Research Article

Solution Algorithms for Single-Machine Group Scheduling with Learning Effect and Convex Resource Allocation

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This paper deals with a single-machine resource allocation scheduling problem with learning effect and group technology. Under slack due-date assignment, our objective is to determine the optimal sequence of jobs and groups, optimal due-date assignment, and optimal resource allocation such that the weighted sum of earliness and tardiness penalties, common flow allowances, and resource consumption cost is minimized. For three special cases, it is proved that the problem can be solved in polynomial time. To solve the general case of problem, the heuristic, tabu search, and branch-and-bound algorithms are proposed.

1. Introduction

In the conventional scheduling models and problems, it is generally assumed that the job processing times are constants, but in practice, examples can be found to illustrate that the job processing times are not necessarily constants (Shabtay and Steiner [1], Biskup [2], and Azzouz et al. [3]). More recently, Zhu et al. [4] considered resource allocation single-machine scheduling problems with learning effects and group technology. For the linear and convex resource allocation models, they proved that problem of minimizing the weighted sum of makespan and total resource cost can be solved in polynomial time. Lu et al. [5] revisited the same model with Zhu et al. [4], but they considered the case of resource availability is limited. For the makespan minimization subject to limited resource availability, they proposed heuristic and branch-and-bound algorithms. Sun et al. [6] and Lv et al. [7] worked on single-machine scheduling group problems with learning effects and resource allocation. Under the slack (SLK) due-date assignment, for the linear weighted sum of scheduling cost and resource consumption cost minimization, Sun et al. [6] proved that the problem can be solved in polynomial time. However, Lv et al. [7] showed that the results of Sun et al. [6] are incorrect by two counter-examples, and Lv et al. [7] also provided the corrected results under a special case. In this paper, we will consider the same model with Sun et al. [6] and Lv et al. [7], i.e., three popular features in the recent years: group technology, resource allocation, and learning effect. The contributions of this study are given as follows: (1) we study the SLK assignment single-machine group scheduling problem along with learning effect and convex resource allocation; (2) the optimal properties are provided for the total cost (including earliness, tardiness, common flow allowances, and resource consumption cost) minimization; (3) we propose the heuristic, tabu search, and branch-and-bound algorithms to solve the problem.

The reminder of this paper is organized as follows. In Section 2, the relevant literature review is presented. The problem statement is presented in Section 3. Section 4 gives some properties of the problem. In Section 5, some special cases are discussed. In Section 6, for the general case, solution algorithms are proposed. Finally, the conclusions are given in Section 7.

2. Literature Review

In this section, we restrict our literature review to papers that study scheduling problems with learning effects, resource allocation, and/or group technology.
In manufacturing environments, after learning, the time required for workers (machines) to process some jobs is decreasing, which causes scheduling problems with learning effects (Biskup [2]). Wang et al. [8] considered the flow shop problem with a learning effect. Under two-machine and release dates, the goal is to minimize the weighted sum of makespan and total completion time. They proposed a branch-and-bound algorithm and a multiobjective memetic algorithm to solve the problem. Wang et al. [9] considered flow shop problems with truncated learning effects. For the makespan and total weighted completion time minimizations, they proposed heuristics and branch-and-bound algorithms. Yan et al. [10] and Wang et al. [11] studied single-machine scheduling problems with learning effects and release times. Sun et al. [12] investigated flow shop problem with general position weighted learning effects. For the total weighted completion time minimization, they proposed some heuristics and a branch-and-bound algorithm to solve the problem.

In addition, scheduling problems with resource allocation (controllable processing times) have also attracted considerable interest from researchers (Shabtay and Steiner [1]), that is, the scheduler can control processing times of jobs by allocating a common continuously nonrenewable resource. Kayvanfar et al. [13, 14] considered single-machine scheduling with controllable processing times. For the total tardiness and earliness minimization, Kayvanfar et al. [13] proposed a mathematical model and three heuristic techniques; Kayvanfar et al. [14] proposed a drastic hybrid heuristic algorithm. Lu and Liu [15] considered single machine scheduling problems with resource allocation and position-dependent workloads. They proposed a bicriteria analysis for the scheduling cost and total resource consumption cost. Tsao et al. [16] considered energy-efficient single-machine scheduling problem with controllable processing time. Under differential electricity pricing, they proposed a mixed-integer programming model and a fuzzy control approach. Mor et al. [17] considered single-machine scheduling problems with resource-dependent processing times. For a large set of that the scheduling criterion can be represented as one that includes positional penalties; they proposed heuristic algorithms to solve the problems. Kayvanfar et al. [18] considered unrelated parallel machines scheduling problem with controllable processing times. For the linear weighted sum of tardiness, earliness, jobs compressing and expanding costs, and makespan minimization, they proposed a mixed integer programming model and some heuristics. Zarandi and Kayvanfar [19] considered a biobjective identical parallel machines scheduling problem with controllable processing times. The goal is to simultaneously minimize total cost of tardiness and earliness as well as compression and expansion costs of job processing times and makespan. They proposed two multiobjective evolutionary algorithms to solve the biobjective problem. Kayvanfar et al. [20] studied identical parallel machine scheduling problem with controllable processing times. For the linear weighted sum of tardiness, earliness, and job compressions/expansion cost minimization, they proposed a mixed integer linear programming model and some heuristic algorithms to solve the problem.

