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A hybrid simulated annealing for scheduling in dual-resource cellular manufacturing system considering worker movement

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\section{1. Introduction}

With rapidly changing customer expectation and global competition, cellular manufacturing system (CMS) has been an important way of producing goods in the last several decades. It shows many advantages such as an effective response to the rising product variety, a reduction in material handling cost and production lead time, streamlined production control, and enhanced productivity. Cell formation including grouping machines and tasks, and task scheduling involving decisions on task dispatching rules and timetable, are two main issues in the CMS. Consequently, these problems have attracted much investigating interest from researchers and practitioners.

For the basic cell formation problem with machine assignment, Rabbani et al. [1] used a two-phase fuzzy linear programming approach to solve a bi-objective cell formation problem with stochastic production quantities. Arkat et al. [2] proposed a branch and bound algorithm to minimize the total number of movements between each pair of machines locating in two different cells. Saraç and Ozcelik [3] used a genetic algorithm to maximize the grouping efficacy. Chung et al. [4] proposed an efficient tabu search algorithm to solve the cell formation problem with alternative routings and machine reliability considerations. Rafiee et al. [5] designed a dynamic cellular manufacturing system to pursue fundamentals of Just-In-Time production philosophy. A nonlinear programming model is proposed with two conflicting objective functions: minimizing the sum of cost, and minimizing the work-in-process. Mar-Ortiz et al. [6] presented a mathematical programming model to minimize the sum of the machine amortization cost, the machine relocation cost, and the intercellular material handling cost. By a reconfigurable approach, the cells are rearranged periodically to deal with demand variability in a multi-period planning horizon. Jayakumar and Raju [7] presented a nonlinear mixed-integer mathematical model for the cell formation problem with the uncertainty of the product mix for a single period. A solution methodology for best possible cell formation using simulated annealing (SA) is presented in order to minimize the total sum of the machine constant cost, the operating cost, the intercell material handling cost, and the intra-cell material handling cost. Some other methods have emerged for cell formation problems, such as particle swarm optimization method [8], clustering method [9] and scatter search algorithm [10]. It should be pointed out that the results in the aforesaid references only consider machine constrained setting.

For the cell formation problem with worker and machine assignment, Mahdavi et al. [11] presented a fuzzy goal programming-based approach for solving a multi-objective mathematical model of cell formation problem and production planning in a dynamic virtual cellular manufacturing system. Bagheri and Bashiri [12] proposed a new mathematical model to solve the worker assignment and inter-cell layout problems. The objective function of the proposed model consists of two main cost categories. The preferred solution...
is obtained by a LP-metric approach. Mahdavi et al. [13] investigated an integer mathematical programming model for the design of CMSs in a dynamic environment. The aim of the proposed model is to minimize holding and backorder costs, inter-cell material handling cost, machine and reconfiguration costs, and hiring, firing and salary costs. Azadeh et al. [14] presented a simulation approach for optimization of operator allocation in the CMS. Süber et al. [15] proposed a three-phase methodology to deal with the problem of cell loading and product sequencing in labour-intensive cells. Bootaki et al. [16] designed a robust method to configure cells in a dynamic CMS to minimize the inter-cell movements and maximize the machine and worker utilisation.

In contrast with the cell formation problem, there are only a small quantity of articles addressing the problem of scheduling in the CMS. Venkataramanaiyah [17] developed a SA for scheduling of parts within a cell for the objective of minimizing weighted sum of makespan, flowtime and idle time. Tavakkoli-Moghaddam et al. [18] designed a scatter search method for a multicriteria group scheduling problem in the CMS. Halat and Bashirzadeh [19] suggested a heuristic for scheduling operations of manufacturing cells considering sequence-dependent family setup times and intercellular transportation times. Arkat et al. [20] presented a mathematical model to concurrently identify the formation of cells, cellular layout and the operations sequence with the objective of minimizing total transportation cost of parts as well as minimizing makespan. Liu et al. [21] developed a discrete bacteria foraging algorithm to solve the model of CMS with the objective of minimizing the material handling costs as well as the fixed and operating costs of machines and workers.

Because of the high complexity of CMS which is subject to dual-resource constrained conditions, the cell formation and group scheduling problems are often analyzed independently. To the best of the authors’ knowledge, few related research has involved the CMS problem simultaneously considering multi-functional machines, multi-skilled workers and task sequence yet. Moreover, the impact of worker movement on task scheduling is also desired to be discussed.

The remainder of this paper is organized in the following: In Section 2, the proposed problem is stated and formulated as a mathematical model integrating cell formation and task scheduling. In Section 3, the PRBHA algorithm is suggested to obtain an initial solution with high quality. In Section 4, the HSA algorithm is designed for further search to get a global optimum. In Section 5, the performance of the proposed HSA is validated in comparison with the conventional SA by computational experiments. Finally, conclusions are drawn followed by some potential research directions in Section 6.

