Artificial Intelligence for Engineering Design, Analysis and Manufacturing

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Research Article

Cite this article: Champatiray C, Raju Bahubalendruni MVA, Mahapatra RN, Mishra D (2023). Optimal robotic assembly sequence planning with tool integrated assembly interference matrix. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing* **37**, e4, 1–13. https://doi.org/10.1017/S0890060422000282

Received: 15 August 2022
Revised: 29 October 2022
Accepted: 16 December 2022

Key words:
CAD-based feasible solution; industry 4.0; robotic assembly sequence planning; robotic gripper; tool integrated axis-aligned bounding box

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Optimal robotic assembly sequence planning with tool integrated assembly interference matrix

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Abstract

Manufacturing industries are looking for efficient assembly planners that can swiftly develop a practically feasible assembly sequence while keeping costs and time to a minimum. Most assembly sequence planners rely on part relations in the virtual environment. Nowadays, tools and robotic grippers perform most of the assembly tasks. Ignoring the critical aspect renders solutions practically infeasible. Additionally, it is vital to test the feasibility of positioning and assembling components while employing robotic grippers and tools prior to their implementation. This paper presents a novel concept named by considering both part and tool geometry to propose "tool integrated assembly interference matrices" (TIAIMs) and a "tool integrated axis-aligned bounding box" (TIAABB) to generate practically feasible assembly sequence plans. Furthermore, the part-concatenation technique is used to determine the best assembly sequence plans for an actual mechanical component. The results show that the proposed approach effectively and efficiently deals with real-life industrial problems.

Introduction

Industry 4.0 propels the manufacturing industries away from mass production and toward mass customization to meet customers' needs with multiple product variants (Daneshmand *et al.*, 2022; Dolgui *et al.*, 2022). Human–robot collaboration can merge the flexibility of humans and the repetitiveness of robots to enhance the overall system capabilities (Inkulu *et al.*, 2022). This revolutionary paradigm lets engineers work in real time with the latest digitalized technologies like IoT, cloud, AI, and cyber-physical systems (Ghosh *et al.*, 2019; Stojadinovic *et al.*, 2021).

Smart manufacturing cannot be accomplished without the use of flexible robotic assembly (Ying *et al.*, 2021). An effective automated assembly plan can assist manufacturers under colossal pressure to produce and market products faster to meet the demands (Rashid *et al.*, 2012). Assembly design is said to be complete when product information and an assembly design co-exist (Hui *et al.*, 2007). Developing an optimal feasible assembly sequence plan (OFASP) for a new product variant in low volume is challenging because of the high cost involved in the designing phase. The assembly planning phase accounts for the majority of the cost and time (20%–40%) of overall production estimates; an OFASP can significantly reduce assembling cost and time (Whitney, 2004; Bahubalendruni and Biswal, 2016). When the number of predicates (liaison predicate, assembly interference predicate, stability predicate, and mechanical feasibility predicate) increases, the solution becomes more acceptable (Bahubalendruni and Biswal, 2018). For any product with an "*n*" number of parts, there can be "*n!*" possible linear assembly sequences (Ghandi and Masehian, 2015*b*). The assembly planners should establish the assembly relations and attributes before extracting the assembly predicates (Tseng *et al.*, 2004). The application of the assembly predicates drastically lowers the number of feasible assembly sequences (De Fazio and Whitney, 1987; De Mello and Sanderson, 1989). The ASP's effectiveness can also be increased by employing a stable subset identification technique (Murali *et al.*, 2019). Several researchers have worked on extracting assembly constraints and relations from virtual CAD models; these constraints and assembly relations are used to validate assembly sequences' feasibility (Pan *et al.*, 2006; Ben Hadj *et al.*, 2015). Literature (Kumar *et al.*, 2022) has suggested an automated way to get the geometric feasibility through a path with no collisions at an angle. A rule-based geometry-enhanced ontology modeling and reasoning framework are suggested to deal with the customized and digitalized manufacturing environment (Qiao *et al.*, 2018).

Researchers used artificial intelligence (AI) techniques for their simplicity to generate optimal assembly sequences for various objective functions with a high convergence rate (Deepak

Table 1. Comparative analysis of the cited literature

Sl. No	Reference	Assembly part relation			Assembly tool relation
		Liaison	Assembly interference	Stability	
1	Bahubalendruni and Biswal (2018)	C	C	C	NC
2	Cao *et al.* (2018)	C	NC	NC	NC
3	Ying *et al.* (2021)	C	C	C	NC
4	Gunji *et al.* (2017)	C	C	C	NC
5	Gulivindala *et al.* (2020)	C	C	C	NC
6	Han *et al.* (2021)	C	C	NC	NC
7	Kumar *et al.* (2022)	C	C	C	NC
8	Qiao *et al.* (2018)	C	C	NC	NC
9	The proposed work	C	C	NC	C

NC, not considered; C, considered.

et al., 2019; Su *et al.*, 2021). AI methods like breakout local search (Ghandi and Masehian, 2015*a*), firefly algorithm (Zhang *et al.*, 2016), advanced immune system (Bahubalendruni *et al.*, 2016), machine learning (Cao *et al.*, 2018), particle swarm optimization (Wang and Liu, 2010; Ab Rashid *et al.*, 2019), ant colony optimization (Han *et al.*, 2021), genetic algorithm (Wu *et al.*, 2022; Lu *et al.*, 2006), rule-based reasoning (Kroll *et al.*, 1989; Lin *et al.*, 2007), neural network (Chen *et al.*, 2010), simulated annealing (Murali *et al.*, 2017), and psychoclonal algorithm (Tiwari *et al.*, 2005). Sometimes, combining different methods like the advanced immune system and GA (Gunji *et al.*, 2017) and neuro-fuzzy by Zha (2001) also provides the optimal solutions faster. Reinforced learning can search for assembly sequences from many solutions and regression, and neural networks can improve the solution faster (Watanabe and Inada, 2020).