A third possible aspect is that scheduling problems with group technology (GT, see studies by Mosier et al. [21] and Webster and Baker [22]), that is, GT is an approach to manufacturing that seeks to improve efficiency in high-volume production by exploiting the similarities of different products and activities in their production (see studies by Yang and Yang [23] and Ji et al. [24]). Xu et al. [25] and Liu et al. [26] considered single-machine group scheduling with deteriorating jobs and ready times. For the makespan minimization, Xu et al. [25] proved that some special cases can be solved in polynomial time; for the general case, Liu et al. [26] proposed a branch-and-bound algorithm. Li and Zhao [27] considered single machine scheduling problem with group technology. Under multiple due windows assignment, they proved that the total cost (including earliness, tardiness, and due windows) minimization can be solved in polynomial time. Zhang and Xie [28] studied the single machine scheduling problem with position dependent processing times. Under group technology and ready times, for the makespan minimization, they proved that a special case can be solved in polynomial time. Ji and Li [29] studied single-machine group scheduling with variable job processing times (including resource allocation, learning effects, and deteriorating jobs). They proved that two versions of problem can be solved in polynomial time. Zhang et al. [30] considered single-machine group scheduling problems with position-dependent processing times. They proved that the makespan and the total completion time minimization can be solved in polynomial-time algorithm, respectively. Muştu, and Eren [31] studied the single-machine scheduling problem with sequence-independent setup times and time-dependent learning and forgetting effects. They proved that the makespan minimization is ordinary NP-hard, and they also proposed an integer nonlinear programming and a dynamic programming to solve the problem. Extensive surveys of different scheduling models and problems with group technology can be found in studies by Allahverdi [32] and Neufeld et al. [33].

More recently, Wang et al. [34] and Lu et al. [35] delved into single-machine resource allocation scheduling problems with learning effects. He et al. [36] considered the single-machine resource allocation scheduling with truncated job-dependent learning effect. Under linear and convex resource allocations, polynomial time algorithms are developed to solve the problem. Li et al. [37] considered single-machine scheduling with general job-dependent learning curves and controllable processing times. They proved that some regular and nonregular objective minimizations can be solved in polynomial time. Wang et al. [38] considered single-machine scheduling with truncated learning effects and resource allocation. For total weighted flow time cost and total resource consumption cost, they provided a bicriteria analysis. Geng et al. [39] and Sun et al. [40] investigated two-machine no-wait flow shop scheduling with resource allocation and learning effect. For the common due date assignment, Geng et al. [39] proved that two versions of the scheduling criteria and resource consumption cost can be solved in polynomial time. For the slack due-date assignment, Sun et al. [40] proved that three versions of the scheduling criteria and resource consumption cost can be solved in polynomial time. Liu and Jiang [41] explored due-date assignment scheduling problems with job-
dependent learning effects and convex resource allocation. Zhang et al. [30] considered single-machine group scheduling problems with position-dependent learning effects. They proved that the makespan and total completion time minimizations can be solved in polynomial time algorithm. Wang and Liang [42] and Liang et al. [43] investigated single-machine resource allocation scheduling with deteriorating jobs and group technology. Liao et al. [44] studied a two-competing group parallel machines scheduling problem with truncated job-dependent learning effects. Under serial-batching machines, for the makespan minimization, they proposed a greedy algorithm.

To the best of our knowledge, apart from the recent papers of Sun et al. [6] and Lv et al. [7], the single-machine slack due-date assignment scheduling problem with resource allocation, group technology, and learning effects has not been investigated. In this paper, we consider the same model as in Sun et al. [6] and Lv et al. [7], but with the tabu search and branch-and-bound algorithms to solve the problem.

### 3. Problem Formulation

We have \( n \) jobs grouped into \( f \) groups (i.e., \((G_1, G_2, \ldots, G_f)\)) to be processed by a single machine, where the number of jobs in the group \( G_i \) (\( i = 1, 2, \ldots, f \)) is \( m_i \), i.e., \( \sum_{i=1}^{f} m_i = n \). Each group \( G_i \) has \( m_i \) jobs which are processed consecutively. Let \( J_{i,j} \) be the \( j \) th job in group \( G_i \), \( i = 1, 2, \ldots, f \), \( j = 1, 2, \ldots, m_i \), i.e., group \( G_i \) has jobs \( J_{i,1}, J_{i,2}, \ldots, J_{i,m_i} \). Let \( J_{i,[j]} \) be the job in the \( i \) th group position and \( j \) th internal job position. As studied by Liang et al. [43], if the job \( J_{i,j} \) is scheduled in \( r \) th position in group \( G_i \), the actual processing time of job \( J_{i,j} \) is

\[
P^A_{i,j} = \frac{P_{i,j}^0}{u_{i,j}} \eta,
\]

where \( \eta \) is a constant positive parameter, \( P_{i,j}^0 \) is the normal processing time of job \( J_{i,j} \), \( u_{i,j} \leq 0 \) is the learning rate (see the study by Biskup [2]) of job \( J_{i,j} \), \( u_{i,j} \geq u_i > 0 \), \( u_i \) is the minimal resource allocation to the jobs of group \( G_i \) if \( u_i \) is close to zero, \( P^A_{i,j} \) will be close to infinity, which is not realistic, hence, we set \( u_{i,j} \geq u_i > 0 \). Let \( C_{i,j} \), \( d_{i,j} \) be the completion time (due-date) of job \( J_{i,j} \). For the slack (SLK) due-date assignment, we assume that the due-date of job \( J_{i,j} \) is \( d_{i,j} \neq P^A_{i,j} + q_i \), where \( q_i \) is the common flow allowance for group \( G_i \) and \( q_i \) is a decision variable. Let \( E_{i,j} = \max \{d_{i,j} - C_{i,j}, 0\} \) \((T_{i,j} = \max \{C_{i,j} - d_{i,j}, 0\}\) be the earliness (tardiness) of job \( J_{i,j} \); our goal is to find the optimal group sequence \( \pi^*_G \), job sequence \( \pi^*_i \) \( i = 1, 2, \ldots, f \) within group \( G_i \), and resource allocation such that the following cost is minimized:

\[
\sum_{i=1}^{f} \sum_{j=1}^{m_i} (a_i E_{i,j} + \beta_i T_{i,j} + \gamma_i q_i) + \sum_{i=1}^{f} \sum_{j=1}^{m_i} \gamma_i u_{i,j},
\]

where \( a_i, \beta_i, \) and \( \gamma_i \) are the nonnegative parameters of group \( G_i \) and \( u_{i,j} \) represents the unit cost of the resource allocated to job \( J_{i,j} \). Using the three-field classification (see the studies by Shabtay and Steiner [1], Biskup [2], and Azzouz et al. [3]), the problem can be denoted as

\[
l(1 \mid GT, s_i, CRA, SLK) \sum_{i=1}^{f} \left( \sum_{j=1}^{m_i} (a_i E_{i,j} + \beta_i T_{i,j} + \gamma_i q_i) + \sum_{j=1}^{m_i} \gamma_i u_{i,j} \right)
\]

where GT denotes the group technology and CRA represents the convex function of resource allocation (1).

### 4. Some Properties

Obviously, an optimal sequence exists that starts at time zero and without any machine idle time between all the jobs. Similar to the study by Adamopoulos and Pappis [45], we have the following.

**Lemma 1.** If \( C_{i,[j]} \leq d_{i,[j]} \rightarrow C_{i,[j-1]} \leq d_{i,[j-1]} \) \((i = 1, 2, \ldots, f; j = 1, 2, \ldots, m_i)\).

**Lemma 2.** For the problem \( l(1 \mid GT, s_i, CRA, SLK) \sum_{i=1}^{f} \sum_{j=1}^{m_i} \left( a_i E_{i,j} + \beta_i T_{i,j} + \gamma_i q_i \right) + \sum_{i=1}^{f} \sum_{j=1}^{m_i} \gamma_i u_{i,j} \), there exists an optimal schedule such that the optimal value of \( q_i \) coincides with the job completion time of the group \( G_i \), i.e., \( q_i = C_{i,(k-1)} = S_i \) \( + s_i + \sum_{j=1}^{k-1} P^A_{i,j} \), where

\[
k_i = \min \left\{ m_i, \max \left\{ 0, \left[ \frac{m_i}{\alpha_i + \beta_i} \right] \right\} \right\},
\]

and \( S_i \) is the starting time of group \( G_i \).

**Lemma 3** (see [43]). For a given sequence \( \pi \), the optimal resource allocation is

\[
u^*_{i,[j]} = \max \left[ u_{i,[j]}, u^*_{i,[j]} \right],
\]

where
From the study by Liang et al. [43], we have

\[
\sum_{i=1}^{f} \sum_{j=1}^{m} \left( \alpha_i E_{i,j} + \beta_j T_{i,j} + \gamma_i q_i \right) + \sum_{i=1}^{f} \sum_{j=1}^{m} \nu_i f_i \mu_i \nu_i \left( \sum_{h=1}^{f} m_{i[h]} Y_{[h]} \right) s_{[i]} \]

\[
= f \left( \sum_{h=1}^{f} m_{i[h]} Y_{[h]} \right) (1/q+1) + \left( \eta^{(1/(q+1))} + \eta^{(-\gamma/(q+1))} \right) \sum_{i=1}^{k} \sum_{j=1}^{k} \left( \alpha_{i[j]}, \gamma_{i[j]} \nu_i f_i \mu_i \nu_i \right) \left( \gamma_{i[j]}, \nu_i f_i \mu_i \nu_i \right)^{(q_i/(q+1))} \]

\[
+ \left( \eta^{(1/(q+1))} + \eta^{(-\gamma/(q+1))} \right) \sum_{i=1}^{k} \sum_{j=1}^{k} \left( \beta_{i[j]} (m_{i[j]} - j) \right) (1/(q+1)) \left( \gamma_{i[j]}, \nu_i f_i \mu_i \nu_i \right)^{(q/(q+1))} \]

Lemma 4 (see [43]). For the problem 1\{GT, s_{i}, CRA, SLK\}

\[
\sum_{i=1}^{f} \sum_{j=1}^{m} \left( \alpha_i E_{i,j} + \beta_j T_{i,j} + \gamma_i q_i \right) + \sum_{i=1}^{f} \sum_{j=1}^{m} \nu_i f_i \mu_i \nu_i \left( \sum_{h=1}^{f} m_{i[h]} Y_{[h]} \right)
\]

if the sequence of groups is given by \( \pi_{G} = \{ G_{1}, G_{2}, \ldots, G_{f} \} \), the optimal job sequence in the group \( G_{i} \) (\( i = 1, 2, \ldots, f \)) can be obtained by the following assignment problem (AP-i):

\[
(AP - i) \min \sum_{j=1}^{m_{i}} \sum_{h=1}^{m} \theta_{i,j,h} x_{i,j,h}, \quad (8)
\]