2. Problem statement and formulation

In this section, the problem of cell formation is formulated as a linear integer programming mathematical model. The objective is minimizing the makespan of the project which is composed of \( m \) tasks (i.e. maximum completion time of all tasks). The following hypotheses are made for the proposed problem.

(1) **Machine and worker hypotheses**: The number of machines and workers are known in advance. The number of machines is more than the number of workers.

(2) **Task hypothesis**: For each task, at least one machine has the ability to process it. For each machine, any worker has the ability to operate it. The processing of each task is not allowed to be interrupted, which implies that each task is processed on only one machine by only one worker. The processing time of task depends on the assigned machine and worker.

There exists precedence relationship among tasks.

(3) **Cell size hypothesis**: The number of machines in each cell can not exceed a specified maximum, because redundant machines in a cell may generate cluttered flows in many routes.

(4) **Worker movement hypothesis**: The workers are permitted to move among different machines, and the movement time is known in advance.

**Subscripts**

\( w \) Index for worker.
\( c \) Index for cell.
\( j \) Index for task.
\( t \) Index for time.
\( m \) Index for machine.
\( r \) Index for continuous time interval (i.e. one worker's \( r \)th task is processed in the worker's \( r \)th continuous time interval).

**Input parameters**

\( W \) The number of workers.
\( J \) The number of tasks.
\( M \) The number of machines.
\( N \) The largest number of tasks that one worker can process, (e.g. \( N = J \) if all the tasks are processed by one worker).

\( B_u \) Upper cell size limit (measured in the number of machines).
\( C \) The number of cells, which is the smallest integer not less than \( M/B_u \).

\( Q_{jm} \) 1 if task \( j \) can be processed on machine \( m \), and 0 otherwise (\( j = 1, \ldots, J; m = 1, \ldots, M \)).

\( \mathcal{M}_j \) The set of machines that have the ability to process the task \( j \) (\( j = 1, \ldots, J \)).

\( p_{jmnw} \) Processing time of task \( j \) on machine \( m \) by worker \( w \) (\( j = 1, \ldots, J; m \in \mathcal{M}_j; w = 1, \ldots, W \)).

\( Y_{mcnc'} \) Movement time of worker moving to machine \( m' \) in cell \( c' \) from machine \( m \) in cell \( c \) (\( m, m' = 1, \ldots, M; c, c' = 1, \ldots, C \)).
The objective function (1) is to minimize the makespan $C_{\text{max}}$.

\[ \text{Min } C_{\text{max}} = \max \{ FT_j | j = 1, \ldots, J \} \]  

Subject to:

\[ \sum_{c=1}^{C} Z_{mc} = 1, \quad \forall m \]  

\[ \sum_{m=1}^{M} Z_{mc} \leq B_c, \quad \forall c \]  

\[ x_{jmwr} \leq Q_{jm}, \quad \forall j, m, w, r \]  

\[ \sum_{m=1}^{M} \sum_{w=1}^{W} \sum_{r=1}^{N} x_{jmwr} = 1, \quad \forall j \]  

\[ \sum_{j=1}^{N} \sum_{m=1}^{M} x_{jmwr} \leq 1, \quad \forall w, r \]  

\[ \sum_{i=1}^{N} \sum_{j=1}^{J} \sum_{m=1}^{M} x_{jmwr} - \sum_{i=1}^{N} \sum_{j=1}^{J} \sum_{m=1}^{M} x_{j,m,w,r-1} \leq 0, \quad \forall w, r = 2, \ldots, N \]  

\[ FT_j - FT_i + L(2 - x_{jmwr} - x_{i,m,w,r-1}) \geq p_{jmw} \]  

\[ FT_j - FT_i \geq \sum_{m=1}^{M} \sum_{w=1}^{W} \sum_{r=1}^{R} p_{jmw} x_{jmwr}, \quad \forall i \in P_j, \quad \forall j \]  

\[ FT_j \geq 0, \quad Z_{mc}, x_{jmwr} \in \{0,1\}, \quad \forall j, m, w, r \]

\( P_j \) The immediate predecessor task set of task \( j = 1, \ldots, J \).

\( L \) A sufficient large number.

**Decision variables**

- \( Z_{mc} \): 1 if machine \( m \) is located in cell \( c \), and 0 otherwise (\( m = 1, \ldots, M; c = 1, \ldots, C \)).
- \( C_m \): The cell in which machine \( m \) is located. \( C_m = c \) if \( Z_{mc} = 1 \).
- \( x_{jmwr} \): 1 if task \( j \) is processed on machine \( m \) by worker \( w \), and the task \( j \) is the \( r \)th one processed by worker \( w \) (i.e. worker \( w \) process task \( j \) on machine \( m \) in his/her \( r \)th continuous time interval), and 0 otherwise (\( j = 1, \ldots, J; m = 1, \ldots, M; w = 1, \ldots, W; r = 1, \ldots, N \)).
- \( FT_j \): The finish time of task \( j = 1, \ldots, J \).