Aside from the AI technique, a few researchers developed heuristic-based mathematical models (Givehchi *et al.*, 2011; Gulivindala *et al.*, 2020). Due to the limited information available about the tool and robotic gripper in assembly relation data (liaison and assembly interference data) in the previous work. The solutions derived by utilizing these optimization algorithms are often not optimal and are practically not feasible. Moreover, AI techniques must search the entire solution space to arrive at the optimal solution.

The cost function can be reduced by implementing robotic assembly to minimize the orientation, the number of tool changes, and the length of paths (Rodríguez *et al.*, 2019). Many researchers focus on tool selection or assignments by incorporating expertise-based or knowledge-based approaches (Yin *et al.*, 2003; Wu *et al.*, 2011). Wilson *et al.* explain the tool representation that includes the tool use volume and the minimum free space in an assembly to apply the tool (Wilson, 1998). The author also categorized the tools based on their application (before, after, and during assembling).

Table 1 delineates a comparative analysis of cited articles and the proposed method. It can be observed from Table 1 that most of the existing literature considered only part attributes and ignored the tools. Due to this, the solution may not be practically feasible. In the current research, tool geometry is also considered for assembling a component to ensure practical feasibility. A novel concept named the tool integrated assembly interference matrix (TIAIM) is proposed.

OFASP without considering tooling

A list of preconditions (given below) has been adopted to simplify complex assembly planning-related problems.

1. The parts and tools used for the assembly operations are rigid; no change in size and shape is permitted during the assembly operation.
2. All the parts of the product are considered for the assembly operation.
3. The stability of the components within the assembly is not evaluated.
4. The parts have been assembled linearly.
5. The assembly operation is considered the reverse of disassembly sequence planning to ease assembly interference testing.
6. While generating the TIAIM, the moveable parts are replaced by a combined geometry of the tool and the part.
7. This article considered the number of direction changes as the optimal criteria.

The proposed method that generates the OFASP without considering tooling is presented in Figure 1, which first processes the assembly relations data and generates the assembly sequence plan for a specific objective function. The conditions through which the input data is processed noted as Q1, Q2, Q3, and Q4 are depicted in Table 2. The assembly relation data can produce a stable and feasible solution. In many cases, the assembly jigs/fixtures may be used to obtain the stability of any component.

The establishment of the mathematical relationship is the fundamental step. Boolean representations (0, 1) are being used to determine whether there is contact or geometrical interference. The assembly relations used for OFASP are given in Table 3 with the retrieval process. The current research uses CATIA API (application program interface) to interface with CAD models to extract the assembly attribute data stated in Table 3.

Moreover, the clash test was performed in the CATIA environment to acquire the assembly relations, that is, liaison and assembly interference relations. There are three ways the outputs display, namely contact (=0), clearance (<0), and clash (>0) while performing the clash test. So, the contact analysis process records the conflict elements having a value equal to zero. However, the retrieval system called snap class analysis, as

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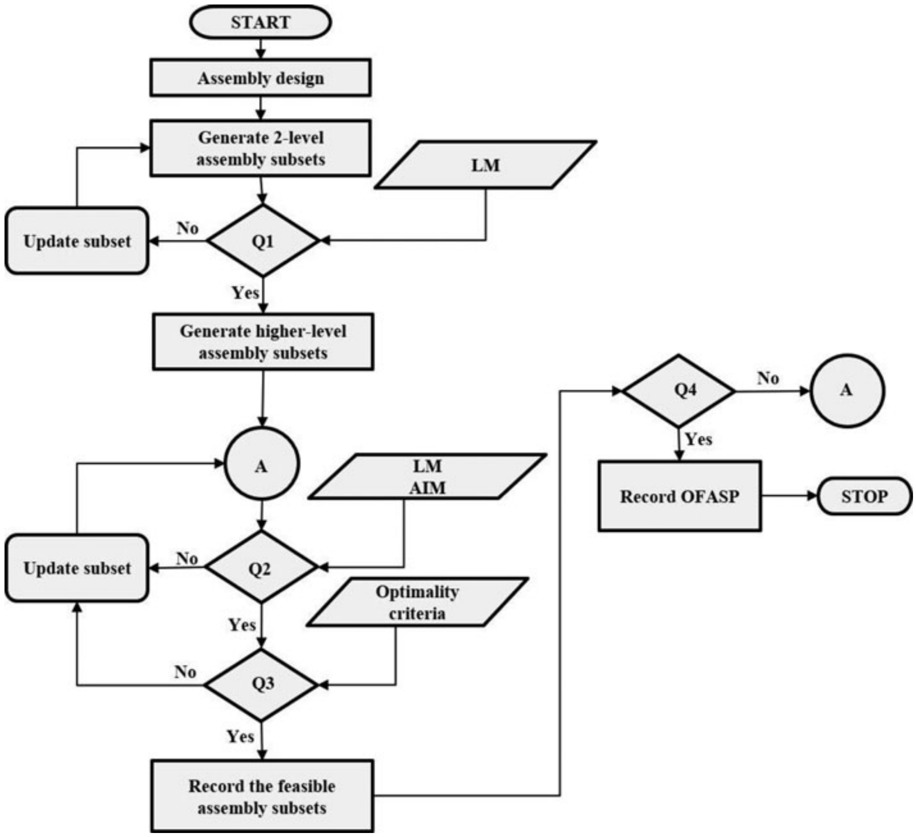

Fig. 1. Structural outline of the proposed method.

