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Efficient hybrid group search optimizer for assembling printed circuit boards

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Research Article

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Abstract

Assembly optimization of printed circuit boards (PCBs) has received considerable research attention because of efforts to improve productivity. Researchers have simplified complexities associated with PCB assembly; however, they have overlooked hardware constraints, such as pick-and-place restrictions and simultaneous pickup restrictions. In this study, a hybrid group search optimizer (HGSO) was proposed. Assembly optimization of PCBs for a multihead placement machine is segmented into three problems: the (1) auto nozzle changer (ANC) assembly problem, (2) nozzle setup problem, and (3) component pick-and-place sequence problem. The proposed HGSO proportionally applies a modified group search optimizer (MGSO), random-key integer programming, and assigned number of nozzles to an ANC to solve the component picking problem and minimize the number of nozzle changes, and the place order is treated as a traveling salesman problem. Nearest neighbor search is used to generate an initial place order, which is then improved using a 2-opt method, where chaos local search and a population manager improve efficiency and population diversity to minimize total assembly time. To evaluate the performance of the proposed HGSO, real-time PCB data from a plant were examined and compared with data obtained by an onsite engineer and from other related studies. The results revealed that the proposed HGSO has the lowest total assembly time, and it can be widely employed in general multihead placement machines.

Introduction

Multihead placement machines, which can be adapted to process various components, are the most flexible machines for assembling printed circuit boards (PCBs). However, the production efficiency of multihead placement machines is limited. Problems in the related optimization of production efficiency can be classified into three typical subproblems:

(1) Auto nozzle changer (ANC) assembly problem;
(2) Nozzle setup problem;
(3) Component pick-and-place sequence problem.

Various optimization methods have been developed to address these subproblems. For example, Grunow *et al.* (2004) proposed a three-step heuristic algorithm to solve the pick-and-place problem. For multihead placement machines with a specific place sequence, Knuutila *et al.* (2007) employed a greedy algorithm to optimize nozzle assignment and reduce the number of picks. The concept of component batches was employed by Ashayeri *et al.* (2011) to formulate a multihead placement optimization problem for a mixed integer program designed to balance placement head loadings and reduce the number of nozzle changes. Ball and Magazine (1998) defined the place sequence for a multihead machine as a postman problem. Leipälä and Nevalainen (1989) considered a place sequence for a multihead machine to be a traveling salesman problem. Kumar and Li (1995) used linear programming for feeder assignment and place sequence, where the local search was accompanied by 2 and 3 changes. Recently, meta-algorithms, including greedy algorithms, genetic algorithms (GAs), and particle swarm optimization (PSO), have been successfully applied to multihead machine problems. For example, Fu and Su (2000) employed a GA, simulated annealing algorithm, and Tabu search-based algorithm to solve a dynamically combinatorial problem. Moreover, Loh *et al.* (2007) applied a GA to auto nozzle changer (ANC) assignment and place sequence for a placement machine. Jiang *et al.* (2010a, 2010b, 2010c) employed an improved ant colony algorithm to optimize place sequence and minimize nozzle changes. A memetic algorithm was proposed to solve a placement machine scheduling problem (Neammanee and Reodecha, 2009). For PCB assembly, Du *et al.*, focused on feeder assignment and component pick-and-place sequence problems and presented a hybrid GA combining heuristic and genetic algorithms for evaluating the performance of feasible solutions (Du and Li, 2008). In another study of multihead placement

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machines, a GA with a distinct crossover operation and mutation operators was applied to yield satisfactory results on robot assembly time by reducing movement distance of a feeder carrier and PCB table (Lin and Zhu, 2008). An efficient neural network approach was presented to minimize the cycle time of a schedule for a cyclic job shop problem (Kechadi *et al.*, 2013). Al-Anzi and Allahverdi focused on modeling a two-stage multimachine assembly scheduling problem by employing an artificial immune system to minimize total assembly time (Al-Anzi and Allahverdi, 2013). Other related studies include Smed *et al.*, 1999; Chen *et al.*, 2011; Chen and Shen, 2010; Jiang *et al.*, 2010a, 2010b, 2010c; Luo *et al.*, 2010; Zhang *et al.*, 2010; Alkaya and Duman, 2013; Chen *et al.*, 2012a, 2012b; Csaba and Nevalainen, 2015; Jensen, 2003; Chen and Chang, 1995; Park *et al.*, 2005.

Kim *et al.*, developed an ontology-based model representing morphological characteristics related to assembly joints (Kim *et al.*, 2009). A two-phase automatic generation of assembly plans was designed. First, a graph-based procedure with topological and geometric description provided a layout of an assembled product. Second, heuristic knowledge of mechanical components and assembly processes were used to plan selected assembly sequences (Kroll *et al.*, 1989). A new GA encoding scheme and selection criteria were proposed for automatic generation of electromechanical engineering designs (Peysakhov and Regli, 2003). Zeng *et al.* developed probability increment-based swarm optimization (PIBSO) through roulette wheel selection and probability updating to solve a PCB assembly optimization problem. PIBSO provides improved tour length and CPU running time (Zeng *et al.*, 2014). Chen and Wichman (1993) developed a novel system that integrated neural networks to capture a design concept and instigated a rule-based system for automatically generating an assembly plan. Intelligent selective disassembly with an ant colony algorithm has been used to solve combinatorial optimization problems (Wang *et al.*, 2003).

To simplify the investigated problems, the aforementioned studies have ignored some practical limitations of placement machines. This study aimed to overcome these limitations and the following hardware constraints: (1) component height restrictions, (2) time consumption for nozzle changes, (3) picking restrictions, (4) placing restrictions, (5) simultaneous pickup restrictions, and (6) component shape restrictions. Moreover, a hybrid group search optimizer (HGSO) is proposed to generate feasible and efficient scheduling solutions for PCB assembly.

Machine description

Surface mount technology (SMT) equipment, also termed placement machines, are the most crucial and complex equipment in SMT production. Figure 1 presents the multihead placement machine examined in this study. The machine has eight heads for eight nozzles, and different nozzles can be selected according to the shape of the component to be installed. One ANC accommodates 16 small nozzles and 4 large nozzles. For continuous assembly of components, 90 feeder slots are integrated using tape or stick feeders. The head moves along the X–Y axis to pick components from a feeder slot and place them at appropriate positions on the PCB. A pick-and-place cycle is completed when all the picked components are placed at their appropriate positions.

The primary parts of a placement machine are as follows:

(1) Head: Each head has one nozzle that can pick one component.
(2) Nozzle: A nozzle is installed on a head and used to pick components. A nozzle of a specified shape can only pick up components of the same shape.
(3) ANC: An ANC is designed for holding and exchanging nozzles.
(4) Feeder: A feeder stores and supplies components. Each feeder can store one component.
(5) Slot: A slot is designed for feeder insertion.
(6) Feeder station: A feeder station holds feeders.
(7) PCB table: A PCB table is designed to fix PCBs.
(8) Arm: An arm moves the heads in an X–Y axis direction to appropriate positions for picking and placing components.
(9) Fly vision: This is designed to ensure that the components are correct and defect-free and to relocate X–Y coordinates.

