

Unrelated Parallel-Machine Scheduling Problems with General Truncated Job-Dependent Learning Effect

Jibo Wang¹, Chou-Jung Hsu^{2*}

¹School of Science, Shenyang Aerospace University, Shenyang, China

²Department of Industrial Management, Nan Kai University of Technology, Taiwan

Email: wangjibo75@163.com, jrsheu@nkut.edu.tw

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Abstract

In this paper, we consider scheduling problems with general truncated job-dependent learning effect on unrelated parallel-machine. The objective functions are to minimize total machine load, total completion (waiting) time, total absolute differences in completion (waiting) times respectively. If the number of machines is fixed, these problems can be solved in $O(n^{m+2})$ time respectively, where m is the number of machines and n is the number of jobs.

Keywords

Scheduling, Unrelated Parallel Machines, Truncated Job-Dependent Learning

1. Introduction

In modern planning and scheduling problems, there are many real situations where the processing time of jobs may be subject to change due to learning effect. An extensive survey of different scheduling models and problems with learning effects could be found in Biskup [1]. More recently, Janiak *et al.* [2] studied a single processor problem with a S-shaped learning model. They proved that the makespan minimization problem is strongly NP-hard. Lee [3] considered scheduling jobs with general position-based learning curves. For some single machine and a two-machine flowshop scheduling problems, they presented the optimal solution respectively. Lee [4] considered single-machine scheduling jobs with general learning effect and past-sequence-dependent setup time. For some single machine scheduling problems, they presented the optimal solution respectively. Lee and Wu [5], and Wu and Lee [6] considered scheduling jobs with learning effects. They proved that some single machine and flowshop scheduling problems can be solved in polynomial time respectively. Lee *et al.* [7] considered a single-machine scheduling problem with release times and learning effect. Lee *et al.* [8] considered a makespan minimization uniform parallel-machine scheduling problem with position-based learning curves. Lee and Chung [9], Sun *et al.* [10] [11], and Wang *et al.* [12] considered flow shop scheduling with learning effects. Wu *et al.* [13], Wu *et al.* [14], Wu *et al.* [15] and Wang *et al.* [16] considered scheduling problems with the

*Corresponding author.

truncated learning effect.

Recently, Wang *et al.* [17] considered several scheduling problems on a single machine with truncated job-dependent learning effect, *i.e.*, the actual processing time of job J_j is $p_{jr}^A = p_j \max\{r^{a_j}, b\}$ if it is scheduled in the r th position of a sequence, where $a_j \leq 0$ is the job-dependent learning index of job J_j , and b is a truncation parameter with $0 < b < 1$. In this paper, we study scheduling problems with general truncated job-dependent learning effect on unrelated parallel-machine. The objective is to minimize total machine load, total completion (waiting) time, total absolute differences in completion (waiting) times respectively.

2. Problems Description

There are n independent jobs $N = \{J_1, J_2, \dots, J_n\}$ to be processed on m unrelated parallel-machine $M = \{M_1, M_2, \dots, M_m\}$. Let (n_1, n_2, \dots, n_m) denote a job-allocation vector, where n_i denotes the number of jobs assigned to machine M_i , and $\sum_{i=1}^m n_i = n$. In this paper, we assume that the actual processing time of job J_j scheduled on machine M_i is

$$p_{ijr}^A = p_{ij} \max\{f_{ij}(r), b\}, \quad i = 1, 2, \dots, m; \quad r, j = 1, 2, \dots, n, \quad (1)$$

where $p_{ij} \geq 0$ denotes the normal (basic) processing time of job J_j ($j = 1, 2, \dots, n$) on machine M_i , r is the position of a sequence, b is a truncation parameter with $0 < b < 1$, $f_{ij}(r)$ is the general case of positional learning for job J_j on machine M_i , special $f_{ij}(r) = r^{a_{ij}}$ is the polynomial learning index for job J_j on machine M_i ($a_{ij} < 0$), $f_{ij}(r) = b_{ij}^{r-1}$ is the exponential learning index for job J_j on machine M_i ($0 < b_{ij} < 1$).