Table 2. Description of the conditions used in this method

Q1	Assembly attribute for a 2-level subset (Yes: Liaison predicate – True, Else No)
Q2	Assembly attribute for a higher-level subset (Yes: Liaison predicate, Geometric feasibility predicate – True, Else No)
Q3	To identify similar subsets with the most negligible fitness value (Yes – The fitness value is minimum; Else, Delete the redundant subset and go for the following subset generation)
Q4	All parts in the product are finished (Yes – Record the OFASP; Else, Generate the following higher-order subset)

Table 3. Representation and retrieval of assembly relations

Assembly relation	Representation	Retrieval
Liaison matrix (LM)	LM (P_i, P_j) = *1, If* part "*i*" and part "*j*" are in contact = 0, *otherwise*	Contact analysis
Assembly interference matrix (AIM)	AIM *(dir,* P_i, P_j*) = 1, If* in the presence of P_i, P_j can be disassembled along a specific direction, "*dir.*" = *0, otherwise*	Snap clash analysis

shown in Table 3, reads the conflict elements having values other than zero and tests for assembly interference along the cartesian directions through iteration. Equations (1)–(3) validate the OFASP using the above-mentioned assembly relations.

$$\begin{aligned} &\mathrm{AS}[2] = P_i + P_j \ \forall\ i \neq j, \\ &\text{If } \mathrm{LM}(P_i, P_j) = 1, \end{aligned} \tag{1}$$

where $i, j \in (1, 2, 3, \ldots n)$

$$\begin{aligned} &\mathrm{AS}[k] = \mathrm{AS}\ [k-1] + P_j, \\ &\text{If } \mathrm{LM}(P_i, P_j) = 1;\ P_i \in \mathrm{AS}\ [k-1]\ \forall\ i \in k-1, \\ &\text{If } \sum_{i=1}^{k-1} \mathrm{AIM}(\mathrm{dir}, P_j, P_i) = i - 1, \end{aligned} \tag{2}$$

where $\mathrm{dir} \in (1, 2, \ldots 6)$

$$\sum_{i=1}^{n} (\mathrm{DC}_i)_{\min}, \tag{3}$$

where n is the number of parts of a product and DC_i is the number of direction changes.

Implementation

An optimal solution is needed to find out without considering the tooling to acknowledge the influence of tooling in generating OFASP. Different assembly relations needed to be extracted, such as a liaison matrix, an axis-aligned bounding box with part geometry data, and assembly interference matrices. Figure 2 depicts a 3D CAD (CATIA platform) model named bench vice consisting of seven components. The necessary assembly relations, such as the liaison matrix (contact information about the parts of a product) and assembly interference matrix along six cartesian directions, are extracted through the CATIA environment with the help of programmed macros. Furthermore, the proposed algorithms for generating optimal assembly sequence planning are also tested using the same environment.

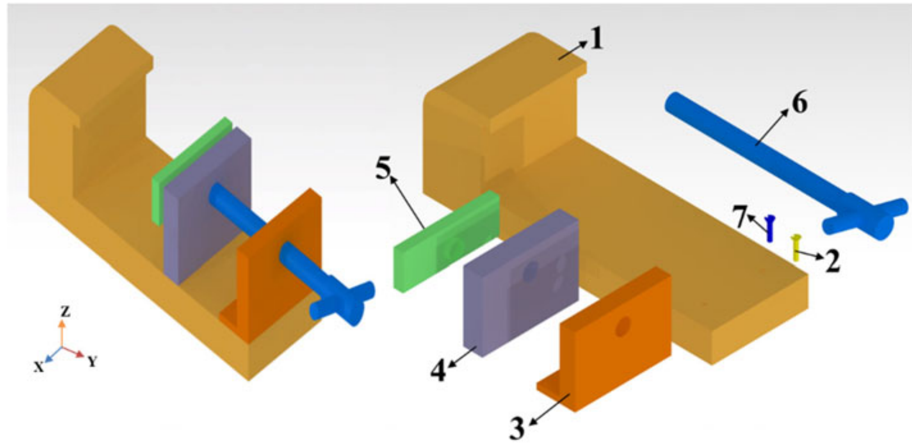

Fig. 2. 7-part bench vice assembly.

(a) Assembled view (b) Exploded view with nomenclature

Table 4. Liaison matrix for the bench vice

0	1	1	1	0	0	1
1	0	1	0	0	0	0
1	1	0	0	0	1	1
1	0	0	0	1	1	0
0	0	0	1	0	1	0
0	0	1	1	1	0	0
1	0	1	0	0	0	0

Table 5. Axis-aligned bounding box (AABB) of part geometry

	Minimum coordinate values (mm)			Maximum coordinate values (mm)		
Part no	X_1	Y_1	Z_1	X_2	Y_2	Z_2
1	−25	−0.5	0	25	150	50
2	14	134	10	17	138	20
3	−25	130	15	25	150	50
4	−25	92	15	25	102	50
5	−25	84	33	25	92	50
6	−21	89	40	21	199	41
7	−17	134	10	−14	138	20

The liaison matrix (LM) is extracted by following the necessary conditions given in Eq. (1). Table 4 represents the result LM for the above CAD model. The DMU (Digital Mock-Up) optimizer provided the bounding box values. Table 5 shows the AABB for the 7-part bench vice, including the minimum and maximum coordinates along the three dimensions (X, Y, and Z).

Table 6 presents the geometric feasibility (GF) through interference matrices along with $\pm X$, $\pm Y$, and $\pm Z$ directions. After extracting all the essential data, the OFASP, as shown in Table 7, is generated by employing the optimality criteria.