where

\[
\theta_{i,j,h} = \begin{cases} \left( \eta^{(1/(q+1))} + \eta^{(-\gamma/(q+1))} \right)^{(1/(q+1))} \left( \alpha_{i[j]} h + \sum_{h=1}^{m_{i[h]} Y_{[h]} \right)^{(q/(q+1))}, \quad i = 1, 2, \ldots, f; j = 1, 2, \ldots, m_{i[h]}; h = 1, 2, \ldots, k_{i} - 1 \\
\left( \eta^{(1/(q+1))} + \eta^{(-\gamma/(q+1))} \right)^{(1/(q+1))} \left( \beta_{i[j]} (m_{i[j]} - h) \right)^{(q/(q+1))}, \quad i = 1, 2, \ldots, f; j = 1, 2, \ldots, m_{i[h]}; h = k_{i}, k_{i} + 1, \ldots, m_{i[h]}. \quad (12)
\end{cases}
\]

Lemma 5. The term \( \sum_{i=1}^{f} \left( \sum_{h=1}^{m_{i[h]} Y_{[h]} \right) s_{[i]} \) is minimized if \( s_{[1]} \leq s_{[2]} \leq \cdots \leq s_{[f]} \).

Proof. It is similar to the proof of Liang et al. [43]. □

Lemma 6. If the optimal job sequence within each group is given, the term,

\[
\left( \eta^{(1/(q+1))} + \eta^{(-\gamma/(q+1))} \right) \sum_{i=1}^{f} \sum_{j=1}^{k_{i}-1} \left( \alpha_{i[j]} j + \sum_{h=1}^{m_{i[h]} Y_{[h]} \right)^{(1/(q+1))} \left( \gamma_{i[j]}, \nu_i f_i \mu_i \nu_i \right)^{(q/(q+1))} \]

\[
+ \left( \eta^{(1/(q+1))} + \eta^{(-\gamma/(q+1))} \right) \sum_{i=1}^{f} \sum_{j=1}^{k_{i}-1} \left( \beta_{i[j]} (m_{i[j]} - j) \right)^{(1/(q+1))} \left( \gamma_{i[j]}, \nu_i f_i \mu_i \nu_i \right)^{(q/(q+1))}, \quad (13)
\]
is minimized if \( m_{[1]} y_{[1]} \geq m_{[2]} y_{[2]} \geq \cdots \geq m_{[f]} y_{[f]} \).

**Proof.** By using simple group interchanging technique, the result can be easily obtained. \(\square\)

### 5. Polynomial Time Solvable Cases

#### 5.1. Case 1

As in the study by Liao et al. [44], if the groups have agreeable conditions, i.e., if \( s_i \leq s_k \) implies \( m_i y_i \geq m_k y_k \) for all groups \( G_i \) and \( G_k \), the problem 1\(|GT, s_i, CRA, SLK\), \( (s_i \leq s_h) \implies (m_i y_i \geq m_h y_h)\) can be solved in polynomial time.

**Lemma 7** (see [44]). For the problem 1\(|GT, s_i, CRA, SLK\), \( (s_i \leq s_h) \implies (m_i y_i \geq m_h y_h)\) can be solved in polynomial time.

### Complexity

For the problem 1\(|GT, s_i, Con\), \( (s_i \leq s_k) \implies (m_i y_i \geq m_h y_h)\), the optimal solution algorithm is given as follows:

**Theorem 1** (see [44]). The problem, 1\(|GT, s_i, CRA, SLK\), \( (s_i \leq s_h) \implies (m_i y_i \geq m_h y_h)\), can be solved by Algorithm 1 in \( O(n^2) \) time.

#### 5.2. Case 2

In this subsection, a special case will be considered, i.e., if \( s_i = s, m_i y_i = \overline{m y} \) for \( i = 1, 2, \ldots, f \).

**Lemma 8.** For the problem 1\(|GT, s_i, CRA, SLK\), \( s_i = s, m_i y_i = \overline{m y}\), the optimal group sequence \( \pi^*_G \) can be obtained by an assignment problem.

**Proof.** From Lemma 4, the sequence \( \pi^*_G (i = 1, 2, \ldots, f) \) within the group \( G_i \) can be obtained. For the group \( G_i \), if \( s_i = s_m, m_i y_i = \overline{m y} \), from (7), we have

\[
\sum_{i=1}^{f} \sum_{j=1}^{m_i} (\alpha_i E_{i,j} + \beta_i T_{i,j} + \gamma_i q_i) + \sum_{i=1}^{f} \sum_{j=1}^{m_i} \gamma_i u_{i,j}
\]

\[
= \frac{f(f+1)\overline{m y}}{2} + \left( \frac{\overline{m y}}{i} \right) \left( \sum_{j=1}^{k_{i-1}} \left( \alpha_i + j + (f-i+1)\overline{m y} \right) \left( \sum_{j=1}^{m_i} \left( \beta_i (m_i - j) \right) \right) \right)
\]

\[
+ \left( \frac{\overline{m y}}{i} \right) \left( \sum_{j=1}^{k_{i-1}} \left( \alpha_i + j + (f-i+1)\overline{m y} \right) \right)
\]

\[
\text{Let } x_{i,r} = 1, \text{ if group } G_i \text{ is assigned to position } r, \text{ and } x_{i,r} = 0 \text{ otherwise. For } (f(f+1)\overline{m y})/2 \text{ is a constant, hence the optimal group sequence } \pi^*_G \text{ can be obtained by an assignment problem (AP-G):}
\]