Problem definition

Restrictions of placement machine

To generate an efficient schedule for the placement machine in this study, the following restrictions were considered:

(1) Component height: The component heights are different. To avoid collisions with already installed components, components with lower heights should be placed with higher priority.
(2) Nozzle setup: Components with different shapes require nozzles with the corresponding shapes, but changing the nozzles increases production time and cost.
(3) Picking restrictions: The moving distance of each head is practically limited. For example, in Figure 2a, b, heads 3–8 cannot reach components in slot c, and heads 1–2 cannot pick components in slot d, respectively.
(4) Placing restrictions: Not all heads can place components in all slots. For example, in Figure 3a, heads 7–8 cannot place components at position a, and in Figure 3b, heads 1–2 cannot place components at position b.
(5) Simultaneous pickup restrictions: Simultaneous pickup is essential for reducing the number of pickups and therefore production time. The following conditions are necessary for simultaneous pickup:
    a. Components are stored in the tape feeder.
    b. One feeder slot between component feeders.
    c. Picking angles for all components are the same.
    d. The same camera is used for fly vision.

In the first run, eight heads, excluding heads #5 and #6, can simultaneously pick components R6, H2, M2, H3, M3, and H5 (Fig. 4a). In the second run, components H2 and M2 can be picked by heads #5 and #6 (Fig. 4b). The increased number of simultaneously picked components reduces the number of pickups required.

(6) Component shape restrictions: When a component is larger than 15 mm, it requires the space of more than one head. In such cases, the adjacent head cannot be used. In our example in Figure 5, the sizes for components V1 and V2 are 36 and 45 mm, respectively; therefore, heads #2, #4, and #6 are idle when heads #3 and #5 are used (Fig. 5).

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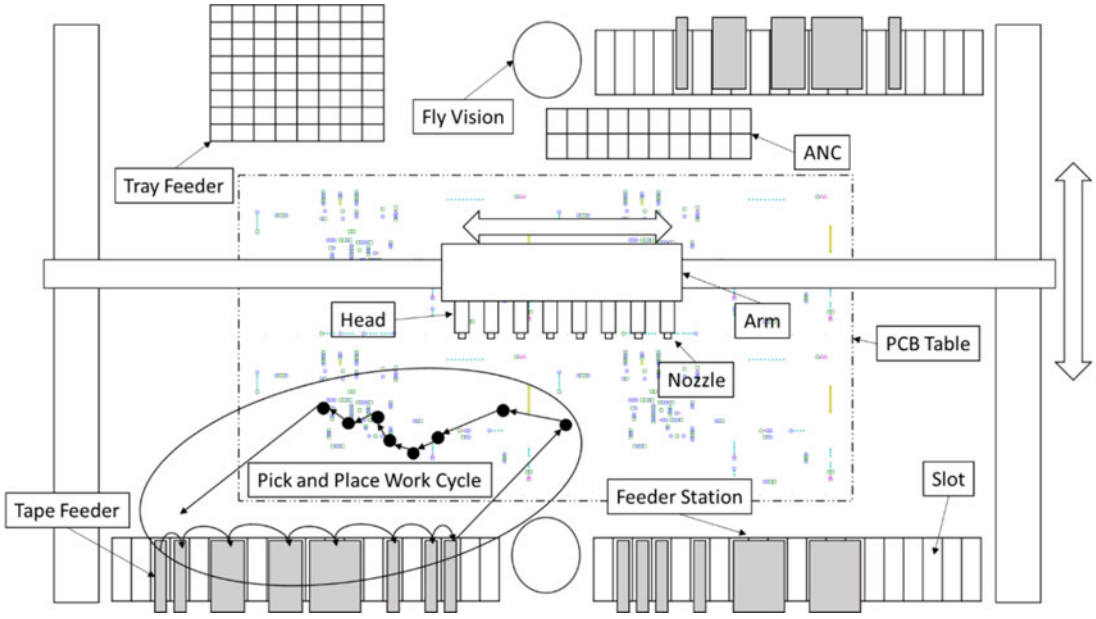


Fig. 1. Schematic of the multihead placement machine used in this study

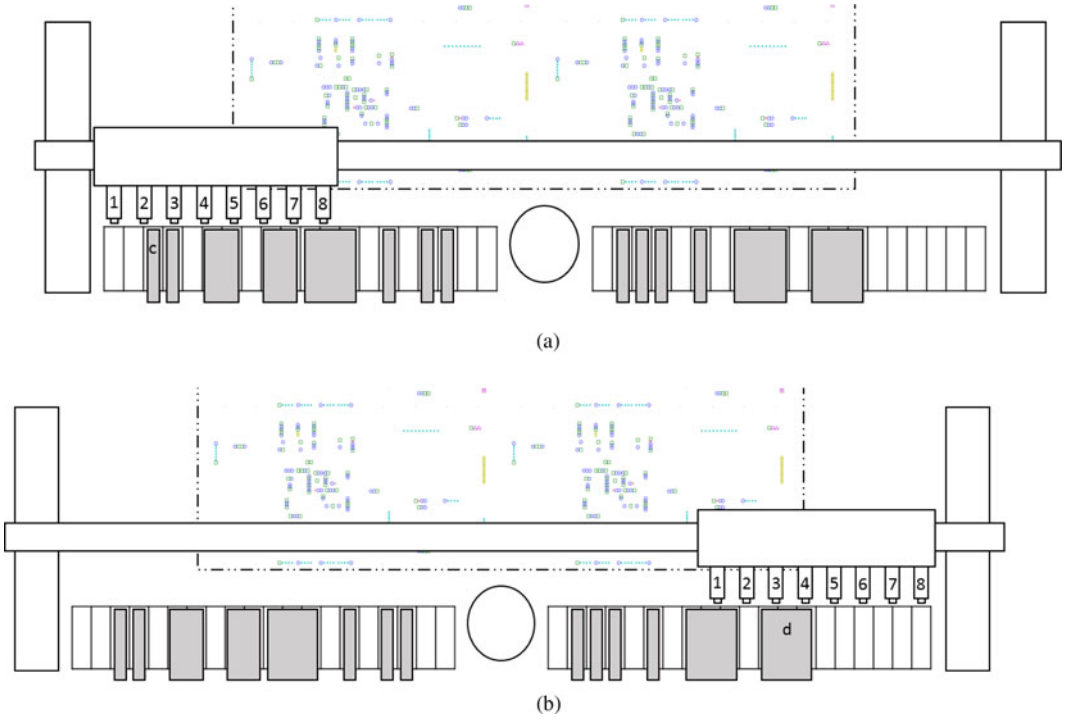


Fig. 2. Picking restrictions

Problem statement

This study aimed to provide efficient scheduling with minimum production time for assembling PCBs. An interview with the site engineer responsible for the placement machine revealed that although the component positions in the feeders are not fixed, the arrangement seldom varies in practice. If the same components are used in different PCBs, their positions in the feeders are generally retained. The following three interacting problems are discussed herein:

(1) ANC assignment: component pick-and-place sequences interact with each other to enable determination of the optimal ANC.