The proposed problem is formulated as the following linear integer programming model:

- \( s.t. \) : subject to
- \( \sum_{c=1}^{C} Z_{mc} = 1, \quad \forall m \)
- \( \sum_{m=1}^{M} Z_{mc} \leq B_c, \quad \forall c \)
- \( x_{jmwr} \leq Q_{jm}, \quad \forall j, m, w, r \)
- \( \sum_{m=1}^{M} \sum_{w=1}^{W} \sum_{r=1}^{N} x_{jmwr} = 1, \quad \forall j \)
- \( \sum_{j=1}^{N} \sum_{m=1}^{M} x_{jmwr} \leq 1, \quad \forall w, r \)
- \( \sum_{i=1}^{N} \sum_{j=1}^{J} \sum_{m=1}^{M} x_{jmwr} - \sum_{i=1}^{N} \sum_{j=1}^{J} \sum_{m=1}^{M} x_{j,m,w,r-1} \leq 0, \quad \forall w, r = 2, \ldots, N \)
- \( FT_j - FT_i + L(2 - x_{jmwr} - x_{i,m,w,r-1}) \geq p_{jmw} \)
- \( FT_j - FT_i \geq \sum_{m=1}^{M} \sum_{w=1}^{W} \sum_{r=1}^{R} p_{jmw} x_{jmwr}, \quad \forall i \in P_j, \quad \forall j \)
- \( FT_j \geq 0, \quad Z_{mc}, x_{jmwr} \in \{0,1\}, \quad \forall j, m, w, r \)

3. **Priority rule based heuristic algorithm**

In this section, we develop a priority rule based heuristic algorithm (PRBHA) that is embedded in SA for determining an initial feasible schedule. The PRBHA consists of \( n \) iterations (\( n \) is the total number of takes). At each iteration, a prior task is selected according to the EFT (earliest finishing time first) rule. Assuming there is a dummy task \( s \) with 0 unit of processing time at the beginning of the project. Moreover, assuming the machine that processes the dummy task \( s \) is a dummy machine 0, and the cell where the dummy machine 0 is located is a dummy cell 0.

The variables used for the PRBHA are listed in the following:

- \( D \): The decision task-set, i.e. the unscheduled tasks whose immediate predecessor tasks have been completed.
- \( \mathcal{R} \): The completed task-set, i.e. the tasks that have been completed.
- \( \theta_j \): The maximum finish time of the immediate predecessors of task \( j \).
- \( IM_m \): The start idle time of machine \( m \).
- \( IW_w \): The start idle time of worker \( w \).
- \( W_m \): The worker who operates machine \( m \).
- \( M_w \): The machine operated by worker \( w \).
The hypothesis completion time of task $j$ which is processed by worker $w$ on machine $m$.

$(j^*, m^*, w^*)$ The prior triple form, where $j^*$ denotes the prior task, $m^*$ denotes the prior machine, and $w^*$ denotes the prior worker.

$FT_j$ The finish time of task $j$.

$ST_j$ The start time of task $j$.

We give a pseudo-code description of the PRBHA (see Algorithm 1) as follows:

**Algorithm 1** Priority Rule Based Heuristic Algorithm (PRBHA)

$$D = \{ j \mid j \notin \mathcal{N}, P_j \subseteq \mathcal{M} \}$$

1. Initialize: $FT_s = 0$, $\mathcal{N} = \{ s \}$, $IW_w = 0$, $IM_m = 0$, $\mathcal{N}_0 = 0$, $Y_{0w}, Y_{m} = 0$, $\forall w, \forall m$, $\forall c$, and randomly generate the values of $\mathcal{C}_m$.
2. for $g = 1 \rightarrow n$ do
   3. Compute $D$.
   4. $\theta_j = \max\{ FT_k | h \in P_j \}$, $\forall j \in D$.
   5. $f_{jw} = \max\{ \theta_j, IM_m, IW_w + Y_{m}+ Y_{cm}, m, c \}$
   6. $(j^*, m^*, w^*)$: $f_{jw}^{m,w} = \min\{ f_{jw} | j \in D, m \in M \}$.
   7. $FT_j = f_{jw}^{m,w}$.
   8. $IW_{w'} = FT_j, IM_{m'} = FT_j, M_{w'} = m^*, \mathcal{N} := \mathcal{N} \cup \{ j^* \}$.
9. end for
10. $C_{\text{max}} = \max\{ FT_j | j = 1, \ldots, J \}$