**AP-G** Min \[ \sum_{i=1}^{f} \sum_{r=1}^{f} \theta_{i,r} x_{i,r} \]

\[
\text{s.t. } \sum_{r=1}^{f} x_{i,r} = 1, \quad i = 1, 2, \ldots, f,
\]

\[
\sum_{i=1}^{f} x_{i,r} = 1, \quad r = 1, 2, \ldots, f,
\]

\[
x_{i,r} = 0 \text{ or } 1,
\]

where the optimal sequence of group \( G_i \) is \( \pi^*_G = (I_{i,(1)}, I_{i,(2)}, \ldots, I_{i,(m_i)}) \) (by Lemma 4), and
Step 1. Calculate $k_{(i)}$ by using (4), $i = 1, 2, \ldots, f$.
Step 2. The optimal sequence between groups is arranged in nondecreasing order of $s_{(i)}$.
Step 3. The jobs in each group are arranged according to the assignment problem AP (Lemma 4).
Step 4. Calculate the optimal resource allocation $u_{(i,l)}$ according to (5).
Step 5. Calculate the optimal common flow allowance $d_{(i)} = C_{(i)} + k_{(i)} - 1$ and the corresponding optimal objective function

$$
\sum_{i=1}^{f} \sum_{j=1}^{m_{i}} (a_{i,j} + \beta_{i} T_{i,j} + \gamma_{i} q_{i,j}) + \sum_{i=1}^{f} \sum_{j=1}^{m_{i}} v_{i,j} u_{i,j}
$$

by using (7).

**Algorithm 1: Optimal solution for Case 1.**

6. **General Case**

For the general case of the problem, $1|\text{GT}, s_{i}, \text{CRA}, \text{SLK}| \sum_{i=1}^{f} \sum_{j=1}^{m_{i}} (a_{i,j} + \beta_{i} T_{i,j} + \gamma_{i} q_{i,j}) + \sum_{i=1}^{f} \sum_{j=1}^{m_{i}} v_{i,j} u_{i,j}$, the complexity is an open question. Hence, the heuristic algorithm and branch-and-bound (B&B) algorithm might be a good way to solve the problem.

6.1. **Heuristic Algorithm.** From Lemma 4, the optimal job sequence within the same group can be obtained, and the optimal resource allocation of a given schedule can be obtained by Lemma 3. In this subsection, we apply the well-known heuristic procedure from the study by Nawaz et al. [46], and the following heuristic algorithm can be proposed.

6.2. **Tabu Search Algorithm.** Tabu search (TS) algorithm is a metaheuristic algorithm first proposed by Glover [47]. In this subsection, tabu search (TS) is used to find a near-optimal solution (Xu et al. [48]). The initial sequence used in the TS algorithm is chosen by the nondecreasing order of $s_{i}$, and the maximum number of iterations for the TS algorithm is set at 100 $f$, where $f$ is the number of groups. As in the study by Wu et al. [49], the implementation of the TS algorithm is given as follows:

6.3. **A Lower Bound.** Let $\pi_{GS} = [\pi_{GS}, \pi_{GS}]$ be a sequence of groups in which $\pi_{GS}$ is the scheduled part, and $\pi_{GS}$ is an unscheduled part. Assume that there are $g$ groups in $\pi_{GS};$ from (7), it is noticed that the terms,
Step 1. Calculate $k_{(i)}$ by using (4), $i = 1, 2, \ldots, f$.
Step 2. The optimal sequence between groups can be obtained by Lemma 8.
Step 3. The jobs in each group are arranged according to the assignment problem AP (Lemma 4).
Step 4. Calculate the optimal resource allocation $u_{[k_{(i)}]}$ according to (5).
Step 5. Calculate the optimal common flow allowance $q_{[r]} = C_{[r]}[k_{(r-1)}]$ and the corresponding optimal objective function $\sum_{i=1}^{f} \sum_{j=1}^{m_{[i]}} \alpha_{[r]}(a_{ji} + x_{[r]} Y_{i,j} + g_{[r]} q_{[r]})) + \sum_{i=1}^{f} \sum_{j=1}^{m_{[i]}} v_{i} u_{j}$ by using (7).

Algorithm 2: Optimal solution for Case 2.

can be minimized by Lemmas 5–6. Hence, the lower bound can be obtained by the following formula:

$$
LB = \sum_{i=1}^{g} \left( \sum_{h=1}^{g} m_{[h]} Y_{[h]} + \sum_{h=g+1}^{f} m_{[h]} Y_{[h]} \right) s_{[i]} + \sum_{i=g+1}^{f} \left( \sum_{h=1}^{g} m_{[h]} Y_{[h]} \right) s_{[i]} + \left( \eta^{(1/\eta+1)} + \eta^{-\eta^{(1/\eta+1)}} \right) \left( \sum_{i=g+1}^{f} \sum_{j=1}^{m_{[i]}} \left( \alpha_{[r]}(a_{ji} + x_{[r]} Y_{i,j} + g_{[r]} q_{[r]})) + \sum_{i=1}^{f} \sum_{j=1}^{m_{[i]}} v_{[i]} u_{[j]} \right) \right)
$$

where $s_{[g+2]} \leq s_{[g+2]} \leq s_{[f]}$ and $m_{[g+1]} Y_{[g+1]} \geq m_{[g+2]} Y_{[g+2]} \geq \cdots \geq m_{[f]} Y_{[f]}$ (note that $s_{[i]}$ and $m_{[i]} Y_{[i]}$ ($i = g + 1, r + 2, \ldots, f$) do not necessarily correspond to the same group).