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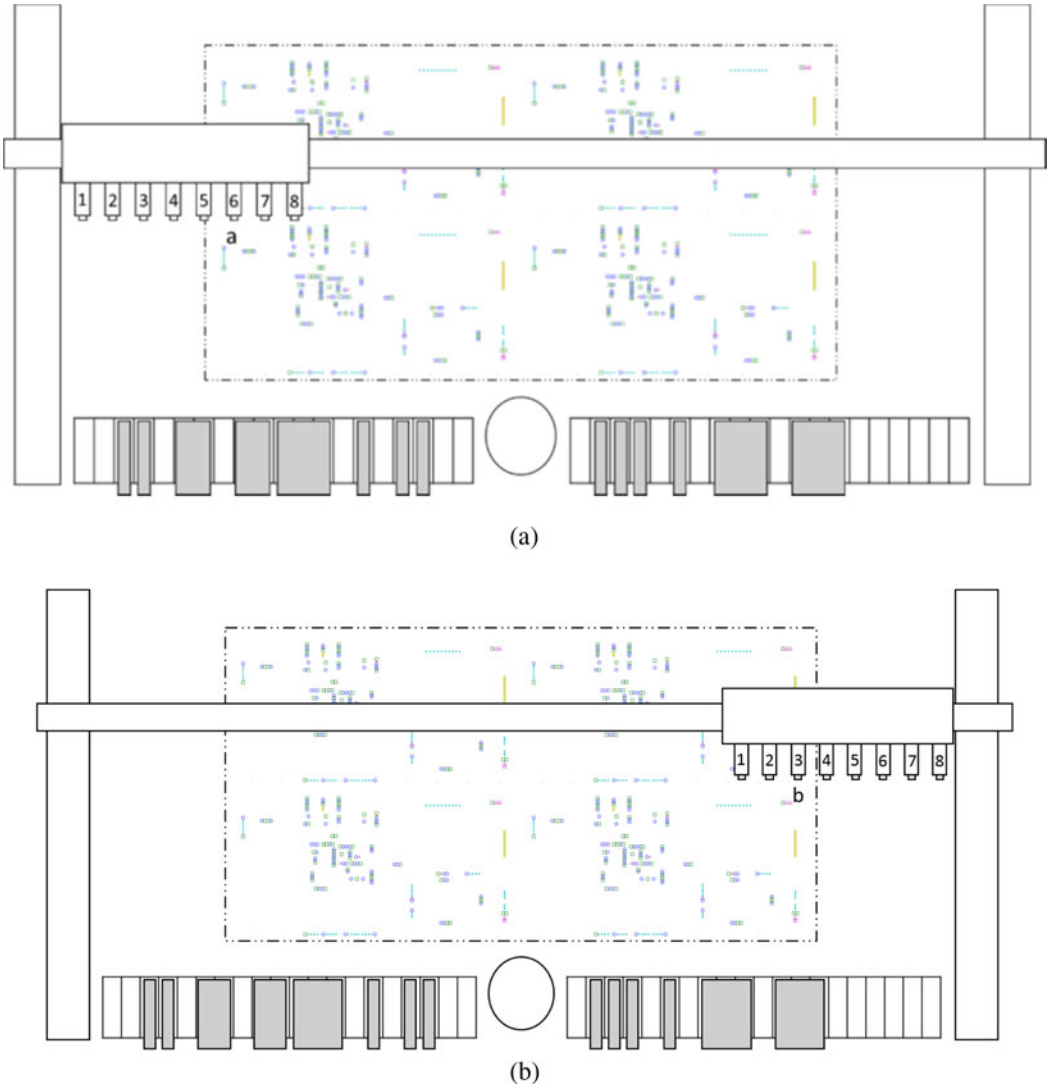


Fig. 3. Placing restrictions

(2) Nozzle assignment: The nozzle must be assigned by considering the pick, place, component height, and simultaneous pickup restrictions to reduce the number of pickups and nozzle changes, thereby reducing the total assembly time.
(3) Component pick-and-place sequence: The component pick-and-place sequence must be optimized so that head movement for pick-and-place operations uses the shortest path.

Problem formulation

Considering limitations in the practical operation of a multihead placement machine, a mathematical model is proposed for optimizing the total assembly time, which includes pick time, place time, and ANC time. Eq. (1) can be applied to minimize the total assembly time for PCB production.

$$T_{\text{total}} = \sum_{c=1}^{NC}(T_{\text{pick}}(c))(+T_{\text{place}} + T_{\text{change}}) \tag{1}$$

where T_{total}, T_{pick}, T_{place}, and T_{change} are the total production time for PCB assembly, total pick time, total placing time, and total nozzle change time, respectively. T_{pick}, T_{place}, and $T_{\text{change}}$are given as follows:

$$T_{\text{pick}} = \begin{cases} \sum_{i=1}^{NP-1}(T(d(S_i,S_{i+1})) + T_z(\text{i}+1) + \text{TD}_{i+1} + \text{TP}_{i+1}), & c=1 \\ T(d(\text{PC}_N,S_1)) + T_z(1) + \text{TD}_1 + \text{TP}_1 + \\ \sum_{i=1}^{NP-1}(T(d(S_i,S_{i+1})) + T_z(i+1) + \text{TD}_{i+1} + \text{TP}_{i+1}), & \text{otherwise} \end{cases} \tag{2}$$

$$T_{\text{place}} = T(d(S_N,\text{PC}_1)) + T_z(1) + \text{TB}_1 + \text{TL}_1 + \sum_{j=2}^{N}(T(d(\text{PC}_{j-1},\text{PC}_j)) + T_z(\text{j}) + \text{TB}_j + \text{TL}_j) \tag{3}$$

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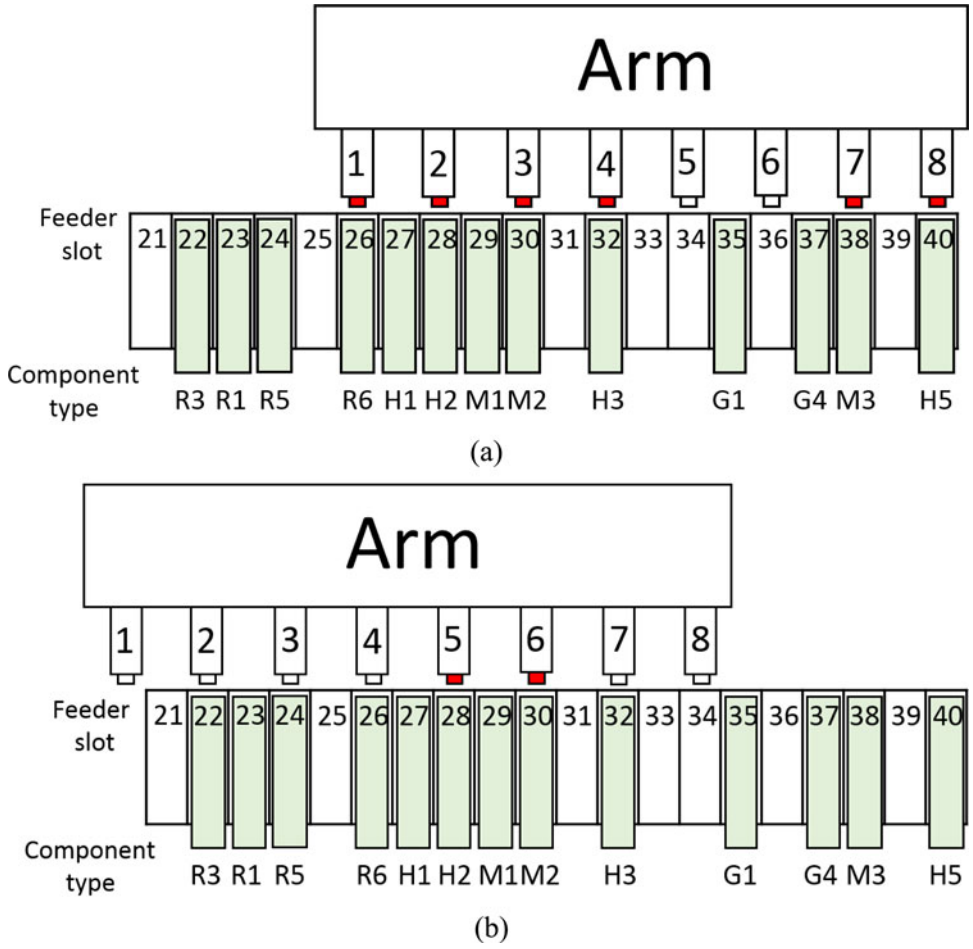


