Minimize the Mean KTE	Maximize the number of the pairs	Minimize the Inertia
$BM1^{Spur\ gear} * BM1^{Crown\ wheel}$	Mean KTE = **20.10** Number of pairs = **710** Inertia = **23.85** Spur class 1 is paired with Crown class **2** Spur class 2 is paired with Crown class **1** Spur class 3 is paired with Crown class **3**	Number of pairs = **728** Mean KTE = **20.11** Inertia = **23.85** Spur class 1 is paired with Crown class **3** Spur class 2 is paired with Crown class **2** Spur class 3 is paired with Crown class **1**	Inertia = **23.85** Mean KTE = **20.10** Number of pairs = **710** Spur class 1 is paired with Crown class **2** Spur class 2 is paired with Crown class **1** Spur class 3 is paired with Crown class **3**
$BM1^{Spur\ gear} * BM2^{Crown\ wheel}$	Mean conformity = **19.66** Number of pairs = **666** Inertia = **23.40** Spur class 1 is paired with Crown class **2** Spur class 2 is paired with Crown class **1** Spur class 3 is paired with Crown class **3**	Number of pairs = **693** Mean KTE = **19.67** Inertia = **23.40** Spur class 1 is paired with Crown class **3** Spur class 2 is paired with Crown class **2** Spur class 3 is paired with Crown class **1**	Inertia = **23.40** Mean KTE = **19.66** Number of pairs = **666** Spur class 1 is paired with Crown class **2** Spur class 2 is paired with Crown class **1** Spur class 3 is paired with Crown class **3**
$BM2^{Spur\ gear} * BM1^{Crown\ wheel}$	Mean KTE = **20.00** Number of pairs = **653** Inertia = **23.75** Spur class 1 is paired with Crown class **2** Spur class 2 is paired with Crown class **1** Spur class 3 is paired with Crown class **3**	Number of pairs = **702** Mean KTE = **20.01** Inertia = **23.75** Spur class 1 is paired with Crown class **3** Spur class 2 is paired with Crown class **2** Spur class 3 is paired with Crown class **1**	Inertia = **23.75** Mean KTE = **20.01** Number of pairs = **702** Spur class 1 is paired with Crown class **3** Spur class 2 is paired with Crown class **2** Spur class 3 is paired with Crown class **1**
$BM2^{Spur\ gear} * BM2^{Crown\ wheel}$	Mean KTE = **19.55** Number of pairs = **617** Inertia = **23.30** Spur class 1 is paired with Crown class **2** Spur class 2 is paired with Crown class **1** Spur class 3 is paired with Crown class **3**	Number of pairs = **674** Mean KTE = **19.57** Inertia = **23.33** Spur class 1 is paired with Crown class **1** Spur class 2 is paired with Crown class **3** Spur class 3 is paired with Crown class **2**	Inertia = **23.30** Mean KTE = **19.56** Number of pairs = **663** Spur class 1 is paired with Crown class **3** Spur class 2 is paired with Crown class **2** Spur class 3 is paired with Crown class **1**

Note: The optimal solutions are faded in and the mixed solutions are faded .



(a). QCMM overall combination KTE evaluation

(b). PNM\MS2 overall combination KTE evaluation

(C). QCIM overall combination KTE evaluation

(d). MS1 overall combination KTE evaluation

Fig. 11. Overall combination evaluation for gear pairing.

Table 4
Optimal IA pairs associated with the GOQC algorithm.

Spur gear label	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	…	S1000
Crown wheel label	C689	C936	C893	C890	C154	C606	C703	C13	C776	C745	…	C255
Evaluated KTE (μm)	11.7	18.7	16.0	18.3	20.1	9.4	22.8	13.9	17.3	14.9	…	15.2

The SA algorithm, which has been designed to group components into bins and combines bins as opposed to IA algorithms that match gears one-by-one, converges faster than IA strategies as a result.

5. Conclusion and future works

Assembly is a process to create products that function accurately and reliably, and that meet specifications required by various applications, such as in aerospace, medical, and electronics industries. Assembly can lead to increase efficiency in production processes and can result in product performance efficiency. However, the assembly process may vary depending on the specific requirements for each assembly. The significance of assembly becomes evident in complex assemblies that require a well-defined assembly plan. Therefore, this paper is dedicated to the primary definition of an inventive adaptive assembly which receives the tolerance analysis model of the assembly and proposes the fittest strategy by assessing several assembly strategies. Adaptive assembly can be particularly beneficial for high-precision products as it allows manufacturers to quickly adjust the assembly process to optimize the specific requirements of each product. By adjusting the process, manufacturers can improve the accuracy and consistency of their assembly, which is essential for high-precision products such as micro gears.