6.4. Branch-and-Bound (B&B) Algorithm. The branch-and-bound (B&B) algorithm search follows a depth-first strategy; this algorithm assigns groups in a forward manner starting from the first position (assign a group to a node).

6.5. An Example for B&B Algorithm. Consider an example in which there are 13 jobs belonging to 5 groups $G_1 = \{J_{11}, J_{12}\}$, $G_2 = \{J_{21}, J_{22}, J_{23}\}$, $G_3 = \{J_{31}, J_{32}, J_{33}\}$, $G_4 = \{J_{41}, J_{42}\}$, and $G_5 = \{J_{51}, J_{52}, J_{53}\}$. The processing times of each job, learning rate, and setup time of each group and other parameters are shown in Tables 1 and 2.

From Algorithm 3 (HA), the initial sequence is $[G_1, G_2, G_3, G_4, G_5]$, and the objective function value (upper bound) is $\sum_{i=1}^{f} \sum_{j=1}^{m_{[i]}} (a_{ji} E_{i,j} + x_{[r]} T_{i,j} + g_{[r]} q_{[r]})) + \sum_{i=1}^{f} \sum_{j=1}^{m_{[i]}} v_{i} u_{j} = 295.8274$. According to Algorithm 4 (B&B algorithm), the following search tree can be obtained, which is represented by Figure 1. The numbers in Figure 1 represent the lower bound values, and $G_0$ is defined as the level 0.

At level 1, i.e., $g = 1$, for group $G_1$, from formula (8), the lower bound is
(1) Input: \( k_{ij} \leftarrow \) using equation (4) for \( i = 1, 2, \ldots, f \); the internal job sequence \( \pi_i^* \leftarrow \) using Lemma 4 for each group \( G_i \), \( i = 1, 2, \ldots, f \).

(2) Output: the suboptimal resource allocation \( \pi_i^* \), suboptimal common flow allowance \( q_{il}^* = C_{il}[k_{ij} - 1] \), and corresponding objective function value \( \sum_{l=1}^{f} \sum_{j=1}^{m} (a_i E_{il} + \beta_i T_{ij} + y_i q_{il}) + \sum_{l=1}^{f} \sum_{j=1}^{m} \eta_{ij} u_{ij} \).

(3) For each \( \pi_i^* \), groups are scheduled by the nondecreasing order of \( s_i \), \( i = 1, 2, \ldots, f \);

(4) For each \( \pi_i^* \), groups are scheduled by the nonincreasing order of \( m_i y_i \), \( i = 1, 2, \ldots, f \);

(5) From Step 3 and Step 4, the smallest objective function value \( \sum_{l=1}^{f} \sum_{j=1}^{m} (a_i E_{il} + \beta_i T_{ij} + y_i q_{il}) + \sum_{l=1}^{f} \sum_{j=1}^{m} \eta_{ij} u_{ij} \) is selected as the original group sequence \( \pi_{ij} \);

(6) Pick the two groups from the first and second position of the list of Step 5 and find the best sequence for these two groups by calculating \( \sum_{l=1}^{f} \sum_{j=1}^{m} (a_i E_{il} + \beta_i T_{ij} + y_i q_{il}) + \sum_{l=1}^{f} \sum_{j=1}^{m} \eta_{ij} u_{ij} \) for the two possible sequences. Do not change the relative positions of these two groups with respect to each other in the remaining steps of the algorithm.

(7) Pick the group in the \( i \)th position of the list generated in Step 5 and find the best sequence by placing it at all possible \( i \) positions in the partial sequence found in the previous step, without changing the relative positions to each other of the already assigned groups. The number of enumerations at this step equals \( i \);

(8) If \( i > f \), then stop

(9) Otherwise,

(10) \( i \leftarrow i + 1 \), and return to Step 7;

(11) Calculate the suboptimal resource allocation \( u_{il}^* \) according to (5). Calculate the suboptimal common flow allowance \( q_{il}^* = C_{il}[k_{ij} - 1] \) and the corresponding optimal objective function \( \sum_{l=1}^{f} \sum_{j=1}^{m} (a_i E_{il} + \beta_i T_{ij} + y_i q_{il}) + \sum_{l=1}^{f} \sum_{j=1}^{m} \eta_{ij} u_{ij} \) by using (7).

**Algorithm 3: HA.**

Step 1. Finding the upper bound: use Algorithm 3 to obtain an initial solution for the problem.

Step 2. Bounding: calculate the lower bound (see (8)) for the node. If the lower bound for an unsearched partial schedule of groups is larger than or equal to the value of the objective function of the initial solution, eliminate the node and all the nodes following it in the branch. Calculate the objective function value of the completed schedule; if it is less than the initial solution, replace it as the new solution; otherwise, eliminate it.

Step 3. Termination: continue until all nodes have been explored.