Fig. 4. Simultaneous pickups

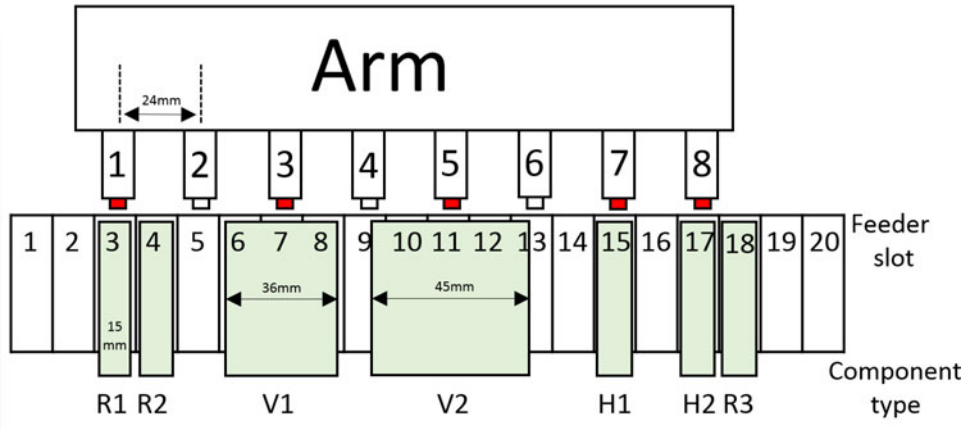


Fig. 5. Component shape restrictions

$$T_{\text{change}} = T(\mathrm{d}(PC_N, A_1)) + T(d(A_{CN}, S_1)) + \sum_{k=1}^{\mathrm{CN}} T(d(A_k, A_{k+1})) + \mathrm{TN}_k] \quad (4)$$

where $\mathrm{Min}(T_{\text{total}})$ indicates that the objective is to minimize the total assembly time; NC, N, and NP are the total number of cycles in the assembly, heads in the placement machine, and pickups in the assembly, respectively; and TD, TP, TB, and TN are the vacuum on delay time, total waiting time for picking components, total waiting time for placing components, load wait time, and

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total time for changing nozzles, respectively. Furthermore, CN is the total number of nozzle changes; PC is the component picking position; S is the position of the active slot; A is the position of nozzle change in the ANC; $d()$ is the movement distance of the head; $T()$ is the time required for head movement; and$T_z(c)$ is the movement time in both directions along the Z axis.

HGSO for scheduling optimization

The GSO is a heuristic algorithm that was developed in 2009 (He *et al*., 2009). The SO mimics the behavior of animals searching for food, resources, and places. The GSO reaches global optimum through a local search of team members. It involves few control parameters, and the associated calculations are easy. Under most circumstances, only slight adjustments are required to both parameters and team members in order to apply the GSO to different optimization problems.

Based on the GSO, an HGSO algorithm is proposed herein for optimizing PCB assembly time. The proposed HGSO overcomes several hardware limitations, including (1) component height restrictions, (2) time consuming nozzle changes, (3) picking restrictions, (4) placing restrictions, (5) simultaneous pickup restrictions, and (6) component shape restrictions. The proposed HGSO divides PCB assembly into three problems: the (1) ANC assembly problem, (2) nozzle setup problem, and (3) component pick-and-place sequence problem. The first step of the HGSO is to proportionally distribute nozzles to the ANC according to required nozzle usage, which is determined by the component picking sequence. The component heights must be considered to avoid collision (i.e., shorter components must be placed earlier). Then, the HGSO generates an efficient picking schedule by considering picking, simultaneous picking, component shape, and placing restrictions. Chaos local search and a population manager are utilized to increase the diversity of placing routes and reduce total PCB assembly time. Figure 6 presents the procedures of the proposed method.

Proportional distribution of nozzles to the ANC

During production, any head in the placement machine may require nozzle change to pick the subsequent component. The ANC has 20 cells, with 16 small and 4 large cells (Table 1). PCBs are different with different numbers of components. For efficient production, the nozzles must be assigned to the ANC before commencing operation. In this study, the nozzles were distributed to the ANC according to the number of pickups by each nozzle. Table 1 presents nozzle arrangement involving one large nozzle (ANV1) and four small nozzles (AN3, AN5, AN6, and AN7).

Step 1: Ensure that at least one nozzle is assigned in the ANC to each component in Table 2, namely ANV1, AN3, AN5, AN6, and AN7.

Step 2: Subtract the number of cells that have been occupied in step 1 (i.e., 20−5 = 15). Compute the number of nozzles required for each nozzle type (Table 3) according to the components to be picked up (Table 6).

Step 3: Ensure that the number of nozzles assigned for each type is not higher than the number of heads. For example, if the number of nozzles assigned for type AN3 exceeds the number of heads, reduce the number of nozzles to the maximum number of heads (Table 4).

Step 4: Repeat steps 2 and 3 until all cells in the ANC are occupied (Tables 5 and 6, Fig. 7).

HGSO algorithm

To avoid collision during component placement, shorter components must be placed earlier. In the following example, components with a height of 0.6–2.6 mm (see Table 7) are grouped together and can be arbitrarily placed if height restriction is 2 mm.

A random number between 0 and 1 is generated and assigned to each member for executing the GSO algorithm (Table 8). N and x_i are the total number of components and the i^{th} member in the GSO, respectively. Each member represents a scheduling solution.

The traditional GSO cannot be employed to schedule placement machines because this problem is a type of integer optimization. In this study, an MGSO with an added random key (Snyder and Daskin, 2006) was proposed for scheduling optimization of PCB assembly. Tables 9–11 illustrates the procedure. The first random number in Table 9 is 0.95. Component 6 is assigned to the first cell after considering component height, component shape, nozzle assignment, and picking restrictions. In Table 10, the initial solution with random numbers in Table 9 is adjusted by placing the elements in an ascending order: 0.12, 0.15, 0.75, 0.76, 0.88, 0.93, 0.95, and 0.99. Element 0 is assigned to the lowest random number (0.12), element 1 is assigned to the subsequent number (0.15), and so on (Table 11). Table 12 presents the solutions for the large components, where head #3 and #5 are idle in the first cycle because component 9 occupies the space beneath them.

The 2-opt method is employed to the solution of the initial path derived from Table 12. Table 13 presents the improved solution. A mathematical model that calculates the total assembly time is then applied to evaluate the performance of the probable solutions. Table 14 presents the final result.

Chaos local search

Chaos local search (Liu *et al*., 2005), which is a new optimization technique, is applied to improve MGSO evolution performance. Chaos local search has several advantages for obtaining the initial solution, such as sensitivity and dependence, which ensure the diversity and appropriate search behavior of the entire space. The chaos search formula is as follows:

$$x_{n+1} = \mu \times x_n(1 - x_n),\ 0 \le x_0 \le 1 \tag{5}$$

where μ and x are a control parameter and a random variable, respectively, with $n = 0,\ 1,\ 2,\ \ldots$ However, when $\mu = 4$, $x_0\{0,\ 0.25,\ 0.5,\ 0.75,\ 1\}$ can be applied to Eq. (5). Chaos is sensitive and dependent on initial conditions, and a slight initial difference can generate considerable variances given a long enough timeframe. The MGSO searches the entire space by using particular characteristics of chaos [Eq. (6)]:

$$cx_i^{(k+1)} = 4cx_i^{(k)}(1 - cx_i^{(k)}),\ i = 1,\ 2,\ \ldots\ldots, N \tag{6}$$