Practical infeasibility of solution

The generated optimal assembly sequence plan is going to verify its feasibility by considering tooling. Figure 3 tests whether the generated OFASP is feasible or not by considering assembly tools (screwdrivers) and robotic grippers (grippers). Additionally, the construction of the generation of feasible and infeasible subsets is broken down into individual steps and depicted in Figure 3.

Figure 3a indicates that the gripper attached to part 3 can be assembled to part 1 (base part) along the ($-Z$) direction. Similarly, a screwdriver affixed with part 2 can be appended to the (1-3) subset along a collision-free path, as shown in Figure 3b. Part 4 can be assembled to form a (1-3-2) subset along the ($-Z$) direction (see Fig. 3c). However, the subset (1-3-2-4-5) becomes infeasible as a collision occurs while positioning part 5 to part 4, as displayed in Figure 3d.

Figure 4 provides more clarity regarding the occurrence of interference between the appended parts 4 and 5. Figure 4a shows that part 5 can be assembled to its appropriate location when the presence of the gripper is ignored. However, part 5 cannot be appended to the (1-3-2-4) subset as the gripper is interfering with part 4, as indicated by Figures 3d, 4b. The interference (with a clash value of −0.48) during assembling is observed between the tool holding the appended part (part 5) and the pre-existing part (part 4). Thus, the subset (1-3-2-4-5) becomes infeasible as a collision occurs while positioning part 5 to its final position.

Although the OFASP generated by the traditional approach is theoretically valid, it cannot be applied to real assembly-based industrial applications due to the non-consideration of the tool predicate.

Generation of TIAABB and TIAIMs

It is evident that improved assembly sequence planning should be designed for the actual case situations. The proposed method considered a novel assembly attribute by considering tool geometry. The soundness of the proposed approach is validated using a 13-part 3D CAD model. Figure 5 shows the assembled and exploded view of a 13-part CAD product.

The LM, as shown in Table 8, describes the contact information of the parts of a product. The bounded box that is used for

Table 6. Assembly interference matrices

(+*X*) direction							(−*X*) direction							(+*Y*) direction						
0	0	1	1	1	1	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0
0	0	0	1	1	1	1	0	0	0	1	1	1	0	0	0	0	1	1	1	1
1	0	0	1	1	0	0	1	0	0	1	1	0	0	1	0	0	1	1	0	0
1	1	1	0	1	0	1	1	1	1	0	1	0	1	1	0	0	0	1	0	0
1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	0	0	0	0	1
1	1	0	0	0	0	1	1	1	0	0	0	0	1	1	1	1	1	1	0	1
0	0	0	1	1	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	0
(−*Y*) direction							(+*Z*) direction							(−*Z*) direction						
0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
0	0	0	0	1	1	1	1	0	1	1	1	1	1	0	0	0	1	1	1	1
0	0	0	0	0	1	0	1	0	0	1	1	0	0	0	1	0	1	1	0	1
0	1	1	0	0	1	1	1	1	1	0	1	0	1	0	1	1	0	1	0	1
0	1	1	1	0	1	1	1	1	1	1	0	0	1	0	1	1	1	0	0	1
0	1	0	0	0	0	1	1	1	0	0	0	0	1	0	1	0	0	0	0	1
0	1	0	0	1	1	0	1	1	1	1	1	1	0	0	1	0	1	1	1	0

Table 7. Optimal feasible assembly sequence plan (OFASP)

Sl. No	OFASP	Direction matrix	Number of DC
1	1-3-2-4-5-7-6	−*Z*, −*Z*, −*Z*, −*Z*, −*Z*, −*Z*, −*Y*	1

generating OFASP in the previous method is not competent enough to deliver a solution related to real-life assembly sequence planning problems. Therefore, the typical bounding box of the part needs to be upgraded to a tool or gripper-integrated axis-aligned bounding box. We can observe that the parts which are needed to be appended require to design along with the