In this paper, an adaptive assembly strategy is proposed. This approach assesses several assembly strategies for an assembly with specific requirements, evaluates the quality response, and returns the fittest strategy which satisfies the customer and/or manufacturer the most. The results illustrate the applicability of the approach for gear pairing. The analyses of different assemblies demonstrate the importance of assembly strategy investigation where the assembly for an assembly may vary from another. Therefore, the benefits (+) and shortcomings (-) of different assemblies in this paper are listed:

Random assembly:

1. Cost savings, as assembly often requires less skill and training than other manufacturing processes.
2. High scalability, as random assembly may be applied for high-volume production runs.

- Increased risk of non-conformed assemblies.

Selective assembly:

1. Greater flexibility in production, as individual components or sub-assemblies can be tailored to specific customer needs or market demands.
2. Reduced waste, as only the necessary components are assembled.
3. Improved product quality, as selective assembly allows for more precise and accurate assembly of components.

- Greater complexity in planning and calculation.
- Increased risk of errors and defects, as selective assembly requires more attention to detail and quality control.
- Limited scalability, as selective assembly may not be feasible for high-volume production runs.

Individual assembly:

1. A high degree of customization, as each product can be tailored to the specific needs and preferences of individual customers.
2. Improved product quality, as individual assembly allows for more precise and accurate assembly of components.

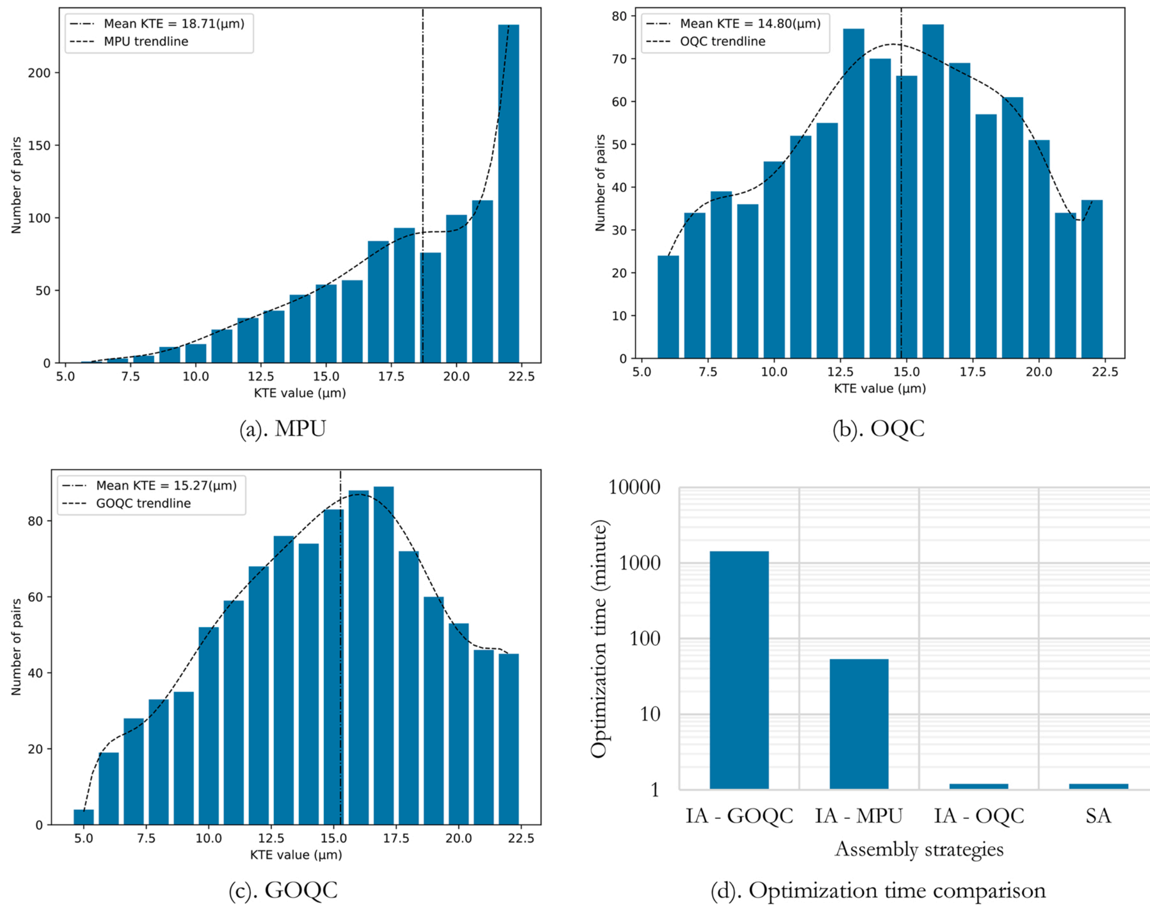


Fig. 12. Individual assembly strategies‘ comparison.