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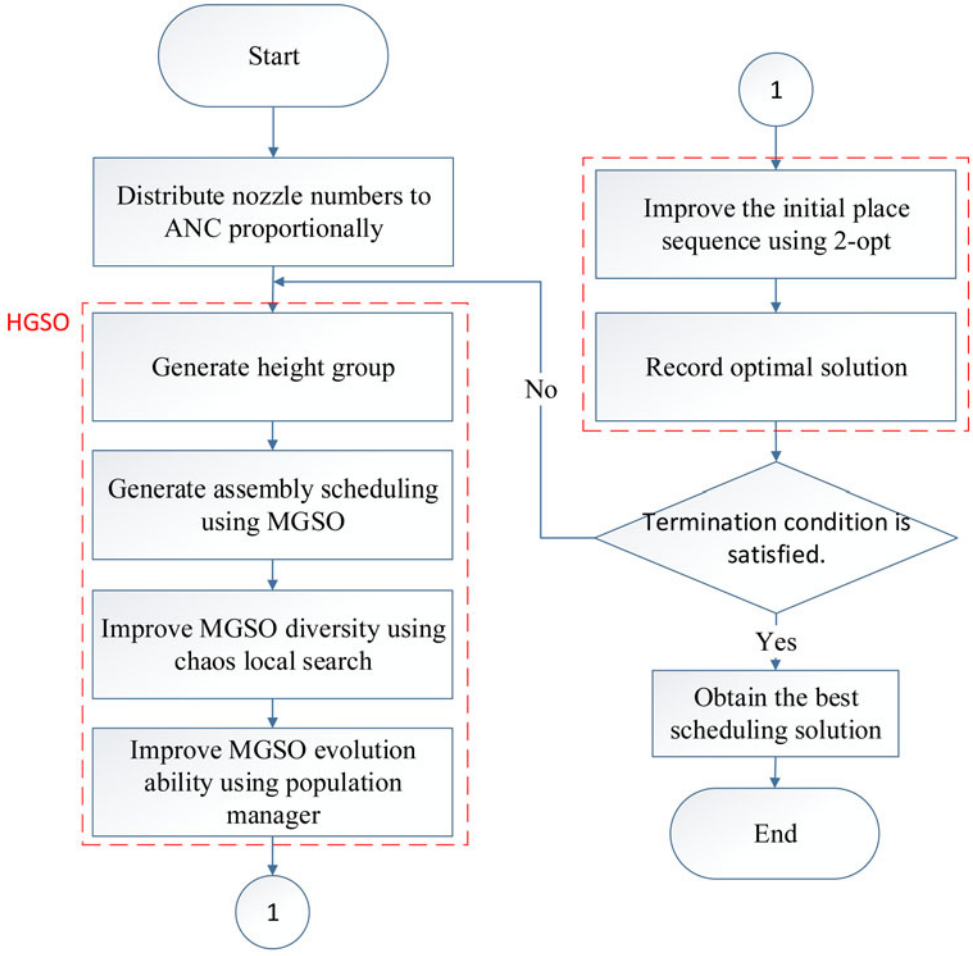


Fig. 6. Systematic procedures within HGSO

Table 1. Nozzle arrangement in ANC

Size	Big Nozzle		Small Nozzle							
No.	1	2	3	4	5	6	7	8	9	10
Nozzle	ANV1	ANV1	AN3	AN5	AN6	AN7	AN3	AN3	AN3	AN3
	ANV1	ANV1	AN3	AN3	AN3	AN5	AN5	AN5	AN5	AN6
No.	11	12	13	14	15	16	17	18	19	20

Table 2. ANC arrangement step 1

Size	Big Nozzle		Small Nozzle							
No.	1	2	3	4	5	6	7	8	9	10
Nozzle	ANV1		AN3	AN5	AN6	AN7				
No.	11	12	13	14	15	16	17	18	19	20

Table 3. Number of nozzles per type

Nozzle types	ANV1	AN3	AN5	AN6	AN7
Number	3	9	2	0	0

where cx_i and k are a chaos variable and the number of iterations, respectively. $cx_i^{(k)}$ has a range of [0, 1] and satisfies $cx_i^{(0)} \in (0, 1)$, $cx_i^{(0)} \notin \{0.25, 0.5, 0.75\}$. The procedure of chaos search is as follows:

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Table 4. Nozzle arrangement checklist

Nozzle types	ANV1		AN3		AN5		AN6			AN7
Number	3		7		2		1			0
Size	Big Nozzle		Small Nozzle							
No.	1	2	3	4	5	6	7	8	9	10
Nozzle	ANV1	ANV1	AN3	AN5	AN6	AN7	AN3	AN3	AN3	AN3
	ANV1	ANV1	AN3	AN3	AN3	AN5	AN5	AN6		
No.	11	12	13	14	15	16	17	18	19	20

Table 5. Final nozzle arrangement

Size	Big Nozzle		Small Nozzle							
No.	1	2	3	4	5	6	7	8	9	10
Nozzle	ANV1	ANV1	AN3	AN5	AN6	AN7	AN3	AN3	AN3	AN3
	ANV1	ANV1	AN3	AN3	AN3	AN5	AN5	AN5	AN5	AN6
No.	11	12	13	14	15	16	17	18	19	20

Table 6. Components per nozzle type

Nozzle	Component shape	Number of component	Proportion of nozzle (%)
AN3	Small	330	71
AN5	Small	90	19
AN6	Small	30	6
AN7	Small	18	4
ANV1	large	18	100

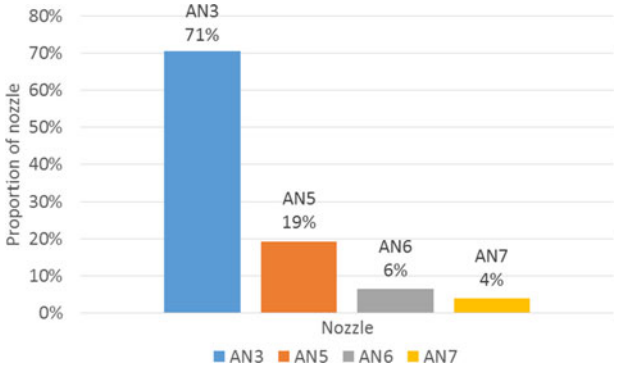


Fig. 7. Proportion of small nozzles

Step 1: Use Eq. (6) to produce chaos variables for the subsequent generation.

$$cx_i^{(k+1)}, cx_i^{(k)} = x_i \tag{7}$$

Step 2: Compare the new solution $cx_i^{(k+1)}$ with the original solution $cx_i^{(k)}$. Use the more favorable solution.

$$x_i = cx_i^{(k+1)} \tag{8}$$

Step 3: Repeat steps 1 and 2 until $i = N$.