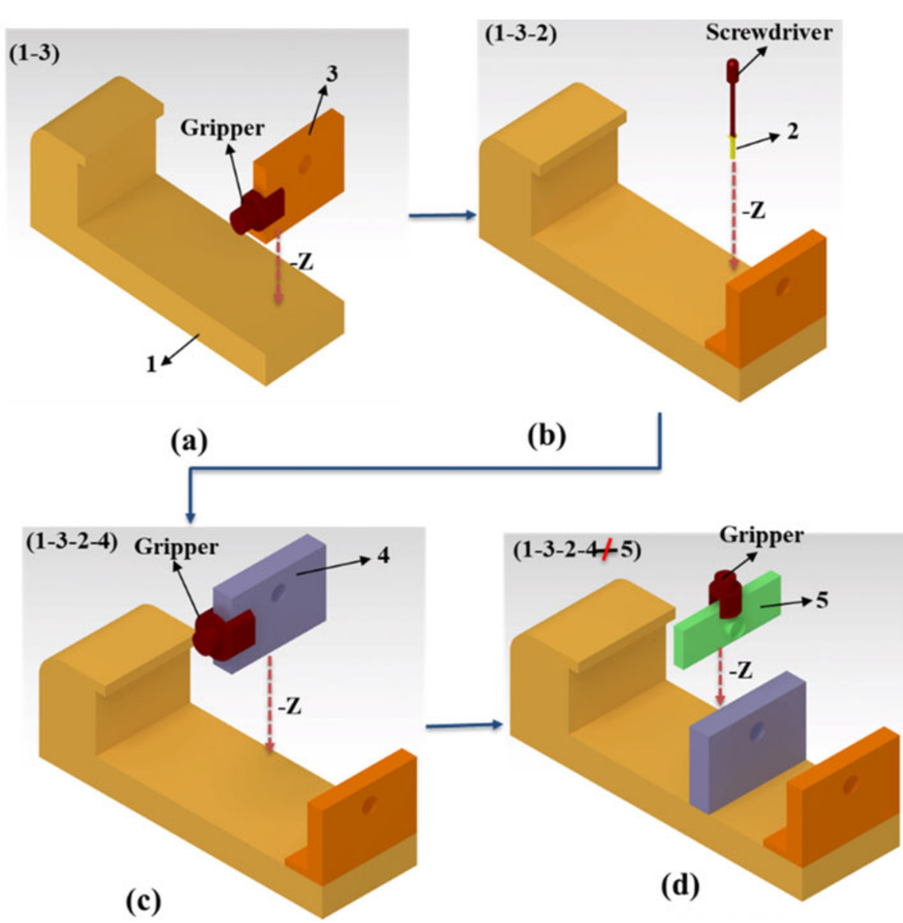

Fig. 3. Practical infeasibility of the generated OFASP.

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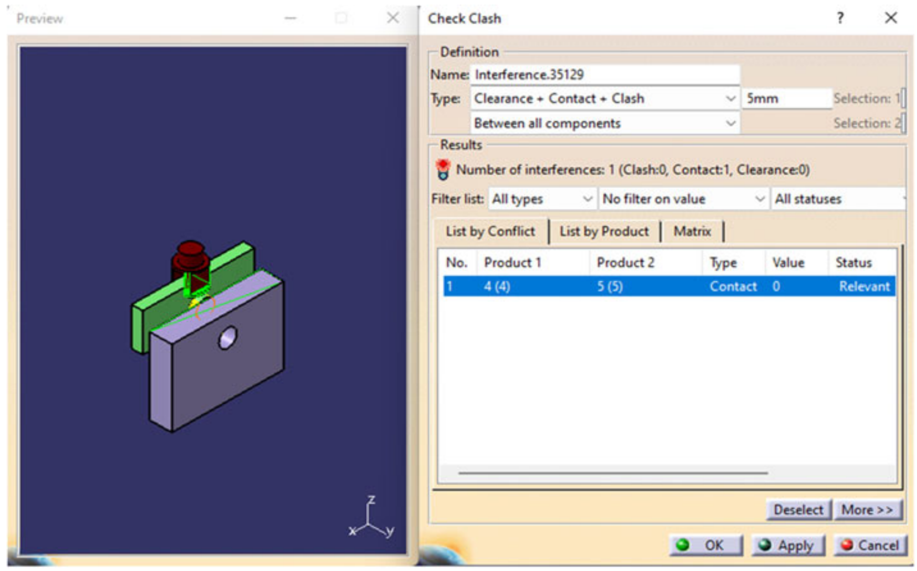
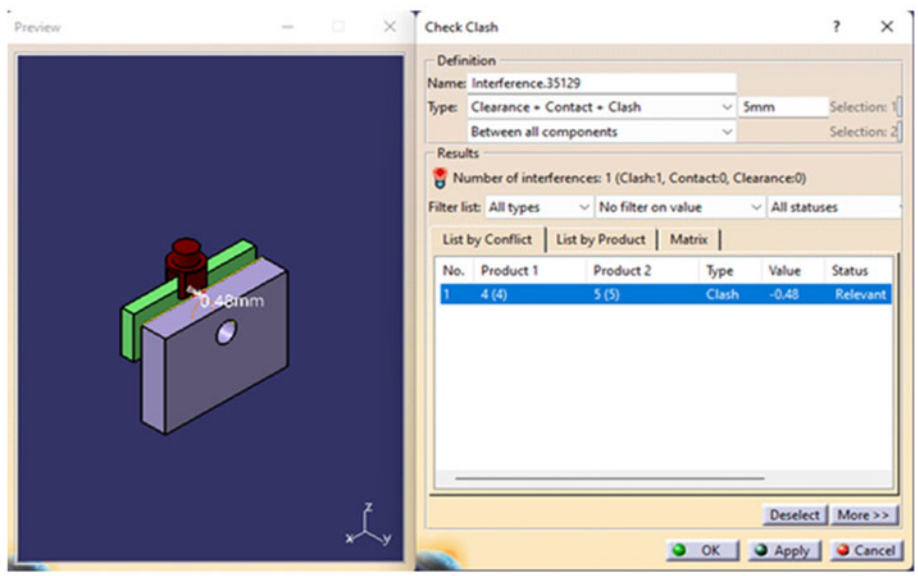


(a) Clash result of part 4 and part 5



(b) Clash result of part 4 and gripper holding part 5

Fig. 4. Clash test results between parts 4 and 5.

assembly tool or robotic gripper that is associated with it. Similar to the typical approach, the current TIAABB needed to be formulated as follows.

$$\text{Bounding Box (BB) } [P(i)] = (X_{L_i} Y_{L_i} Z_{L_i}, X_{H_i} Y_{H_i} Z_{H_i}), \quad (4)$$

(*P(i)* is a stationary part and without tools/gripper)

$$\begin{aligned} BB[P(j)] = &\{\min(X_{L_j}, X_{j_t}),\ \min(Y_{L_j}, Y_{j_t}),\ \min(Z_{L_j}, Z_{j_t})\}, \\ &\{\max(X_{H_j}, X_{j_t}),\ \max(Y_{H_j}, Y_{j_t}),\ \max(Z_{H_j}, Z_{j_t})\}, \end{aligned} \quad (5)$$

(*P(j)* is a moving part with tools/grippers)

Figure 6a–6c shows a few examples of the preceding description of bounding boxes for a set of primary components, with and without consideration of tooling (robotic gripper or assembly tool). The parts (part 8 and part 9) shown below are taken from Figure 6 for better visual analysis. Figure 6a represents the bounding boxes of parts 8 and 9 without tools, Figure 6b represents the bounding boxes of part 9 with tools and part 8 without tools, and Figure 6c represents the bounding boxes of part 8 with tools and part 9 without tools.