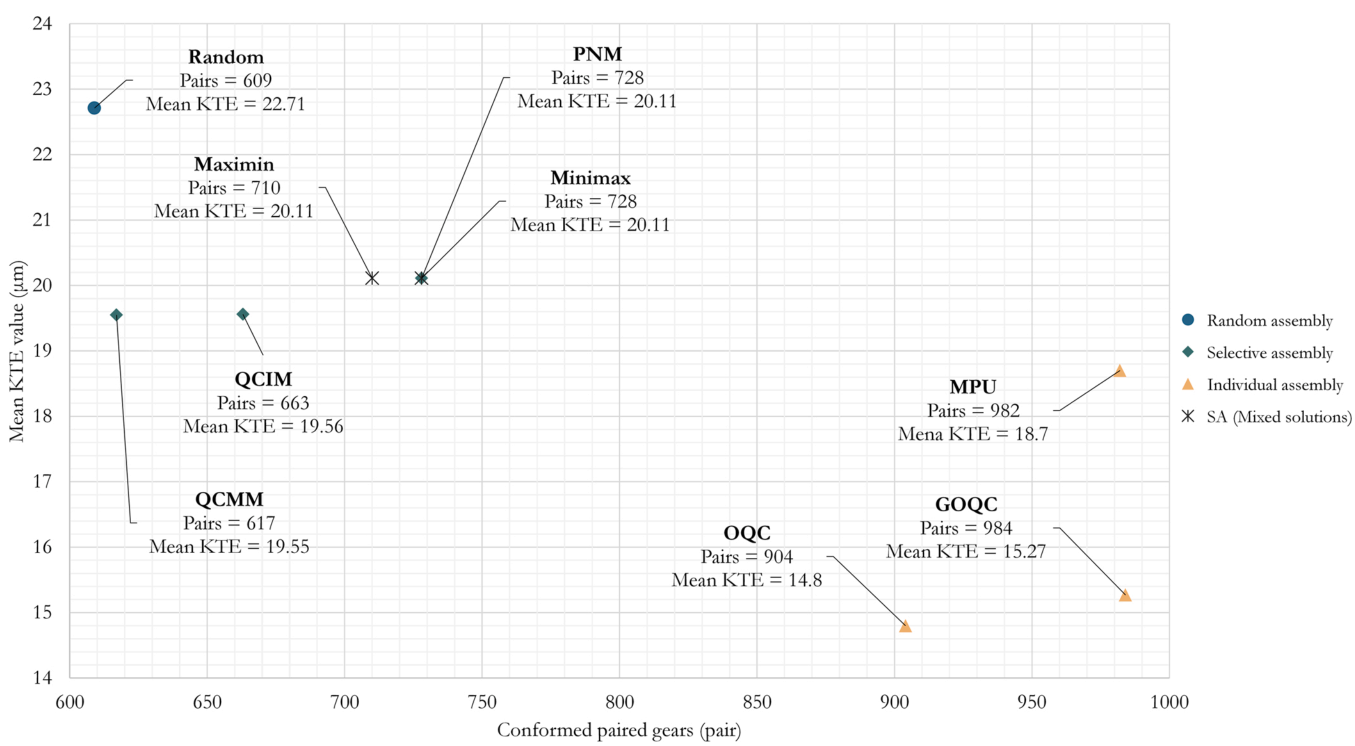
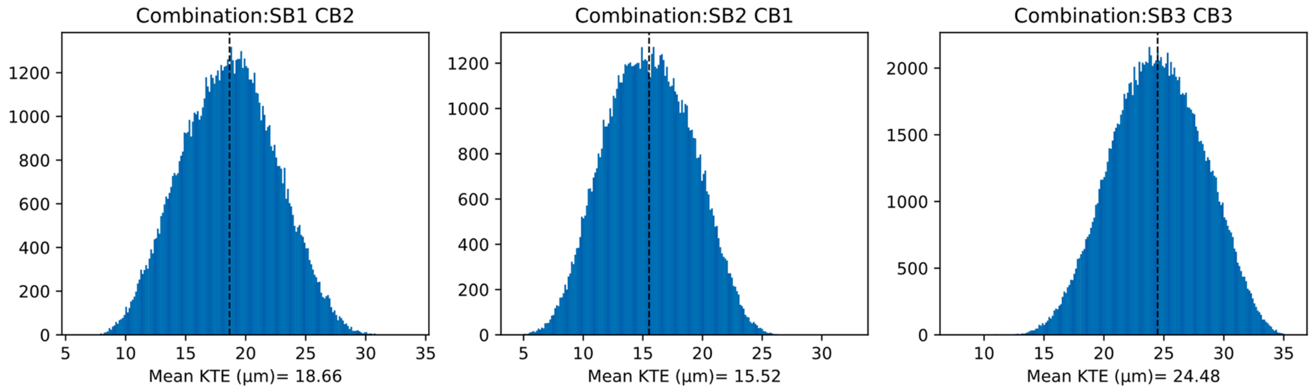
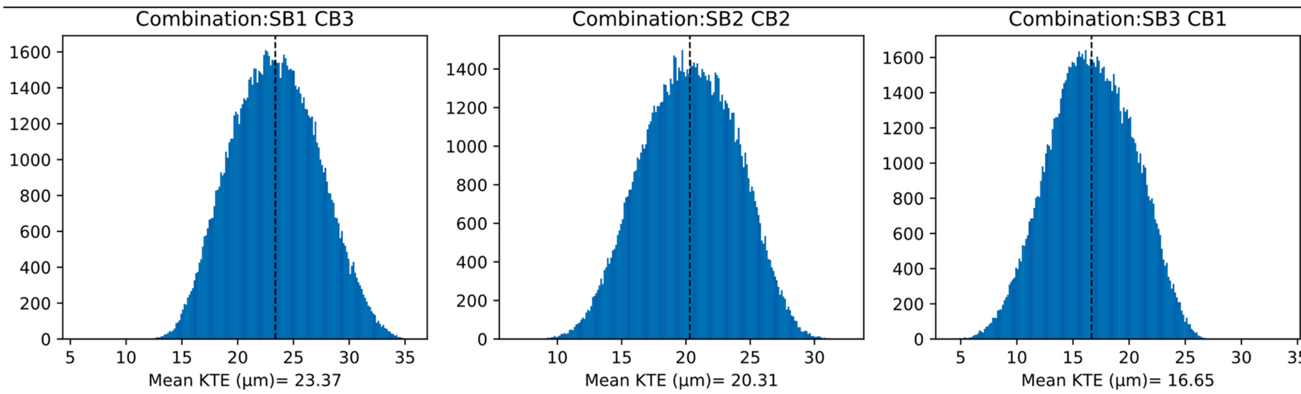