Population manager

Because similar subjects have similar fitness values and converge to likely positions, the worse subjects must be eliminated to improve efficiency and reduce computation. Similarity is evaluated as follows (Liang and Lee, 2015):

$$\left|\frac{f(x_i) - f(x_j)}{f(x_j)}\right| < \delta_{\mathrm{m}}, \quad x_{\mathrm{i}} - x_{\mathrm{j}} < r_{\mathrm{m}} \tag{9}$$

where δ_{m} and r_{m} are threshold values, representing the average fitness value and average distance of the entire space, respectively; $\|\cdot\|$ denotes the distance betweenx_{i} and x_{j}. Figure 8 illustrates this concept. Subjects Q3 and Q4 have similar fitness values (less than δ_{m}); however, the distance is larger than r_{m}. The positions for Q5 and Q6 are close (less than r_{m}); however, the fitness values are considerably different. The fitness values and positions

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Table 7. Component information

Component height (mm)	Component type	Number of component	Nozzle	Component shape	Slot
0.6	R12	132	AN3	Small	35
	R13	36	AN3	Small	38
	R6	36	AN3	Small	36
	R8	18	AN3	Small	34
	R10	18	AN3	Small	53
	R5	36	AN3	Small	37
	R3	18	AN3	Small	54
1	D5	18	ANV1	Large	5
1.4	C2	36	AN3	Small	52
1.5	D1	18	AN5	Small	42
2.2	A1	72	AN5	Small	56
3.5	D2	30	AN6	Small	45
4	V1	18	AN7	Small	58

Table 8. Coding method for GSO members

Dimensions	1				…….				*N*
x_i	0.95	0.99	0.15	0.76	0.75	0.93	0.12	0.88	……

Table 9. Initial solution: random numbers

x_i	0.95	0.99	0.15	0.76	0.75	0.93	0.12	0.88	…
Element	6	4	5	8	3	0	7	1	…

Table 10. Members arranged in ascending order

x_i	0.93	0.76	0.88	0.99	0.75	0.12	0.95	0.15	…
Element	6	4	5	8	3	0	7	1	…

Table 11. Final solution of members

x_i	0.93	0.76	0.88	0.99	0.75	0.12	0.95	0.15	…
Element	6	4	5	8	3	0	7	1	…
Head No	1	2	3	4	5	6	7	8	…
Number of cycle	1	1	1	1	1	1	1	1	…
Slot No	34	36	38	34	52	38	56	42	…
Pick sequence	1	1	1	2	3	2	3	2	…
Place sequence	1	2	3	4	5	6	7	8	…

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Table 12. MGSO of large components

x_i	0.91	0.74	0.84	0.83	0.71	0.13	0.81	0.14	…
Element	6	4	9	8	3	0	7	1	…
Head No	1	2	4	6	7	8	1	2	…
Number of cycle	1	1	1	1	1	1	2	2	…
Slot No	34	36	5	34	52	38	56	42	…
Pick sequence	1	1	2	3	4	3	1	2	…
Place sequence	1	2	3	4	5	6	1	2	…

Table 13. The 2-opt method

x_i	0.93	0.76	0.88	0.99	0.75	0.12	0.95	0.15	…
Element	6	4	5	8	3	0	7	1	…
Head No	1	2	3	4	5	6	7	8	…
Number of cycle	1	1	1	1	1	1	1	1	…
Slot No	34	36	38	34	52	38	56	42	…
Pick sequence	1	1	1	2	3	2	3	2	…
Place sequence	1	2	3	4	5	6	7	8	…
Place sequence 1	2	1	3	4	5	6	7	8	…
Place sequence 2	2	3	1	4	5	6	7	8	…
Place sequence 3	2	3	4	1	5	6	7	8	…
Place sequence….	2	3	4	5	6	7	8	1	…

Table 14. Final scheduling results

Cycle	Head	Pick sequence	Place sequence	Component No	Slot	Nozzle
1	1	1	2	6	34	AN3
1	2	1	3	4	36	AN3
1	3	1	4	5	38	AN3
1	4	2	5	8	34	AN3
1	5	3	6	3	52	AN3
1	6	2	7	0	38	AN3
1	7	3	8	7	56	AN5
1	8	2	1	1	42	AN5
n	1	2	1	40	34	AN3
n	2	3	2	46	52	AN3
n	3	2	3	26	38	AN3
n	4	3	4	8	56	AN5
n	5	2	5	2	42	AN5
n	6	1	6	39	34	AN3
n	7	1	7	44	36	AN3
n	8	1	8	43	38	AN3

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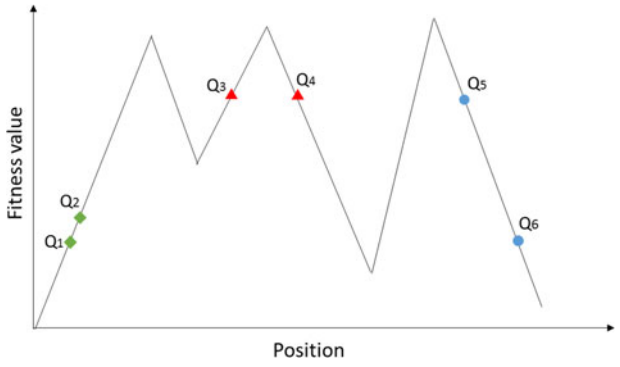


Fig. 8. Fitness value and position



Fig. 9. Placement machine EM-780

for Q1 and Q2 are similar, which satisfy Eq. (9), and the lower value (Q1) can be deleted.

Experimental results and comparisons

The real-time data from a placement machine (EM-780, Evest Corporation, Taoyuan, Taiwan; Figure 9) were used to evaluate the feasibility of the proposed method. In this study, 10 PCBs with different numbers and types of components, nozzle types, and feeders (Table 15) were assembled.

According to Section 'GSO for scheduling optimization', the initial settings are as follows: $N = 100$, iterations = 3000, scroungers = 80%, rangers = 20%, and head angle = 0.25π. The maximum iteration is $a = \text{round}\sqrt{n+1}$. If the producer cannot determine the improved area after a iterations, U_i and L_i are equal to 1 and −1. Here, n and $l_{\max} = \sqrt{\sum_{i=1}^{N}(U_i - L_i)^2}$ are the number of components and maximum pursuit distance, respectively. Figure 10 displays the number of pickups, total assembly time, and moving distance obtained using the proposed method.

Table 15. PCB information

PCB ID	Components	Component types	Nozzle types	Enable feeders
PCB_1	796	6	1	6
PCB_2	198	3	1	3
PCB_3	396	14	4	14
PCB_4	100	11	3	14
PCB_5	48	3	1	3
PCB_6	59	8	3	8
PCB_7	78	2	1	2
PCB_8	735	7	2	7
PCB_9	151	7	2	7
PCB_10	291	6	1	6

Yan *et al.* (2011) proposed GSPSO, which integrates high-speed computation in PSO with the favorable high-dimensional performance of GSO. Chen *et al.* (2012*a*, 2012*b*) presented an improved group search optimizer (IGSO) with a quantum-behaved operator for scroungers according to a certain probability of improving GSO convergence performance. In this method, the scroungers are categorized into two types: the scroungers that update their positions with quantum PSO operators and those that search for opportunities to join the resources found by the producer. Nian *et al.* (2013) proposed a differential evolution (DE) GSO, which is a hybrid of DE and GSO. DE prevents traditional GSO from falling into local optimal and enhances its accuracy. Table 16 compares the proposed method and related algorithms. The proposed method required the least total PCB assembly time for the 10 PCBs out of the compared algorithms. Figure 11 shows the learning curve for PCB_7, revealing that the total assembly times of PCB_7 using the proposed method and IGSO are similar [38]. Table 16 shows that the total average assembly times for the 10 PCBs (i.e., PCB_1–PCB_10) were 531.8, 523.3, 517.7, 495.3, and 394.3 s for the GSO (He *et al.*, 2009), GSPSO (Yan and Shi, 2011), IGSO (Chen *et al.*, 2012*a*, 2012*b*), DEGSO (Nian *et al.*, 2013), and proposed method, respectively. Therefore, the total average assembly time of the proposed method is superior to that of other methods (He *et al.*, 2009; Yan and Shi, 2011; Chen *et al.*, 2012*a*, 2012*b*; Nian *et al.*, 2013).