In Step 1, some variables $\mathcal{N}$, $IW_w$, $IM_m$, and $M_w$ are initialized. Let $Y_{0cm} = 0$, $FT_s = 0$, $\mathcal{N}_0 = 0$. The machines are randomly assigned to the cells. In Step 2, each job is scheduled at each iteration. In each iteration, firstly, compute the decision task-set $D$ in Step 3, and then compute the hypothesis completion time of each task $j$ in $D$ with different workers and different machines in $\mathcal{M}$ in Steps 4–5. Secondly, according to the EFT rule, select a prior task $j^*$, a prior machine $m^*$, and a prior worker $w^*$ in Step 6. Finally, record the finish time of task $j^*$, and update the start idle time of machine $m^*$, the start idle time of worker $w^*$, the machine operated by the worker $w^*$, and the completed task-set $\mathcal{N}$ in Steps 7–8. In Step 10, the makespan of the project is computed according to the finish time of each task.

### 4. Hybrid simulated annealing algorithm

Since SA was introduced by Kirkpatrick et al. [22], it has become one of the most popular metaheuristic methods to solve complex optimization problems in manufacturing systems [23, 24]. The name of SA and its inspiration comes from annealing in metallurgy. The main mechanism is that SA decreases the probability of accepting worse solutions as the temperature drops gradually. Accepting worse solutions allows for a more extensive search in the solution space, and provide the chances to jump out the local optima. In this section, we propose a hybrid simulated annealing (HSA) which combines the PRBHA approach with conventional SA algorithm.

#### 4.1. Initial solution

By the PRBHA, the value of the $\mathcal{C}_m$, $FT_j$, $C_{\text{max}}$ and $(j^*, m^*, w^*)$ are generated. From the prior triple form $(j^*, m^*, w^*)$, we can see that task $j^*$ is processed on machine $m^*$ by worker $w^*$. From the values of $\mathcal{C}_m$, $FT_j$ and $C_{\text{max}}$, we know the location cell $\mathcal{C}_m$ for machine $m$, the finish time of task $j$, and the makespan $C_{\text{max}}$. Therefore, the PRBHA generates a feasible initial solution in the HSA.

#### 4.2. Neighborhood generation strategy

It is important to design superior solution mutation(SM) operators for the search of HSA. In this research, three different mutation strategies are provided in the following:

1. Machine-cell mutation(SM1): Randomly select a machine $m$ in cell $c$ and move it to different cell $c'$ if the number of machines in cell $c'$ does not reach the upper cell size limit, otherwise randomly...
select a machine $m'$ in cell $c'$, and then exchange machines $m$ and $m'$ between the two cells.

(2) Task-machine mutation (SM2): A task which can be processed by more than one machine is randomly selected, and then randomly reassigned to another machine that can process the task.

(3) Task-worker mutation (SM3): A task is randomly selected, and then randomly reassigned to another worker.

The objective function values (i.e., makespan $C_{\text{max}}$) of the neighbourhood solutions can be calculated by the revised forward recursion algorithm (see Algorithm 2).

### Algorithm 2 Revised Forward Recursion Algorithm (RFRA)

1. Initialize: The unallocated task set $U = \{1, \ldots, n\}$; The start idle time of machine $m$ and worker $w$, $IM_m = 0$, $IW_w = 0$, $\forall w$.
2. while $U \neq \emptyset$ do
   3. Randomly select a job $j$ from $U$.
   4. Allocate task $j$ to machine $m$ operated by worker $w$ (from solution schedule, the values $m$ and $w$ are known).
   5. If the finish time of predecessor $i$ of task $j$ has not been determined, recursively execute Step 4 for predecessor $i$.
   6. Compute the start time of task $j$, $ST_j = \max\{\theta_j, IM_m, IW_w + YM_w, C_{m,w} \}$, and the finish time of task $j$, $FT_j = ST_j + \phi_{j,mw}$.
   7. Update the unallocated task set, the start idle time of machine $m$ and worker $w$, and the value of $M_u$: $U := U \setminus \{j\}$, $IM_m = FT_j$, $IW_w = FT_j$, $M_u = m$.
8. end while
9. $C_{\text{max}} = \max\{FT_j | j = 1, \ldots, l\}$.

### 4.3. Cooling schedule

(1) Parameters of HSA algorithm: Initial temperature $T_0$, final temperature $T_f$, cooling rate $\alpha$ and Markov chain length $L_{\text{max}}$ are set to 200, 0.5, 0.95 and 200, respectively. The temperature $T$ is decreased by using the following common equation: $T := \alpha T$.

(2) Termination condition: Let the best schedule up to now is $x_{\text{best}}$, the HSA algorithm is stopped if $x_{\text{best}}$ is not changed after three consecutive temperature levels or the final temperature $T_f$ is reached.