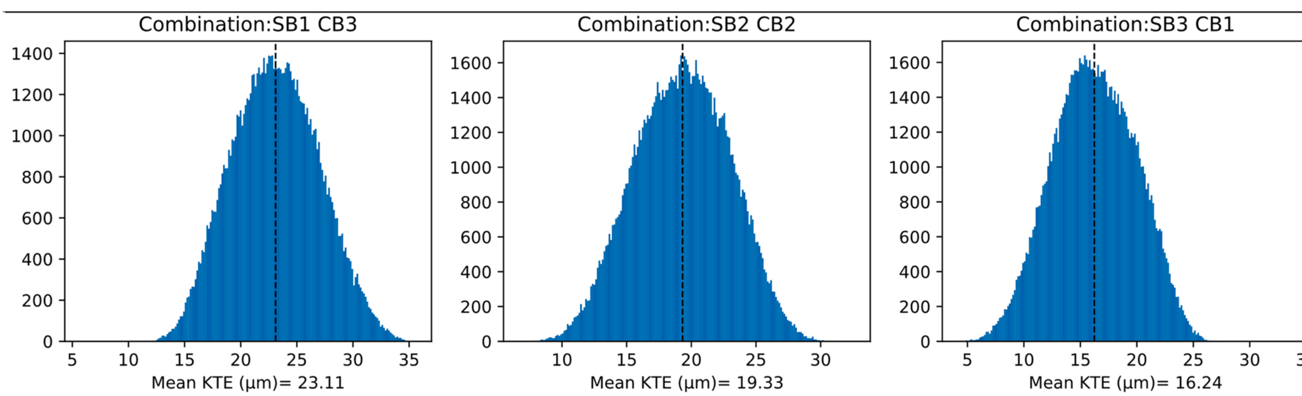
Fig. 13. Gears’ pairing strategies comparison.