Algorithm performance in this study is determined in terms of the (1) total number of pickups, (2) total head movement distance, and (3) total assembly time. The results of the proposed method were compared with those of related algorithms, such as GAs or the improved shuffled frog leaping algorithm (Loh *et al.*, 2001; Sun *et al.*, 2005; Chang *et al.*, 2007; Ho and Ji, 2010; Zhu and Zhang, 2014). The number of pickups considerably influences PCB assembly, with total assembly time reducing with decreasing number of pickups. The proposed method required the least number of pickups for all experimental PCBs, excluding PCB_2 (Table 17). Figures 12–14 exhibit improvements calculated using the following equation:

$$\text{Improvement} = \frac{\text{Onsite_Engineer} - \text{Our_method}}{\text{Onsite_Engineer}} \times 100\% \quad (10)$$

Assembly time reduces with decreasing total head movement

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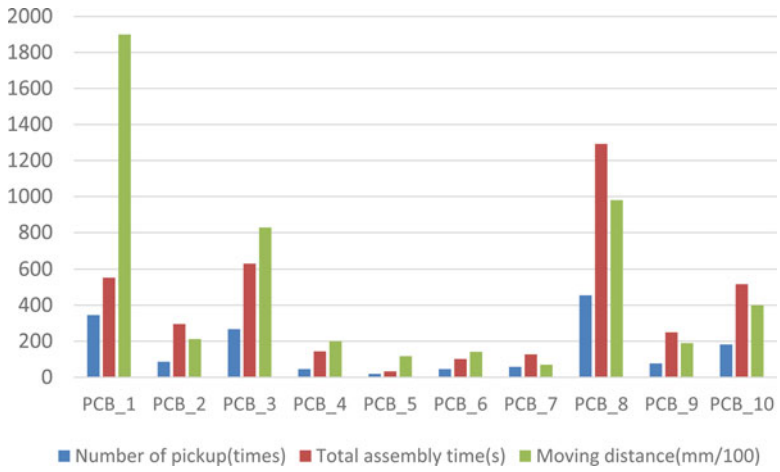


Fig. 10. Number of pickups, total assembly time, and moving distance obtained through the proposed method

Table 16. Total assembly time in the proposed method and related GSOs

	Total PCB assembly time (s)				
PCB ID	GSO [33]	GSPSO[37]	IGSO[38]	DEGSO[39]	Proposed method
PCB_1	701.41	689.781	682.031	671.252	552.925
PCB_2	385.43	371.9	367.25	312.35	295.796
PCB_3	861.31	821.63	792.12	701.33	630.982
PCB_4	255.296	252.988	254.596	247.52	143.316
PCB_5	40.4064	38.125	37.8533	37.7147	32.8864
PCB_6	162.536	156.132	152.722	150.22	101.261
PCB_7	132.289	130.927	127.917	130.135	127.857
PCB_8	1710.431	1694.912	1660.29	1672.94	1292.1
PCB_9	367.913	389.897	390.124	354.163	249.459
PCB_10	701.416	687.198	711.79	675.61	516.653
Average	531.8	523.3	517.7	495.3	394.3

distance. Table 18 presents the experimental results, which indicate that the proposed algorithm can effectively reduce total head movement distance. Table 18 outlines the operation for PCB_6, showing that the head movement distance generated by the proposed algorithm is longer than that produced by an onsite engineer. Figure 13 reveals improvement in the total head movement distance achieved using the proposed algorithm.

From Table 19 and Figure 14, the proposed HGSO algorithm outperforms other algorithms and the onsite engineer in terms of assembly time. Although the total number of pickups for PCB_1, PCB_3, and PCB_8 in Table 17 did not differ substantially, the total head movement distances (Table 18) were clearly different. Figure 14 shows the excellent performance of the proposed HGSO in terms of total assembly time. In practice, onsite engineers can appropriately design optimal pickup sequences but not path optimization. The proposed HGSO considers the total number of pickups and the total head movement distance to reduce the total assembly time. In the total assembly time, considerably more time is spent on pickups than it is on head movement. Table 20 presents the percentages of pickup time, placing time, and ANC time. To reduce total assembly time, a higher head movement distance is traded off for fewer pickups. Studies (Loh *et al.*, 2001) and (Jiang *et al.*, 2010*a*, 2010*b*, 2010*c*) have decomposed the scheduling problem into two stages: optimization (minimization) of (1) the number of pickups and (2) the place movement based on the results of stage one. The proposed HGSO is less complicated than the two-stage method.

Discussion and conclusions

This study aimed to perform scheduling optimization for reducing total PCB assembly time. Scheduling for a placement machine is a highly comprehensive task. Several studies have overlooked machine limitations to simplify the problem. However, the generated schedules produced by these studies cannot be practically applied to production lines. By contrast, this study proposed an HGSO that considers the limitations of placement machines to generate an applicable schedule are summarized as follows.

(1) Component height: The height of each component could be different, and the components are picked and placed in the ascending order of the height to avoid collision, i.e., The component with the lowest height must be placed first at the beginning of the placement machine during work.

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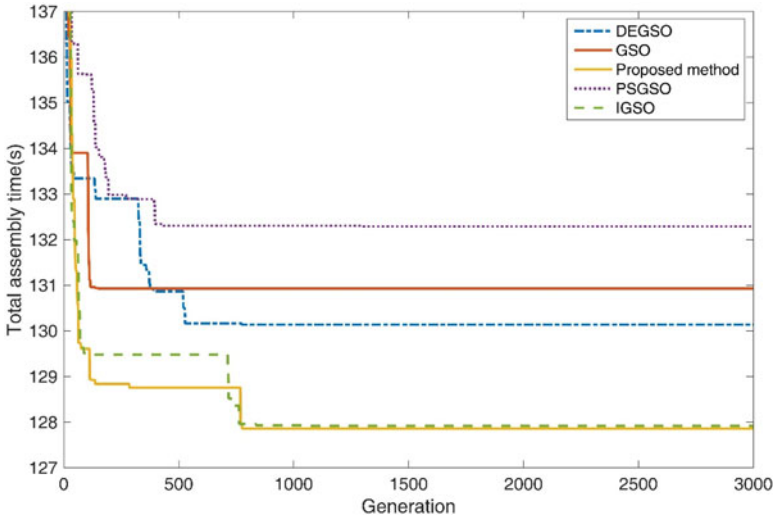


Fig. 11. Learning curve of PCB_7

Table 17. Comparison of total number of pickups

PCB ID	Total number of pickups (times)						
	Onsite engineer	Loh *et al.*, [8]	Sun *et al.*, [18]	Zhu *et al.*, [19]	Ho *et al.*, [20]	Chang *et al.*, [21]	Proposed method
PCB_1	345	358	335	601	557	586	345
PCB_2	82	87	91	90	81	91	86
PCB_3	267	286	254	367	356	374	267
PCB_4	60	85	83	93	87	87	45
PCB_5	19	26	34	35	34	39	19
PCB_6	55	47	43	53	52	54	45
PCB_7	59	58	63	67	61	65	58
PCB_8	455	442	428	585	594	588	455
PCB_9	80	82	91	119	122	115	77
PCB_10	182	215	198	235	232	228	182