The TIAABB proposed is comparatively less computational. The TIAABB is employed to compute the distance between two parts where one part is at its result position and another need to be moved iteratively by a small unit distance to test for collision.

Table 5 shows the bounding box coordinates to determine the AIM of the part in the presence of other parts without considering tooling. Table 5 is extracted based on the part data only, whereas Table 9 is prepared considering tools or grippers along with the affix parts. The procedure to calculate the bounding box is the same, but the conditions are different. However, two

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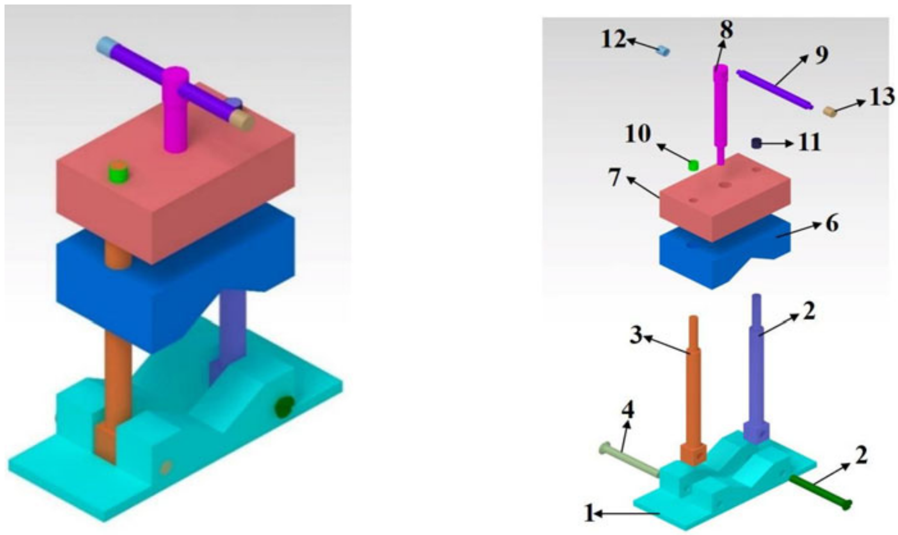

(a) Assembled view (b) Exploded view with nomenclature

Fig. 5. 13-part CAD model.

Table 8. Liaison matrix (LM)

0	1	1	1	1	0	0	0	0	0	0	0	0
1	0	0	0	1	1	1	0	0	0	1	0	0
1	0	0	1	0	1	1	0	0	1	0	0	0
1	0	1	0	0	0	0	0	0	0	0	0	0
1	1	0	0	0	0	0	0	0	0	0	0	0
0	1	1	0	0	0	0	1	0	0	0	0	0
0	1	1	0	0	0	0	1	0	1	1	0	0
0	0	0	0	0	1	1	0	1	0	0	0	0
0	0	0	0	0	0	0	1	0	0	0	1	1
0	0	1	0	0	0	1	0	0	0	0	0	0
0	1	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0	0

scenarios of the TIAABB are scanned when considering tooling to ensure assembly interference for the current case. First, as shown in Figure 6b, the condition for the interference of $P(i)$ (part 8) (appended part) is required to be checked in the presence of $P(j)$ (part 9), where the coordinate values of $P(j)$ are without considering tooling and the coordinate values of $P(i)$ is with considering tooling. Second, the GF of $P(j)$ (appended part) needed to be checked in the presence of $P(i)$, where $P(i)$ data is without considering tooling and $P(j)$ data is with considering tooling, as shown in Figure 6c. The TIAABB includes tooling-related and non-tooling-related coordinate values shown in Table 9. TIAABB is calculated using Eqs (4) and (5). These conditions can be altered and vice versa to attain symmetric elements.

Similarly, a set of matrices known as TIAIM depicted in Table 10 needs to be extracted along all the principal axes. The extraction of TIAIM is vital and includes information about the feasible direction of the appended part (the part with an assembly tool or robotic gripper) in the presence of other parts.

Practically feasible solution

The extracted TIAABB and TIAIM can now be used to determine assembly sequence-related issues. The base part must be assembled first, followed by the other. As a result, the base part must be determined. The number of assembly sequences obtained is less and practically feasible compared with the typical method where the effect of tool and gripper is not considered. Table 11 shows the generated OFASP.

The solution obtained in this approach is practically feasible. The above OFASP can be verified for a practical feasibility test.

Figure 7 represents the OFASP considering tooling in a visual format. The presentation of each feasible subset follows the previous one. It shows the feasible directions in which the tools (gripper or screwdriver) can move to position the appended part correctly. The tools are represented as yellow color. The number of directional changes in the proposed approach is used as the optimality criteria. Hence at every