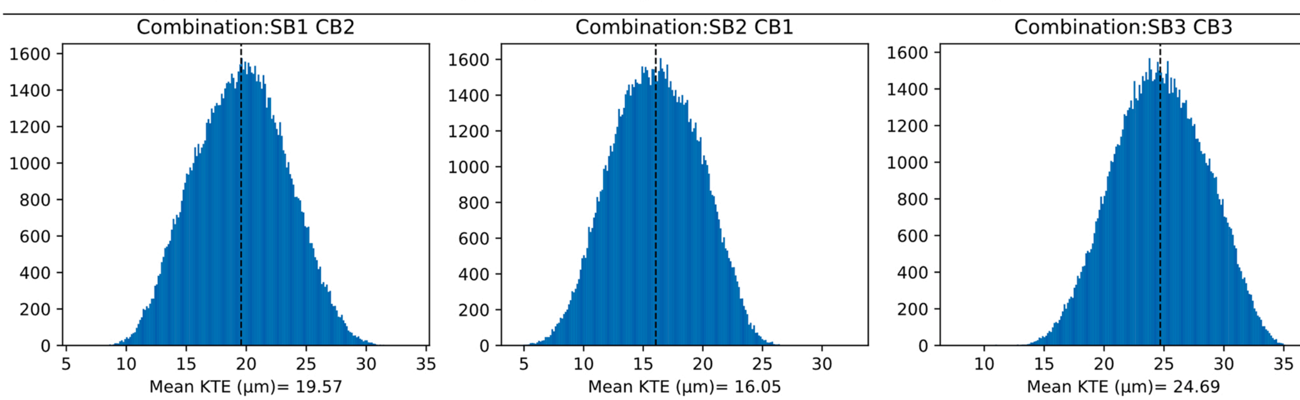
(a). QCMM random internal pairing among optimal combinations evaluation (BM1-based bins)



(b). PNM\MS2 random internal pairing among optimal combinations evaluation (BM1-based bins)



(c). QCIM random internal pairing among optimal combinations evaluation (BM2-based bins)



(d). MS1 random internal pairing among optimal combinations evaluation (BM2-based bins)

Fig. 14. Random internal pairing among optimal combinations.

3. Increased flexibility in production, as individual assembly can be easily adapted to accommodate changes in customer needs or market demands.
4. Reduced waste, as only the necessary components are assembled.

- Greater complexity in planning and calculation than selective assembly.

- Limited scalability, as individual assembly may not be feasible for high-volume production runs.
- Longer lead times, as individual assembly takes longer to produce than mass assembly due to its nature of tailoring to specific needs.

Additionally, the proposed assembly strategies are proposed under certain limits due to time-consuming and deep computations. As an example, optimal yielded combinations in selective assembly would combine the specified bins, therefore, in case one bin related to one type of component runs out of components the other bins related to another type of component will store the redundant component for the next production. For future work, an enhancement of this approach can be to improve combinations in which the redundant can be combined with other bins in a way that quality responses don't drop. Furthermore, since GOQC originated from Kuhn–Munkres algorithm, it has been proved that the complexity of the problem increases quickly with the dimensionality of the problem. Consequently, the approach can be adapted for solving high-dimensional assignment problems using appropriate heuristic or meta-heuristic approaches.

Author contributions

A. Khezri contributed to conceptualization, modelization, analyzing, coding, visualization, writing-original draft, and editing. V. Schiller contributed to methodology, coding, writing-original draft, and reviewing. L. Homri contributed to conceptualization, advising, and reviewing. A. Etienne contributed to conceptualization, methodology, advising, and reviewing. J-Y. Dantan contributed to conceptualization, reviewing and editing, supervision, project administration, and funding acquisition. G. Lanza contributed to reviewing, supervision, project administration, and funding acquisition.

Declaration of Competing Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

Data Availability

The data that support the findings of this study are available in the Recherche Data Gouv https://doi.org/10.57745/E3DW9W.

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Appendix: finding data depository

The data that support the findings of this study on the case of micro gears are available in the Recherche Data Gouv https://doi.org/10.57745/E3DW9W.This dataset comprises 1000 Spur gears and 1000 Crown wheels with distinct geometric deviations that result from inaccuracies during the manufacturing process. The dataset includes both the inputs and outputs of the proposed adaptive assembly system for gear pairing. The inputs consist of labeled gears and the Kinematic Transmission Error (KTE) values for various combinations of the two types. The outputs entail the results of selective assembly binning analysis and individual assembly analysis for the specific pairing of the two gears.

For instance, a more comprehensive glance into the random pairings among the optimal combinations of selective assembly approaches is shown in Fig. 14 (a)-(d), depicting the histogram analysis of the frequency of gear pairs within several KTE value ranges.

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