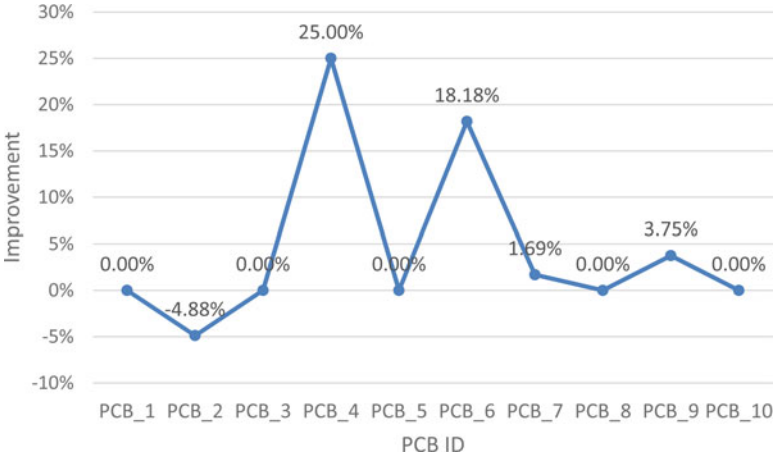


Fig. 12. Improvement in total number of pickups

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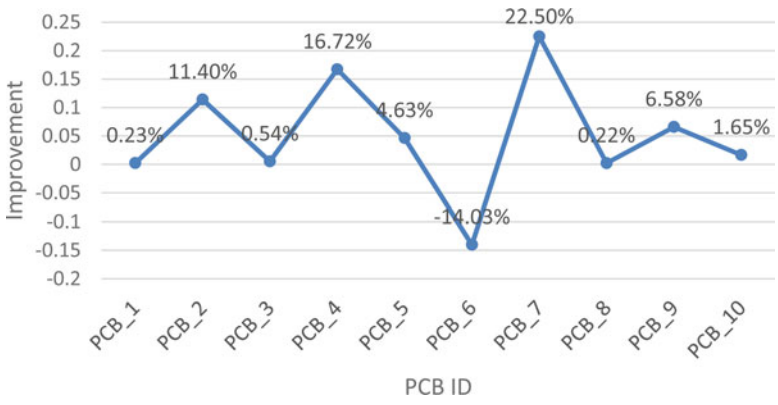


Fig. 13. Improvement in total head movement distance

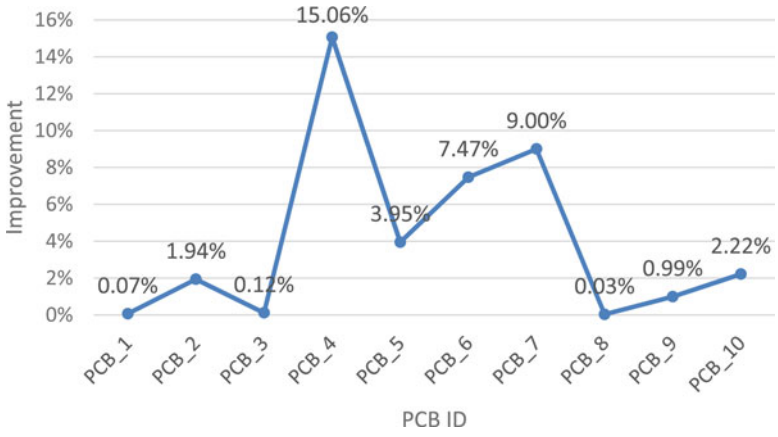


Fig. 14. Improvement in total assembly time

Table 18. Total head movement distance

	Total head movement distance (mm)						
PCB ID	Onsite Engineer	Loh *et al.* [8]	Sun *et al.* [18]	Zhu *et al.* [19]	Ho *et al.* [20]	Chang *et al.* [21]	Proposed method
PCB_1	190415	214840	185643	217102	214007	217824	189981
PCB_2	23980	32312.7	33045	28935.4	28629.5	30452.2	21245.9
PCB_3	83275	92201	86887	126815	121632	138081	82828.5
PCB_4	23997.5	34597.2	32089	29007.1	23741.7	33255.7	19984.7
PCB_5	12255.6	14539.5	14319.4	11945.8	11946.4	12700.8	11688.4
PCB_6	12378.1	18313.7	18153.7	17285.2	15513	18163.6	14114.7
PCB_7	9716.34	9033.89	9128.17	8986.48	8951.44	9362.49	7530.61
PCB_8	98201	82474	74497	113480	115105	112546	97981.5
PCB_9	20268.5	24712.7	26175	23234.4	22693.3	24074.8	18934.7
PCB_10	40671.4	48085	46348.9	37400.9	37606.1	37422.9	39999.8

(2) The Time consuming of nozzle changes: shapes of the components are different, and each matches a unique corresponding nozzle. When the nozzle is not applicable, the head need to exchange the nozzle. The process of nozzle changes takes time. Some scholars ignore the time consuming of nozzle changes.
(3) Picking restrictions: In the placement machine, not every head can pick up component in all feeders because there are some positions that the head cannot reach.
(4) Placing restrictions: As above, there are some destinations that head cannot arrive.
(5) Simultaneous pickup restrictions: Simultaneous pickup is important in the placement machine process. Practically, we want to simultaneously pick up components as many as possible to reduce the time consuming on picking components. The restrictions of the head pitch and the feeder pitch should be under consideration.

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Table 19. Total assembly time

	Total PCB assembly time (s)						
PCB ID	Onsite engineer	Loh *et al.* [8]	Sun *et al.* [18]	Zhu *et al.* [19]	Ho *et al.* [20]	Chang *et al.* [21]	Proposed method
PCB_1	553.289	622.377	619.504	677.866	659.701	675.152	552.925
PCB_2	301.64	311.177	313.091	315.512	312.853	314.367	295.796
PCB_3	631.713	745.796	711.205	1278.01	1157.9	1298.3	630.982
PCB_4	168.727	245.167	236.143	291.864	257.51	298.508	143.316
PCB_5	34.2381	38.6468	40.1539	37.7527	36.3122	40.3129	32.8864
PCB_6	109.435	133.457	132.342	173.749	147.372	157.458	101.261
PCB_7	140.505	138.234	141.839	143.838	138.734	143.88	127.857
PCB_8	1292.53	1346.26	1341.29	1658.94	1676.91	1663.76	1292.1
PCB_9	251.964	281.621	307.634	344.778	343.124	345.683	249.459
PCB_10	528.366	539.662	530.19	660.545	645.079	658.863	516.653

Table 20. Total assembly time

PCB ID	Pick time		Place time		ANC change time		Total assembly time
PCB_1	208.701	37.74%	344.224	62.26%	0	0.00%	552.925
PCB_2	134.002	45.30%	161.794	54.70%	0	0.00%	295.796
PCB_3	315.265	49.96%	293.217	46.47%	22.5	3.57%	630.982
PCB_4	58.849	41.06%	51.967	36.26%	32.5	22.68%	143.316
PCB_5	11.8341	35.98%	21.0523	64.02%	0	0.00%	32.8864
PCB_6	38.255	37.78%	30.506	30.13%	32.5	32.10%	101.261
PCB_7	47.466	37.12%	80.391	62.88%	0	0.00%	127.857
PCB_8	488.989	37.84%	758.111	58.67%	45	3.48%	1292.1
PCB_9	101.363	40.63%	143.096	57.36%	5	2.00%	249.459
PCB_10	199.212	38.56%	304.941	59.02%	12.5	2.42%	516.653

(6) Component-shape restrictions: the components differ in shape and size. If the component shape is larger than the limit, the adjacent head cannot pick up the component.

Compared with the related works in this field, this study considers more restrictions than others. This is the first study includes component heights and component shapes in the scheduling problem of a placement machine. In addition, this study modified the traditional group search optimizer for the possible usage for PCB assembly. The results indicate that the proposed HGSO is superior to related algorithms and an onsite engineer in terms of total assembly time. Although the diversity of placement machines for PCB assembly is many, the key structures of placement machines are the same. The proposed hybrid group search optimizer possesses flexibility on adjusting the parameters according to the head numbers, number of nozzle types, etc. and can be widely applied to general multihead placement machines.

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