**Algorithm 4: B&B algorithm.**
Figure 1: Search tree of the B&B algorithm for the example (× denotes pruning).
Step 1. Calculate \( k_{(i)} \) by using (4), \( i = 1, 2, \ldots, f \).
Step 2. The jobs in each group are arranged according to the assignment problem \( \text{AP} \) (Lemma 4).
Step 3. List all the group schedules.
Step 4. For each group schedule, calculate the corresponding objective value \( \sum_{i=1}^{f} \sum_{j=1}^{m_i} \left( a_i E_{i,j} + \beta_j T_{i,j} + \gamma_j q_j \right) + \sum_{i=1}^{f} \sum_{j=1}^{m_i} v_{i,j} h_{i,j} \).
Step 5. Comparing all the objective values \( \sum_{i=1}^{f} \sum_{j=1}^{m_i} \left( a_i E_{i,j} + \beta_j T_{i,j} + \gamma_j q_j \right) + \sum_{i=1}^{f} \sum_{j=1}^{m_i} v_{i,j} h_{i,j} \), the minimum one is optimal, and its corresponding schedule is the optimal sequence of the problem 1|\(G,T_s,\text{CRA,SLK}\)|\(\sum_{i=1}^{f} \sum_{j=1}^{m_i} \left( a_i E_{i,j} + \beta_j T_{i,j} + \gamma_j q_j \right) + \sum_{i=1}^{f} \sum_{j=1}^{m_i} v_{i,j} h_{i,j} \).

**Algorithm 5:** Optimal solution for Case 3.

Step 1. Let the tabu list be empty and the iteration number be zero.
Step 2. Set the initial sequence of the TS algorithm, calculate its objective function, and set the current sequence as the best solution \( \pi^* \).
Step 3. Search the associated neighborhood of the current sequence and resolve if there is a sequence \( \pi^{**} \) with the smallest objective function in associated neighborhood and it is not in the tabu list.
Step 4. If \( \pi^{**} \) is better than \( \pi^* \), then let \( \pi^* = \pi^{**} \). Update the tabu list and the iteration number.
Step 5. If there is not a sequence in associated neighborhood but it is not in the tabu list or the maximum number of iterations is reached, then output the final sequence. Otherwise, update tabu list and go to Step 3.

**Algorithm 6:** TS.

\[
LB(G_1) = (2 \times 1 + 3 \times 1 + 3 \times 1 + 3 \times 1 + 2 \times 1) \times 3
\]
\[
+ (3 \times 1 + 3 \times 1 + 3 \times 1 + 2 \times 1) \times 4 + (3 \times 1 + 3 \times 1 + 2 \times 1) \times 5
\]
\[
+ (3 \times 1 + 2 \times 1) \times 6 + 2 \times 1 \times 7
\]
\[
= \left( 2 \times (2 - 1) \right)^{1/2} \times (4 \times 5)^{1/2}
\]
\[
= \left( 2 \times (2 - 1) \right)^{1/2} \times (4 \times 5)^{1/2}
\]
\[
\times \left( 2 \times (3 - 1) \right)^{1/2} \times (3 \times 6)^{1/2} + (2 \times (3 - 1) \right)^{1/2} \times (2 \times (3 - 2) \right)^{1/2} \times (5 \times 7 \times 2^{-0.22})^{1/2}
\]
\[
+ 2 \times (2 \times (3 - 1) \right)^{1/2} \times (3 \times 7)^{1/2} + (2 \times (3 - 1) \right)^{1/2} \times (2 \times (3 - 2) \right)^{1/2} \times (6 \times 4 \times 2^{-0.23})^{1/2}
\]
\[
+ (2 \times (3 - 1) \right)^{1/2} \times (6 \times 2)^{1/2} + (2 \times (3 - 2) \right)^{1/2} \times (5 \times 5 \times 2^{-0.26})^{1/2}
\]
\[
+ (2 \times (3 - 2) \right)^{1/2} \times (2 \times 2)^{1/2} \times 239.8274.
\]

The calculation process of lower bounds of the remaining node is similar to that of this node. From Figure 1, the optimal sequences are \([G_1, G_2, G_3, G_4, G_5, G_6, G_7]\), \([G_1, G_2, G_3, G_4, G_5, G_6, G_7]\), and \([G_3, G_4, G_5, G_6, G_7]\), and the optimal value of objective function is \( \sum_{i=1}^{f} \sum_{j=1}^{m_i} \left( a_i E_{i,j} + \beta_j T_{i,j} + \gamma_j q_j \right) + \sum_{i=1}^{f} \sum_{j=1}^{m_i} v_{i,j} h_{i,j} \) = 295.8274.

6.6. Computational Experiments. An enumeration algorithm (i.e., Algorithm 5), heuristic algorithm (i.e., Algorithm 3), TS algorithm (i.e., Algorithm 6), and B&B algorithm (i.e., Algorithm 4) were programmed in C++ and carried out on a CPU Intel Core i5-8250U 1.4 GHz PC with 8.00 GB RAM. The number of jobs and groups \( n = 50, 100, 150, 200 \) and \( f = 8, 9, 10, 11, 12 \) were tested, and each group must contain at least one job. The parameters setting can be obtained as follows: \( s_i, v_{i,j}, a_i, \beta_j, \) and \( \gamma_j \) were drawn from a discrete uniform distribution in \([1, 10] \); \( P_{i,j} \) were drawn from a discrete uniform distribution in \([1, 100] \); \( a_{i,j} \) were drawn from a uniform distribution in \([-0.1, -1] \); and \( \eta = 2 \). To avoid the contingency, each problem instance was conducted 20 times, setting the maximum CPU time per instance at 3600 seconds. The percentage relative error of the solution produced by Algorithms 3 and 6 is calculated as

\[
Z(\text{AI}) - Z^* \times 100%.
\]

where \( i = 4, 5 \), \( Z(\text{AI}) \), and \( Z^* \) are the objective function values \( \sum_{i=1}^{f} \sum_{j=1}^{m_i} \left( a_i E_{i,j} + \beta_j T_{i,j} + \gamma_j q_j \right) + \sum_{i=1}^{f} \sum_{j=1}^{m_i} v_{i,j} h_{i,j} \) generated by Algorithm 1 and Algorithm 4, respectively.