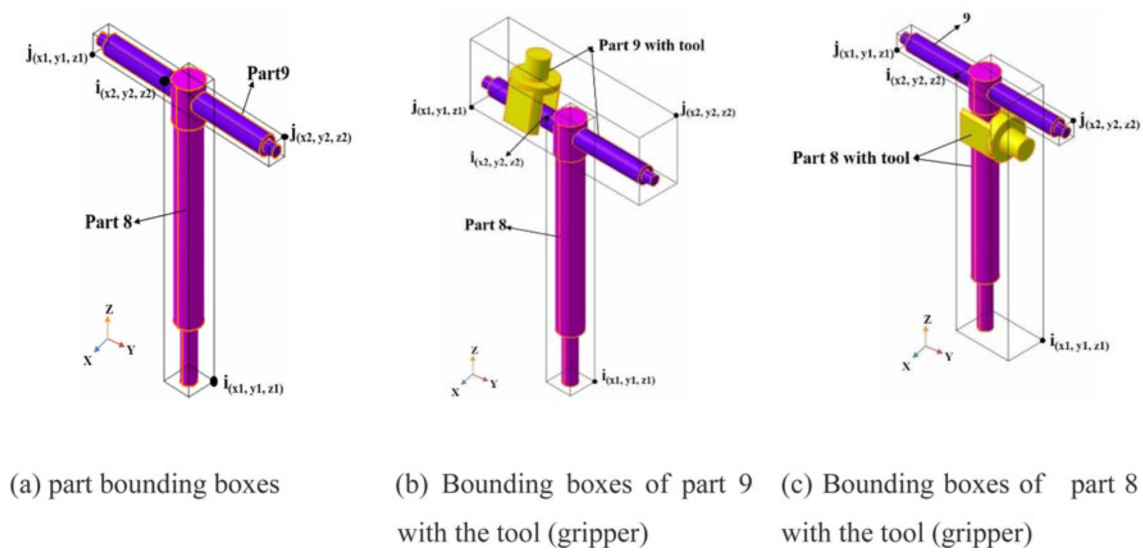

Fig. 6. Representation of bounding box.

Table 9. Tool integrated axis-aligned bounding box (TIAABB)

Parts no	X_1	Y_1	Z_1	X_2	Y_2	Z_2	X_1^1	Y_1^1	Z_1^1	X_2^2	Y_2^2	Z_2^2
1	−50	−20	−2	50	20	17	−50	−20	−7	61	20	17
2	−29	−5	0	−19	5	111	−36	−8	0	−19	8	111
3	19	−5	0	29	5	111	18	−5	0	30	12	111
4	20	−22	2	29	20	11	20	−57	2	29	20	11
5	−30	−20	5	−19	22	8	−30	−20	5	−19	57	8
6	−30	−20	52	30	20	74	−30	−20	52	30	20	81
7	−30	−20	86	30	20	106	−30	−21	86	30	20	113
8	−4	−4	59	4	4	134	−6	−4	59	6	14	134
9	−3	−28	128	3	28	132	−9	−28	128	7	25	143
10	23	−4	106	26	4	111	22	−7	106	26	4	114
11	−26	−4	106	−23	4	111	−27	−7	106	−20	4	114
12	−3	−31	128	3	−25	133	−4	−36	126	6	−25	135
13	−4	25	130	4	31	131	−8	25	131	5	33	132

subset generation phase, a similar assembly subset with a higher fitness value will be eliminated and finally yields single or multiple optimal solutions with the number of directional changes as the objective function. For the case study, a 13-part product, only one solution is obtained with two directional changes.

Conclusion and future scope

In this research, an OFASP by considering tool geometry (assembly tools and robotic grippers) is proposed to implement the scheme at the physical assembly level. The proposed technique can find a solution that generates a logical solution to a new product/existent product with the tool consideration. The inefficiency of the conventional approaches is demonstrated with the help of a 7-part mechanical bench vice. The issue was well addressed by proposing a novel TIAIM approach. The proposed approach is validated for its completeness by considering a 13-part assembled model. The crucial observations from the proposed research are as follows.

1. The proposed method considers the tool geometry and tool feasibility to perform the assembly operation.
2. Unlike the cited literature, the current method generates the most feasible solution that can be practically implemented on any physical product.

Furthermore, the proposed method can be expanded to generate robotic assembly sequence plans for the product with soft/flexible components. In addition, the proposed method can be integrated with an augmented reality platform for assembly instruction generation.

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Table 10. Tool integrated assembly interference matrices (TIAIMs)

(+X) direction													(−X) direction												
0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	1	1	0	0	0	1	1	1	0	1	1
0	1	0	0	1	0	0	1	1	0	1	1	1	0	0	0	0	0	0	0	0	1	0	0	1	1
0	1	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	1	1	0	1	1	1	1	1	1	1	1
1	0	0	1	1	0	1	0	1	1	1	1	1	1	0	0	1	1	0	1	0	1	1	1	1	1
1	0	0	1	1	1	0	0	1	0	1	1	1	1	0	0	1	1	1	0	0	1	1	0	1	1
1	1	0	1	1	0	0	0	0	0	1	1	1	1	0	1	1	1	0	0	0	0	1	0	1	1
1	1	1	1	1	1	1	0	0	1	1	0	0	1	1	1	1	1	1	1	0	0	1	1	0	0
1	1	0	1	1	1	1	1	1	0	1	1	1	1	0	0	1	1	1	1	0	1	0	0	1	1
1	0	0	1	1	1	1	0	1	0	0	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1
1	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	0	1
1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1	1	0
(+Y) direction													(−Y) direction												
0	0	0	1	0	1	1	1	1	1	1	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1
0	0	1	1	0	0	0	1	1	1	0	1	1	0	0	1	1	1	0	0	1	1	1	0	1	1
0	1	0	1	1	0	0	1	1	0	1	1	1	0	1	0	0	1	0	0	1	1	0	1	1	1
0	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1
1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	1	1	0	1	1	1	1	1	1	1	1
1	0	0	1	1	0	1	0	1	1	1	1	1	1	0	0	1	1	0	1	0	1	1	1	1	1
1	0	0	1	1	1	0	0	1	1	1	1	1	1	0	0	1	1	1	0	0	1	1	1	1	1
1	1	1	1	1	0	0	0	1	1	1	1	0	1	1	1	1	1	0	0	0	1	1	1	0	1
1	1	1	1	1	1	1	0	0	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1	0	1
1	1	0	1	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1
1	0	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1
1	1	1	1	1	1	1	0	0	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	0	1
1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	0	1	1	0	0