Let C_{ij} and $W_{ij} = C_{ij} - p_{ij}$ be the completion and waiting time for job J_j on machine M_i respectively. The goal is to determine the jobs assigned to corresponding each machine and the corresponding optimal schedule so that the following objective functions is to be minimized: the total machine load $\sum_{i=1}^m C_{\max}^i$, the total completion (waiting) times $\sum_{i=1}^m \sum_{j=1}^{n_i} C_{ij}$ ($\sum_{i=1}^m \sum_{j=1}^{n_i} W_{ij}$), the total absolute differences in completion (waiting) times $\sum_{i=1}^m \sum_{k=1}^{n_i} \sum_{j=k}^{n_i} |C_{ik} - C_{ij}|$ ($\sum_{i=1}^m \sum_{k=1}^{n_i} \sum_{j=k}^{n_i} |W_{ik} - W_{ij}|$), where C_{\max}^i denotes the makespan of machine M_i . Using the three-field notation [18] the problems can be denoted as $Rm|Y|Z$, where Y denote the model (1), $Z \in \left\{ \sum_{i=1}^m C_{\max}^i, \sum_{i=1}^m \sum_{j=1}^{n_i} C_{ij}, \sum_{i=1}^m \sum_{j=1}^{n_i} W_{ij}, \sum_{i=1}^m \sum_{k=1}^{n_i} \sum_{j=k}^{n_i} |C_{ik} - C_{ij}|, \sum_{i=1}^m \sum_{k=1}^{n_i} \sum_{j=k}^{n_i} |W_{ik} - W_{ij}| \right\}$.

3. Main Results

Let p_{ij} denote the actual processing time of a job when it is scheduled in position j on machine M_i , then $f_{i[j]}(j)$, $J_{i[j]}$, $C_{i[j]}$, $W_{i[j]}$ are defined similarly.

Lemma 1. For a given permutation $\pi_i = (J_{i[1]}, J_{i[2]}, \dots, J_{i[n_i]})$ on machine M_i ,

$$\begin{aligned} \sum_{i=1}^m C_{\max}^i &= \sum_{i=1}^m \sum_{j=1}^{n_i} p_{i[j]} \max\{f_{i[j]}(j), b\} \\ \sum_{i=1}^m \sum_{j=1}^{n_i} C_{ij} &= \sum_{i=1}^m \sum_{j=1}^{n_i} (n_i - j + 1) p_{i[j]} \max\{f_{i[j]}(j), b\} \\ \sum_{i=1}^m \sum_{j=1}^{n_i} W_{ij} &= \sum_{i=1}^m \sum_{j=1}^{n_i} (n_i - j) p_{i[j]} \max\{f_{i[j]}(j), b\} \\ \sum_{i=1}^m \sum_{k=1}^{n_i} \sum_{j=k}^{n_i} |C_{ik} - C_{ij}| &= \sum_{i=1}^m \sum_{j=1}^{n_i} (j-1)(n_i - j + 1) p_{i[j]} \max\{f_{i[j]}(j), b\} \quad (\text{Kanet [19]}) \\ \sum_{i=1}^m \sum_{k=1}^{n_i} \sum_{j=k}^{n_i} |W_{ik} - W_{ij}| &= \sum_{i=1}^m \sum_{j=1}^{n_i} j(n_i - j) p_{i[j]} \max\{f_{i[j]}(j), b\} \quad (\text{Bagchi [20]}). \end{aligned}$$

If the vector (n_1, n_2, \dots, n_m) is given, let X_{jir} be a 0/1 variable such that $X_{jir} = 1$ if job J_j ($j = 1, 2, \dots, n$) is assigned at position r ($r = 1, 2, \dots, n_i$) on machine M_i ($i = 1, 2, \dots, m$), and $X_{jir} = 0$, otherwise. Then, the problem $Rm|Y|Z$ (where $\sum_{i=1}^m \sum_{k=1}^{n_i} \sum_{j=k}^{n_i} |C_{ik} - C_{ij}|, \sum_{i=1}^m \sum_{k=1}^{n_i} \sum_{j=k}^{n_i} |W_{ik} - W_{ij}|$) can be solved by the following

assignment problem:

$$\min Z = \sum_{i=1}^m \sum_{r=1}^{n_i} \sum_{j=1}^n \lambda_{ir} p_{ij} \max \{ f_{ij}(r), b \} X_{jir} \quad (2)$$

s.t.