### 4.4. The pseudo code of the HSA

Algorithm 3 provides the pseudo-code of the HSA. The major optimization procedure is that: Generate an initial solution by the PRBHA. If $C_{\text{max}}$ of neighbourhood solution $x_i$ is less than $C_{\text{max}}$ of current solution $x_c$, accept $x_i$ as current solution $x_c$, otherwise neighbourhood solution $x_i$ is accepted as current solution $x_c$ by certain probability, which can escape from local optima to reach a global optimum. At the start, the probability of accepting nonimproving solutions is high, but as the search continues (i.e. the temperature drops), the probability of accepting nonimproving solutions decreases.

### Algorithm 3 Hybrid Simulated Annealing (HSA)

1: Initialize parameters: $T = 200, T_f = 0.5, \alpha = 0.95, Total = 0, Change = 0, Unchange = 0.$
2: By algorithm 1, generate initial schedule $x_0$, set $x_c = x_0$, and compute the objective value of schedule, $C_{\text{max}}$.
3: while $T > T_f$ do
   4: while $Total < L_{\text{max}}$ do
      5: A random number $r_1$ is generated from the uniform distribution over the interval $[0, 1]$.
      6: if $r_1 < 1/3$ then
         7: Generate neighborhood $x_i$ by SM1, compute $C_{\text{max}}(x_i)$ by algorithm 2.
      8: else if $1/3 \leq r_1 < 2/3$ then
         9: Generate neighborhood $x_i$ by SM2, compute $C_{\text{max}}(x_i)$ by algorithm 2.
      10: else
         11: Generate neighborhood $x_i$ by SM3, compute $C_{\text{max}}(x_i)$ by algorithm 2.
      12: end if
      13: if $C_{\text{max}}(x_i) \leq C_{\text{max}}(x_c)$ then
         14: $x_c = x_i$
         15: if $C_{\text{max}}(x_c) \leq C_{\text{max}}(x_{\text{best}})$ then
            16: $x_{\text{best}} = x_c$, $Change := Change + 1, Unchange = 0$
         17: end if
      18: else
         19: Randomly generate a number $r_2 \sim U(0, 1)$, let $\Delta = C_{\text{max}}(x_i) - C_{\text{max}}(x_c)$.
         20: if $e^{-\Delta/T} > r_2$ then
            21: $x_c = x_i$
         22: end if
      23: end if
   24: Total := Total + 1
5: end while
6: if $Change = 0$ then
   7: $Unchange := Unchange + 1$
8: end if
9: if $Unchange = 3$ then
   10: Return $C_{\text{max}}(x_{\text{best}})$
11: end if
12: $T := \alpha \times T, Total = 0, Change = 0$
13: end while
14: Return $C_{\text{max}}(x_{\text{best}})$
Table 1. Comparison between SA and HSA with different number of parts \((J)\) \((M = 30, W = 25, T_{pkmw} \sim DU[5, 20], \mathcal{N}_m \sim DU[1, 3], B_u = 4)\).

| \(J\) | \(\text{MIN}\) | \(\text{MAX}\) | \(\text{AVE}\) | \(\text{MIN}\) | \(\text{MAX}\) | \(\text{AVE}\) | \(\text{D-\text{C}\text{MAX}}\)% | \(\text{SA-CPU(s)}\) | \(\text{HSA-CPU(s)}\) | \(\text{D-CPU}\)% |
|------|-------------|-------------|-------------|-------------|-------------|-------------|------------------|----------------|----------------|-------------|
| 150  | 1000        | 1167        | 1104.5      | 332         | 336         | 335.3       | 69.64           | 45.99          | 32.58         | 29.17        |
| 200  | 1200        | 1293        | 1256.6      | 314         | 324         | 318.0       | 74.69           | 101.73         | 63.76         | 37.32        |
| 250  | 1305        | 1427        | 1368.5      | 239         | 268         | 251.4       | 81.63           | 131.55         | 110.72        | 15.84        |
| 300  | 1704        | 1904        | 1792.3      | 394         | 422         | 408.4       | 77.21           | 205.60         | 169.80        | 17.41        |

5. Computational experiments

In order to evaluate the performance of the HSA and SA algorithms for the problem, extensive numerical experiments are conducted. Several impact factors are used for the evaluation, including the number of tasks \((J)\), the number of machines \((M)\), the number of workers \((W)\), upper cell size limit \((B_u)\), and the processing time \((T_{pkmw})\).

To test the effects of varying \(J, M, W\) and \(B_u\), four different values of \(J\) are used, including 150, 200, 250 and 300, four different values of \(M\) and \(W\) are used, which are 30, 40, 50, 60, and four different values of \(B_u\) are used, including 4, 6, 8 and 10. Moreover, to determine whether the range of \(T_{pkmw}\) and \(\mathcal{N}_m\) may have any impact on the performance of the HSA algorithm, four different distributions of \(T_{pkmw}\) are used, including \(DU[5, 20]\), \(DU[5, 20]\), \(DU[5, 20]\) and \(DU[5, 20]\), and four different distributions of \(\mathcal{N}_m\) are used, including \(DU[1, 4]\), \(DU[1, 5]\), \(DU[1, 6]\) and \(DU[1, 10]\), where \(DU[a, b]\) represents a discrete uniform distribution with an integer range from \(a\) to \(b\).