(*Continued*)

Table 10. (*Continued.*)

(+Z) direction													(−Z) direction												
0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1	0	0	1	1	1	1	1	1	1	1
1	0	1	1	0	0	0	1	1	1	0	1	1	0	0	1	1	0	1	1	1	1	1	1	1	1
1	1	0	0	1	0	0	1	1	0	1	1	1	0	1	0	0	1	1	1	1	1	1	1	1	1
0	1	0	0	1	0	0	1	1	0	1	1	1	0	1	0	0	1	1	1	1	1	1	1	1	1
0	0	1	1	0	0	0	1	1	1	0	1	1	0	0	1	1	0	1	1	1	1	1	1	1	1
1	1	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	0	0	1	0	1	1	1	1	1
1	1	1	1	1	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	1	1	1	1
1	1	1	1	1	1	1	0	0	1	1	1	1	0	1	1	1	1	0	0	0	0	1	1	1	1
1	1	1	1	1	1	1	0	0	1	1	0	0	0	1	1	1	1	0	0	0	0	1	1	0	0
1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	0	0	1	0	0	1	1	0	1	1	1
1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	1	1	0	0	0	1	1	1	0	1	1
1	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	0	1
1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1	1	0

https://doi.org/10.1017/S0890060422000282 Published online by Cambridge University Press

Table 11. Optimal feasible assembly sequence plan (OFASP) considering tooling

Sl. No	Final sequence	Feasible direction	NDC
1	1-2-3-6-7-10-11-8-9-12-4-5-13	−Z, −Z, −Z, −Z, −Z, −Z, −Z, −Z, +Y, +Y, +Y, −Y, −Y	2

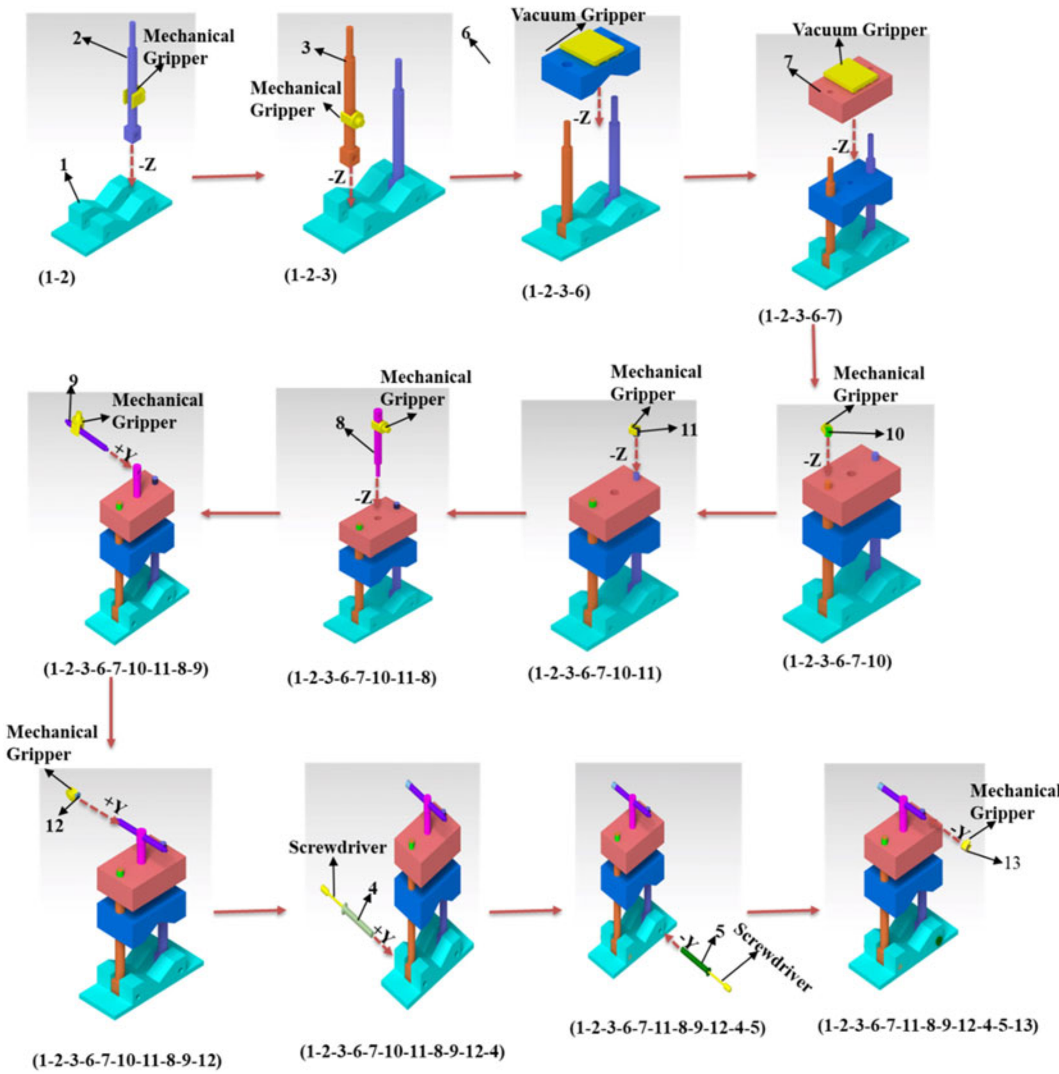

Fig. 7. Pictorial representation of obtained solution by considering tooling.

Financial support. There are no funders to report for this submission.

Conflict of 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.

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