$$\sum_{i=1}^m \sum_{r=1}^{n_i} X_{jir} = 1, \quad j = 1, 2, \dots, n, \quad (3)$$

$$\sum_{j=1}^n X_{jir} = 1, \quad i = 1, 2, \dots, m, \quad r = 1, 2, \dots, n_i, \quad (4)$$

$$X_{jir} = 0 \text{ or } 1, \quad j = 1, 2, \dots, n, \quad i = 1, 2, \dots, m, \quad r = 1, 2, \dots, n_i, \quad (5)$$

where $\lambda_{ir} = 1$ for $\sum_{i=1}^m C_{\max}^i$, $\lambda_{ir} = (n_i - r + 1)$ for $\sum_{i=1}^m \sum_{k=1}^{n_i} C_{ik}$, $\lambda_{ir} = (n_i - r)$ for $\sum_{i=1}^m \sum_{k=1}^{n_i} W_{ik}$, $\lambda_{ir} = (r - 1)(n_i - r + 1)$ for $\sum_{i=1}^m \sum_{k=1}^{n_i} \sum_{j=k}^{n_i} |C_{ik} - C_{ij}|$, $\lambda_{ir} = r(n_i - r)$ for $\sum_{i=1}^m \sum_{k=1}^{n_i} \sum_{j=k}^{n_i} |W_{ik} - W_{ij}|$.

Now, the question is how many vectors (n_1, n_2, \dots, n_m) exist. Obviously n_i may be 0, 1, 2, \dots , n ($i = 1, 2, \dots, m$). So if the numbers of jobs assigned to the first $m - 1$ machines is given, the number of jobs assigned to the last machine is then determined uniquely ($\sum_{i=1}^m n_i = n$). Therefore, the upper bound of (n_1, n_2, \dots, n_m) is $(n + 1)^{m-1}$. Based on the above analysis, we have the following result.

Theorem 1. For a given constant m , $Rm|Y|Z$ can be solved in $O(n^{m+2})$ time, where

$$Z \in \left\{ \sum_{i=1}^m C_{\max}^i, \sum_{i=1}^m \sum_{j=1}^{n_i} C_{ij}, \sum_{i=1}^m \sum_{j=1}^{n_i} W_{ij}, \sum_{i=1}^m \sum_{k=1}^{n_i} \sum_{j=k}^{n_i} |C_{ik} - C_{ij}|, \sum_{i=1}^m \sum_{k=1}^{n_i} \sum_{j=k}^{n_i} |W_{ik} - W_{ij}| \right\}.$$

Proof. As discussed above, to solve the problem $Rm|Y|Z$, polynomial number (i.e., $(n + 1)^{m-1}$) of assignment problems need to be solved. Each assignment problem is solved in $O(n^3)$ time (by using the Hungarian method). Hence, the time complexity of the problem $Rm|Y|Z$ can be solved in $O(n^{m+2})$ time, where

$$Z \in \left\{ \sum_{i=1}^m C_{\max}^i, \sum_{i=1}^m \sum_{j=1}^{n_i} C_{ij}, \sum_{i=1}^m \sum_{j=1}^{n_i} W_{ij}, \sum_{i=1}^m \sum_{k=1}^{n_i} \sum_{j=k}^{n_i} |C_{ik} - C_{ij}|, \sum_{i=1}^m \sum_{k=1}^{n_i} \sum_{j=k}^{n_i} |W_{ik} - W_{ij}| \right\}.$$

Note that if the number of machines m is fixed, then the problem $Rm|Y|Z$ can be solved in polynomial time. Based on the above analysis, we can determine the optimal solution for the problem $Rm|Y|Z$ via the following algorithm:

Algorithm 1

Step 1. For each possible vector (n_1, n_2, \dots, n_m) , solve the assignment problem (2)-(5). Then, obtain the optimal schedule and the corresponding objective function Z .

Step 2. The optimal solution for the problem is the one with the minimum value of the objective function Z , where $Z \in \left\{ \sum_{i=1}^m C_{\max}^i, \sum_{i=1}^m \sum_{j=1}^{n_i} C_{ij}, \sum_{i=1}^m \sum_{j=1}^{n_i} W_{ij}, \sum_{i=1}^m \sum_{k=1}^{n_i} \sum_{j=k}^{n_i} |C_{ik} - C_{ij}|, \sum_{i=1}^m \sum_{k=1}^{n_i} \sum_{j=k}^{n_i} |W_{ik} - W_{ij}| \right\}$.

The following example illustrates the working of Algorithm 1 to find the optimal solution for the problem $Rm|Y|\sum_{i=1}^m \sum_{j=1}^{n_i} C_{ij}$.