Six sets of numerical experiments are conducted. In the first set, \(J\) is allowed to vary, given \(M = 30, W = 25, T_{pkmw} \sim DU[5, 20], \mathcal{N}_m \sim DU[1, 3], B_u = 4\). In the second set, \(M\) is allowed to vary, given \(J = 200, W = 20, T_{pkmw} \sim DU[5, 20], \mathcal{N}_m \sim DU[1, 10], B_u = 4\). In the third set, \(W\) is allowed to vary, given \(M = 50, J = 200, T_{pkmw} \sim DU[5, 20], \mathcal{N}_m \sim DU[1, 10], B_u = 4\). In the fourth set, \(B_u\) is allowed to vary, given \(M = 40, J = 200, T_{pkmw} \sim DU[5, 20], \mathcal{N}_m \sim DU[1, 3], B_u = 4\). In the fifth set, the distribution of generating \(T_{pkmw}\) is allowed to vary, given \(M = 40, J = 200, W = 30, \mathcal{N}_m \sim DU[1, 2], B_u = 5\). In the sixth set, the distribution of generating \(\mathcal{N}_m\) is allowed to vary, given \(M = 40, J = 200, W = 30, T_{pkmw} \sim DU[5, 40], B_u = 5\).

In the experiments, we use the approach presented in [25] for generating the precedence constraints of tasks. To do this, let \(\mathcal{P}_j = \text{Pr}\{\text{arc}(i,j) \text{ exists in the immediate precedence graph}\}\), and let \(D\) represent the target density of the precedence constraint graph, that is \(D = \text{Pr}[\text{arc}(i,j) \text{ exists in the precedence constraint graph}]\), for \(1 \leq i < j \leq J\). The \(D\) and \(\mathcal{P}_j\) satisfy:

\[
\mathcal{P}_j = \frac{D(1 - D)^{j-i-1}}{1 - D(1 - (1 - D)^{j-i-1})},
\]

where \(D \in (0, 1)\).

Randomly generate a number \(r_{ij}\) from the uniform distribution over the interval \([0, 1]\). If \(r_{ij} < D\), then \(\text{arc}(i,j)\) exists in the immediate precedence graph. Given \(Y_{mcw,c} = 0\) for \(m = m', Y_{mcw,c} = 2\) for \(c = c'\) and \(m \neq m'\), \(Y_{mcw,c} = 20\) for \(c \neq c'\), and \(D = 0.5\) in these experiments.

The experiments have been performed on a Pentium-based Dell computer with 2.30 GHz clock-pulse and 4.00 GB RAM. The HSA and SA algorithms have been coded in C++, compiled with the Microsoft Visual C++ 9.0 compiler, and tested under Microsoft Windows 7 (32-bit) operating system.
Table 4. Comparison between SA and HSA with different upper cell size limit \((B_u)\) \((M = 40, \ W = 30, \ J = 200, \ D_{pkmw} \sim \ DU[5, 20], \ N_m \sim DU[1, 3]).\)

| \(B_u\) | \(\text{SA-C}_{\text{max}}\) MIN | \(\text{MAX}\) | \(\text{AVE}\) | \(\text{MIN}\) | \(\text{MAX}\) | \(\text{AVE}\) | \(\text{D-C}_{\text{max}}\) (%) | \(\text{SA-CPU}\) (s) | \(\text{HSA-CPU}\) (s) | \(\text{D-CPU}\) (%) |
|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 4     | 1282  | 1386  | 1332.1| 391   | 395   | 392.6 | 70.53 | 83.88 | 62.47 | 25.53 |
| 6     | 1036  | 1188  | 1110  | 258   | 263   | 260.9 | 72.33 | 83.87 | 62.81 | 25.11 |
| 8     | 1085  | 1293  | 1183.8| 325   | 332   | 327.5 | 73.84 | 83.87 | 62.81 | 25.11 |
| 10    | 1216  | 1336  | 1262.5| 327   | 338   | 330   | 72.33 | 83.87 | 62.81 | 25.11 |