On the other hand, "A5-CPU time (s)" ("A4-CPU time (s)," "A5-CPU time (s)," and "A6-(B&B) CPU time (s)") as the running time of Algorithm 5 (Algorithms 3–4) is defined. The results are summarized in Table 3. From Table 3, it is easy to find that the maximum relative error percentage of Algorithm 3 is less than 6.1% for \( n \leq 200 \), and performance of Algorithm 3 (i.e., the heuristic algorithm) performs very well in terms of the
relative error percentages. Moreover, Table 3 shows that the mean CPU time (s) for the enumeration algorithm (i.e., Algorithm 5) is larger than the B&B algorithm (i.e., Algorithm 4).

| n   | f     | Mean | Max | Mean | Max | Mean | Max | Mean | Max | Error percentage of Algorithm A4 (%) | Error percentage of Algorithm A5 (%) |
|-----|-------|------|-----|------|-----|------|-----|------|-----|-------------------------------------|-------------------------------------|
| 8   | 3.971 | 5.582| 0.032| 0.091| 0.022| 0.052| 27.382| 32.422| 2.561| 5.071| 9.972| 10.063|
| 9   | 28.362| 34.652| 0.053| 0.123| 0.043| 0.194| 39.029| 57.875| 1.361| 2.622| 5.962| 21.044|
| 10  | 104.129| 130.994| 0.048| 0.121| 0.052| 0.354| 42.344| 98.673| 0.961| 1.142| 7.651| 20.212|
| 11  | 1000.221| 1089.481| 0.054| 0.282| 0.115| 0.352| 91.898| 583.131| 1.272| 1.831| 4.033| 14.321|
| 50  | 12    | 3600 | 3600| 0.061| 0.823| 0.133| 0.491| 173.384| 875.419| 4.112| 6.032| 5.841| 28.402|
| 8   | 4.229 | 8.229| 0.034| 0.092| 0.033| 0.194| 32.125| 39.009| 1.371| 2.632| 7.284| 9.792|
| 9   | 43.345| 50.812| 0.032| 0.112| 0.042| 0.194| 39.245| 45.673| 1.854| 1.983| 4.082| 30.125|
| 10  | 264.826| 406.541| 0.044| 0.214| 0.651| 0.423| 36.304| 69.695| 3.114| 3.835| 5.641| 23.164|
| 11  | 1997.841| 3600| 0.052| 0.292| 0.691| 0.784| 66.647| 300.213| 2.812| 3.051| 4.914| 23.815|
| 100 | 12    | 3600 | 3600| 0.076| 0.651| 0.146| 0.802| 195.528| 893.523| 1.343| 1.692| 6.961| 21.573|
| 8   | 7.851 | 19.331| 0.033| 0.112| 0.034| 0.415| 40.554| 49.069| 2.781| 3.742| 6.462| 20.744|
| 9   | 57.825| 89.071| 0.043| 0.255| 0.047| 0.324| 52.417| 82.521| 1.561| 1.952| 10.184| 39.163|
| 10  | 329.781| 497.362| 0.045| 0.291| 0.066| 0.694| 109.697| 209.871| 2.052| 2.931| 7.322| 19.972|
| 11  | 3193.322| 3600| 0.057| 0.331| 0.095| 0.911| 159.225| 323.745| 3.131| 4.052| 6.913| 27.331|
| 150 | 12    | 3600 | 3600| 0.071| 0.992| 0.139| 0.684| 243.252| 904.032| 2.663| 3.054| 9.771| 28.324|
| 8   | 11.861| 32.881| 0.042| 0.212| 0.047| 0.309| 51.859| 69.672| 0.781| 1.516| 4.421| 18.714|
| 9   | 98.651| 122.325| 0.047| 0.215| 0.059| 0.575| 74.957| 194.634| 1.181| 1.844| 5.521| 22.605|
| 10  | 475.841| 779.563| 0.051| 0.421| 0.067| 0.688| 193.577| 488.581| 2.724| 3.114| 8.821| 16.345|
| 200 | 11    | 3600 | 3600| 0.061| 0.985| 0.101| 0.691| 296.335| 723.316| 1.641| 2.954| 6.601| 26.125|
| 12  | 3600 | 3600| 0.079| 1.431| 0.139| 0.704| 435.229| 1012.532| 1.773| 2.265| 8.223| 28.108|

7. Conclusions

In this paper, we studied the single-machine resource allocation scheduling problem with learning effect and group technology. The goal is to determine the optimal sequence of jobs and groups, the optimal common flow allowances, and the optimal resource allocation such that the weighted sum of the scheduling cost and the resource allocation cost is minimized. For some special cases (i.e., cases \( s_i \leq s_h \) \( \rightarrow (m_i, y_i) \geq m_h, y_h \), \( s_i = s \), \( m_i y_i = m_y \), and \( f \) is a given constant), it was shown that the problem can be solved in polynomial time. For the general case of the problem, the heuristic, tabu search, and B&B algorithms were proposed. The results show that the maximum relative percentage error of the proposed heuristic algorithm (i.e., Algorithm 3) from optimal solutions is less than 6.1% for all sizes of instances.

Further research may focus on the extensions of this model to more complicated machine setting (such as flow shop and/or parallel machines) or study other nonregular objective functions (such as due-window assignment scheduling problems with position-dependent weights, see the study by Wang et al. [50]).

Data Availability

The data used to support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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