Example 1. There are $n = 5$ jobs and $f_{ij}(r) = r^{a_{ij}}$. The number of machines is $m = 2$ and $p_{11} = 15$, $p_{12} = 11$, $p_{13} = 14$, $p_{14} = 3$, $p_{15} = 9$, $p_{21} = 12$, $p_{22} = 10$, $p_{23} = 9$, $p_{24} = 16$, $p_{25} = 8$, $a_{11} = -0.23$, $a_{12} = -0.32$, $a_{13} = -0.25$, $a_{14} = -0.35$, $a_{15} = -0.26$, $a_{21} = -0.32$, $a_{22} = -0.21$, $a_{23} = -0.31$, $a_{24} = -0.24$, $a_{25} = -0.29$, $b = 0.7$ are given.

Solution. When $n_1 = 0$, $n_2 = 5$, the positional weights on machine M_2 are $\theta_{21} = 5$, $\theta_{22} = 4$, $\theta_{23} = 3$, $\theta_{24} = 2$, $\theta_{25} = 1$. Then values $\theta_{ir} p_{ij} \max \{ r^{a_{ij}}, b \}$ are given in **Table 1** (the bold value is the optimal solution of the assignment problem (2)-(5)). We solve the assignment problem (2)-(5) to $\sum_{i=1}^m \sum_{j=1}^{n_i} C_{ij} = 339.65119$.

When $n_1 = 1$, $n_2 = 4$, the positional weights on machine M_1 and M_2 are $\theta_{11} = 1$, $\theta_{21} = 4$, $\theta_{22} = 3$, $\theta_{23} = 2$, $\theta_{24} = 1$. Then values $\theta_{ir} p_{ij} \max \{ r^{a_{ij}}, b \}$ are given in **Table 2**. We solve the assignment problem

Table 1. The $\theta_{ir} p_{ij} \max \{r^{a_{ij}}, b\}$ values of Example 1. for $n_1 = 0, n_2 = 5$.

$ij \setminus ir$	θ_{21}	θ_{22}	θ_{23}	θ_{24}	θ_{25}
J_{21}	60	38.45135	25.32933	16.80000	8.40000
J_{22}	50	34.58149	23.81912	14.94849	7.13208
J_{23}	45	29.03910	19.20685	12.60000	6.30000
J_{24}	90	54.19170	36.87501	22.94328	11.20000
J_{25}	40	27.09585	18.43750	11.20000	5.60000

Table 2. The $\theta_{ir} p_{ij} \max \{r^{a_{ij}}, b\}$ values of Example 1 for $n_1 = 1, n_2 = 4$.

$ij \setminus ir$	θ_{11}	θ_{21}	θ_{22}	θ_{23}	θ_{24}
J_{i1}	15	48	28.83852	16.88622	8.40000
J_{i2}	11	40	25.93612	15.87942	7.13208
J_{i3}	14	36	21.77933	12.80457	6.30000
J_{i4}	3	64	40.64377	24.58334	11.20000
J_{i5}	9	32	19.62965	11.63469	5.60000

(2)-(5) to obtain that the optimal schedule on machine M_1 is $[J_4]$, and on machine M_2 is $[J_5, J_3, J_2, J_1]$.

The objective function is $\sum_{i=1}^m \sum_{j=1}^{n_i} C_{ij} = 81.05875$.

When $n_1 = 2, n_2 = 3$, the positional weights on machine M_1 and M_2 are $\theta_{11} = 2, \theta_{12} = 1, \theta_{21} = 3, \theta_{22} = 2, \theta_{23} = 1$. Then values $\theta_{ir} p_{ij} \max \{r^{a_{ij}}, b\}$ are given in **Table 3**. We solve the assignment problem (2)-(5) to obtain that the optimal schedule on machine M_1 is $[J_4, J_2]$, and on machine M_2 is $[J_5, J_3, J_1]$. The objective function is $\sum_{i=1}^m \sum_{j=1}^{n_i} C_{ij} = 61.77443$.