Table 5. Comparison between SA and HSA with different processing times \((T_{pkmw})\) \((M = 40, \ J = 200, \ W = 30, \ N_m \sim DU[1, 2], \ B_u = 5).\)

| \(T_{pkmw}\) | \(\text{SA-C}_{\text{max}}\) MIN | \(\text{MAX}\) | \(\text{AVE}\) | \(\text{MIN}\) | \(\text{MAX}\) | \(\text{AVE}\) | \(\text{D-C}_{\text{max}}\) (%) | \(\text{SA-CPU}\) (s) | \(\text{HSA-CPU}\) (s) | \(\text{D-CPU}\) (%) |
|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| DU[5, 10] | 851   | 912   | 887.9 | 560   | 561   | 560.9 | 36.83 | 84.18 | 61.27 | 27.22 |
| DU[5, 20] | 907   | 1040  | 959.3 | 179   | 198   | 186.6 | 80.55 | 74.00 | 62.81 | 15.12 |
| DU[5, 30] | 1683  | 2016  | 1847.2| 351   | 356   | 353.3 | 80.87 | 89.28 | 62.66 | 29.81 |
| DU[5, 40] | 1880  | 2111  | 1992.2| 328   | 332   | 329.5 | 77.84 | 78.34 | 63.85 | 13.77 |

Table 6. Comparison between SA and HSA with different number of machines that can process the operation \((N_m)\) \((M = 40, \ J = 200, \ W = 30, \ T_{pkmw} \sim DU[5, 40], \ B_u = 5).\)

| \(N_m\) | \(\text{SA-C}_{\text{max}}\) MIN | \(\text{MAX}\) | \(\text{AVE}\) | \(\text{MIN}\) | \(\text{MAX}\) | \(\text{AVE}\) | \(\text{D-C}_{\text{max}}\) (%) | \(\text{SA-CPU}\) (s) | \(\text{HSA-CPU}\) (s) | \(\text{D-CPU}\) (%) |
|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| DU[1, 4] | 2135  | 2588  | 2303.8| 397   | 410   | 401   | 82.59 | 99.04 | 64.11 | 35.26 |
| DU[1, 6] | 2280  | 2539  | 2432.3| 478   | 486   | 483.9 | 80.11 | 99.87 | 65.85 | 34.06 |
| DU[1, 8] | 1713  | 1923  | 1840.7| 171   | 177   | 174.4 | 90.53 | 86.95 | 67.80 | 22.02 |
| DU[1, 10] | 1729  | 2114  | 1914.7| 342   | 356   | 349   | 81.76 | 88.48 | 66.23 | 27.95 |

Table 7. Statistical t-test results from SPSS for sample entries 1–12.

| The nth Sample Entry | Algorithm | Mean | Std. Deviation | Std. Error Mean | Pair | Mean | Lower | Upper | T-Value | P-Value |
|----------------------|-----------|------|----------------|-----------------|------|------|-------|-------|---------|---------|
| 1                    | SA        | 1104.50 | 49.646 | 15.699 | SA-HSA | 769.200 | 718.432 | 819.968 | 49.239  | 0.000   |
| 2                    | SA        | 1256.60 | 27.549 | 8.712  | SA-HSA | 938.600 | 911.774 | 965.426 | 113.707 | 0.000   |
| 3                    | SA        | 1368.50 | 37.340 | 11.808 | SA-HSA | 1117.100 | 1075.718 | 1158.482 | 87.729  | 0.000   |
| 4                    | SA        | 1792.30 | 61.651 | 19.496 | SA-HSA | 1383.900 | 1316.473 | 1451.327 | 66.701  | 0.000   |
| 5                    | SA        | 1443.10 | 53.702 | 16.982 | SA-HSA | 1035.400 | 978.845 | 1091.955 | 59.497  | 0.000   |
| 6                    | SA        | 1558.60 | 36.467 | 11.532 | SA-HSA | 1123.400 | 1084.898 | 1161.902 | 94.823  | 0.000   |
| 7                    | SA        | 1184.10 | 39.411 | 12.463 | SA-HSA | 957.300 | 915.665 | 998.935 | 74.722  | 0.000   |
| 8                    | SA        | 1409.10 | 57.311 | 18.123 | SA-HSA | 902.600 | 843.669 | 961.531 | 49.775  | 0.000   |
| 9                    | SA        | 1161.50 | 35.877 | 11.345 | SA-HSA | 843.400 | 794.302 | 914.098 | 46.345  | 0.000   |
| 10                   | SA        | 1100.80 | 63.215 | 19.990 | SA-HSA | 854.200 | 794.302 | 914.098 | 46.345  | 0.000   |
| 11                   | SA        | 1258.10 | 83.043 | 26.260 | SA-HSA | 838.100 | 752.758 | 923.442 | 31.915  | 0.000   |

Note: Sample size of each pair \(N = 10\), degree of freedom \(df = 9\), significance level = 0.01

The six experiment results are presented in Tables 1–6, respectively. Let \(HSA-C_{\text{max}}\) and \(SA-C_{\text{max}}\) denote the objective function values (i.e. makespan) of the problem using the HSA and SA, respectively. Each table entry represents the minimum, maximum and average of its associated 10 instances. \(D-C_{\text{max}}\) denotes the declining percentage of average \(HSA-C_{\text{max}}\) over average \(SA-C_{\text{max}}\). Let \(HSA-CPU\) and \(SA-CPU\) denote the mean CPU time of the HSA and SA algorithms without including input and output time,
Table 8. Statistical t-test results from SPSS for sample entries 13–24.