When $n_1 = 3, n_2 = 2$, the positional weights on machine M_1 and M_2 are $\theta_{11} = 3, \theta_{12} = 2, \theta_{13} = 1, \theta_{21} = 2, \theta_{22} = 1$. Then values $\theta_{ir} p_{ij} \max \{r^{a_{ij}}, b\}$ are given in **Table 4**. We solve the assignment problem (2)-(5) to obtain that the optimal schedule on machine M_1 is $[J_4, J_5, J_2]$, and on machine M_2 is $[J_3, J_1]$. The objective function is $\sum_{i=1}^m \sum_{j=1}^{n_i} C_{ij} = 59.38394$.

When $n_1 = 4, n_2 = 1$, the positional weights on machine M_1 and M_2 are $\theta_{11} = 4, \theta_{12} = 3, \theta_{13} = 2, \theta_{14} = 1, \theta_{21} = 1$. Then values $\theta_{ir} p_{ij} \max \{r^{a_{ij}}, b\}$ are given in **Table 5**. We solve the assignment problem (2)-(5) to obtain that the optimal schedule on machine M_1 is $[J_4, J_5, J_2, J_1]$, and on machine M_2 is $[J_3]$. The objective function is $\sum_{i=1}^m \sum_{j=1}^{n_i} C_{ij} = 69.93119$.

When $n_1 = 5, n_2 = 0$, the positional weights on machine M_1 and are $\theta_{11} = 5, \theta_{12} = 4, \theta_{13} = 3, \theta_{14} = 2, \theta_{15} = 1$. Then values $\theta_{ir} p_{ij} \max \{r^{a_{ij}}, b\}$ are given in **Table 6**. We solve the assignment problem (2)-(5) to obtain that the optimal schedule on machine M_1 is $[J_4, J_5, J_2, J_3, J_1]$. The objective function is $\sum_{i=1}^m \sum_{j=1}^{n_i} C_{ij} = 98.58071$.

Table 3. The $\theta_{ir} p_{ij} \max \{r^{a_{ij}}, b\}$ values of Example 1 for $n_1 = 2, n_2 = 3$.

$ij \setminus ir$	θ_{11}	θ_{21}	θ_{22}	θ_{23}	θ_{24}
J_{11}	30	12.78952	36	19.22568	8.44311
J_{12}	22	8.81177	30	17.29074	7.93971
J_{13}	28	11.77255	27	14.51955	6.40228
J_{14}	6	2.35375	48	27.09585	12.29167
J_{15}	18	7.51579	24	13.08643	5.81735

Table 4. The $\theta_{ir} p_{ij} \max \{r^{a_{ij}}, b\}$ values of Example 1 for $n_1 = 3, n_2 = 2$.

$ij \setminus ir$	θ_{11}	θ_{21}	θ_{22}	θ_{23}	θ_{24}
J_{11}	45	25.57905	11.65074	24	9.61284
J_{12}	33	17.62354	7.739517	20	8.64537
J_{13}	42	23.54510	10.63770	18	7.25978
J_{14}	9	4.70751	2.10000	32	13.54792
J_{15}	27	15.03158	6.76380	16	6.54322

Table 5. The $\theta_{ir} p_{ij} \max \{r^{a_{ij}}, b\}$ values of Example 1 for $n_1 = 4, n_2 = 1$.

$ij \setminus ir$	θ_{11}	θ_{21}	θ_{22}	θ_{23}	θ_{24}
J_{11}	60	38.36857	23.30147	10.90479	12
J_{12}	44	26.43531	15.47903	7.70000	10
J_{13}	56	35.31765	21.2754	9.89950	9
J_{14}	12	7.06126	4.20000	2.10000	16
J_{15}	36	22.54737	13.52761	6.30000	8

Table 6. The $\theta_{ir} p_{ij} \max \{r^{a_{ij}}, b\}$ values of Example 1 for $n_1 = 5, n_2 = 0$.

$ij \setminus ir$	θ_{21}	θ_{22}	θ_{23}	θ_{24}	θ_{25}
J_{11}	75	51.15809	34.95221	21.80959	10.50000
J_{12}	55	35.24707	23.21855	15.40000	7.70000
J_{13}	70	47.09020	31.91310	19.79899	9.80000
J_{14}	15	9.41501	6.30000	4.20000	2.10000
J_{15}	45	30.06317	20.29141	12.60000	6.30000

Hence, the optimal schedule on machine M_1 is $[J_4, J_5, J_2]$, and on machine M_2 is $[J_3, J_1]$. The optimal objective function is $\sum_{i=1}^m \sum_{j=1}^{n_i} C_{ij} = 59.38394$.

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