| The nth Sample Entry | Algorithm | Mean  | Std. Deviation | Std. Error Mean | Pair    | Mean  | 99% Confidence Interval | T-Value | P-Value |
|----------------------|-----------|-------|----------------|-----------------|---------|-------|-------------------------|---------|---------|
| 13                   | SA        | 1332.10 | 37.323         | 11.802          | SA–HSA | 939.500 | 901.007 to 977.993     | 79.319  | 0.000   |
| 14                   | SA        | 1110.00 | 46.985         | 14.858          | SA–HSA | 849.100 | 800.908 to 897.292     | 57.259  | 0.000   |
| 15                   | SA        | 1183.80 | 69.262         | 21.903          | SA–HSA | 856.300 | 817.098 to 895.502     | 39.084  | 0.000   |
| 16                   | SA        | 1262.50 | 35.120         | 11.106          | SA–HSA | 932.200 | 898.085 to 966.315     | 88.803  | 0.000   |
| 17                   | SA        | 887.90  | 20.344         | 6.433           | SA–HSA | 327.000 | 306.236 to 347.764     | 51.180  | 0.000   |
| 18                   | SA        | 959.30  | 42.266         | 13.366          | SA–HSA | 772.700 | 732.839 to 812.561     | 62.997  | 0.000   |
| 19                   | SA        | 1847.20 | 103.971        | 32.878          | SA–HSA | 1493.900 | 1386.208 to 1601.592 | 45.082  | 0.000   |
| 20                   | SA        | 1992.20 | 91.742         | 29.011          | SA–HSA | 1695.500 | 1599.442 to 1791.558  | 57.362  | 0.000   |
| 21                   | SA        | 2303.80 | 130.843        | 41.376          | SA–HSA | 1902.800 | 1766.682 to 2038.918  | 69.628  | 0.000   |
| 22                   | SA        | 1840.70 | 73.314         | 23.184          | SA–HSA | 1666.300 | 1589.943 to 1742.657  | 70.920  | 0.000   |
| 23                   | SA        | 1914.70 | 113.355        | 35.846          | SA–HSA | 1565.500 | 1447.051 to 1683.949  | 42.952  | 0.000   |

Note: Sample size of each pair \( N = 10 \), degree of freedom \( df = 9 \), significance level \( \alpha = 0.01 \).

respectively. Let \( D_{\text{CPU}} \) denote the declining percentage of HSA-CPU over SA-CPU, i.e. \( D_{\text{CPU}} = (\text{SA-CPU} - \text{HSA-CPU})/\text{SA-CPU} \).

From the obtained results, we can see that \( D_{\text{CPU}} \) reaches 36.83%–90.53% and \( D_{\text{CPU}} \) reaches 5.92%–37.32%. That is to say, the HSA performs more accurately and efficiently than the SA in spite of the variation of six impact factors \( J, M, W, B_u, N_m \) and \( T_{\text{kmw}} \). The reason lies in that the selection method for the prior job, machine and worker in the PRBHA algorithm may be effective to get a good initial solution.

The paired-samples t-test experiment is conducted in SPSS (Statistical Product and Service Solutions) software, so that the performance of HSA and SA can be further validated. Tables 7–8 display the experimental results according to 24 sample entries in Tables 1–6. For example, the first entry shows that \( t \)-value is 49.239 (> \( t_{0.01} (9) = 2.8214 \)), and \( p \)-value is 0.000 (< \( \alpha = 0.01 \)). Since all \( t \)-values and \( p \)-values satisfy the conditions, the HSA is significantly better than the SA with respect to solution quality in statistics.

6. Conclusions

This paper gives a new optimization model of cellular manufacturing system (CMS) under dual resources and task precedence constrained setting. The objective of the problem is to minimize the makespan. The PRBHA, which schedules a prior task on a prior machine by a prior worker according to the priority rule at each iteration, is embedded to the HSA for initial feasible solution that can be improved in further stages. Computational experiments are conducted to show that the quality of results obtained by the HSA is better than the SA regardless of the variation of some important parameters.

A valuable future research direction is to consider the impact of learning and forgetting effects of workers on their assignment and movement. The other possible extension to this research would investigate various efficient priority rules and corresponding heuristics for SA. It is also desired to linearize the proposed model in the future, so that the HSA can be compared with the branch-and-bound approach (B&B) under the ILOG CPLEX software for small or medium sized instances. Moreover, some state-of-the-art heuristics, such as firefly algorithm, league championship algorithm, and migrating birds optimization, can be developed from various aspects on the basis of CMS characteristics. Therefore, we wish to design these heuristic based HSA approaches, and compare them with the proposed HSA in this paper.

Disclosure statement

No potential conflict of interest was reported by the authors.

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