# Single Machine Scheduling with Time-Dependent Learning Effect and Non-Linear Past-Sequence-Dependent Setup Times 

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#### Abstract

This paper studies a single machine scheduling problem with time-dependent learning and setup times. Time-dependent learning means that the actual processing time of a job is a function of the sum of the normal processing times of the jobs already scheduled. The setup time of a job is proportional to the length of the already processed jobs, that is, past-sequence-dependent (psd) setup time. We show that the addressed problem remains polynomially solvable for the objectives, i.e., minimization of the total completion time and minimization of the total weighted completion time. We also show that the smallest processing time (SPT) rule provides the optimum sequence for the addressed problem.


## Keywords

Scheduling, Time-Dependent Learning, Setup Time, Past-Sequence-Dependent, Total Completion Time

## 1. Introduction

In classical scheduling problems, it is reasonable and necessary to consider scheduling problems with setup times. In many realistic situations, the setup times are considered either sequence independent or sequence dependent. In the first case, the setup times are usually added to the job processing times while in the second case, the setup time for the job currently being scheduled depends on the previous one or ones already scheduled. Koulamas and Kyparisis [1] first introduced a scheduling problem with past-sequence-dependent setup times, i.e., the setup time is dependent on all already scheduled jobs. They showed that a standard single machine scheduling problem with psd setup times can be solvable in polynomial time when the objectives are the makespan, the total completion time and the total absolute differences in completion times, respectively. They also

[^0]extended their results to nonlinear psd setup times.
Recently, there is a growing interest in the literature to study scheduling problems with a learning effect [1]-[9] [10]-[12], and some researches take setup times into the study problem as well, such as Kuo and Yang [13] considered a single machine scheduling with past-sequence-dependent setup times and job-independent learning effect and showed the problem remains polynomially solvable for the objectives of the makespan, the total completion time, the total absolute differences in completion times and the sum of earliness, tardiness and common due-date penalty. Wang [14] considered a single-machine scheduling problem with past-sequence-dependent setup times and time-dependent learning effect. He proved that the problem with minimization of some objectives, such as makespan, the total completion time and the sum of the quadratic job completion time can be solved in polynomial time, respectively. Wang [15] considered a single-machine scheduling problem with exponential time-dependent learning effect and past-sequence-dependent setup times. The author indicated that the smallest processing time (SPT) rule can provide an optimum schedule for some performance measures, such as makespan, the total completion time and the sum of the quadratic job completion time, respectively. Although applying learning concepts into the setup or processing operations have been extensively studied in scheduling literature, however, few of them take both considerations into account simultaneously. In this paper, we study a single machine scheduling problem with a learning effects model that includes the psd setup times and the actual processing time of a job as a function of the sum of the normal processing times of the jobs already scheduled. The optimal sequences are developed for the two objectives, minimization of the total completion time and the total weighted completion time.

## 2. Notations and Problem Description

In this section, addressing single machine scheduling problems, the actual processing time of a job is assumed to be a function of the sum of the normal processing times of the jobs already scheduled and the setup time of a job is proportional to the length of the jobs already processed. Let $p_{i}$ denote the normal processing time of job $i$. In addition, let $p_{[k]}$ denote the normal processing time of a job if it is scheduled in the $k$ th position in a sequence. For the proposed learning effect model, the actual processing time of a job $j$ which is scheduled in the position $r$ in a sequence, $p_{[k]}$, is presented as

$$
\begin{equation*}
p_{j[r]}=p_{j}\left(1-\frac{\sum_{i=1}^{r-1} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}=p_{j}\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}, \quad j, r=1, \cdots, n, \tag{1}
\end{equation*}
$$

where $a(a \geq 1)$ is learning effect indexes. Like Koulamas and Kyparisis [1], we assume that the non-linear past-sequence-dependent setup times of job $J_{j}$ if it is scheduled in position $r$ is given as follows:

$$
\begin{equation*}
S_{[r]}=b^{(r-1)} \sum_{j=1}^{r=1} p_{[j]}, \quad r=2,3, \cdots, n \quad \text { and } \quad S_{[1]}=0 \tag{2}
\end{equation*}
$$

where $b(0<b<1)$ is a normalizing constant.

## 3. The Total Completion Time Criterion

Before you begin to format your paper, first write and save the content as a separate text file. Keep your text and graphic files separate until after the text has been formatted and styled. Do not use hard tabs, and limit use of hard returns to only one return at the end of a paragraph. Do not add any kind of pagination anywhere in the paper. Do not number text heads-the template will do that for you. In this section, we consider a single machine scheduling problem with the objective of minimizing the total completion time. We show that the problem $1 / L E, S_{p s d} / \sum_{i=1}^{n} C_{i}$ can be scheduled optimally by the SPT rule. Before proving Theorem 1, two lemmas are presented as follows.

Lemma 1. $\left(b^{r}+1\right)-a x(1-x)^{a-1}-(1-x)^{a}>0$, for $0 \leq x \leq 1, a \geq 1,0<b<1$ and $r=1,2, \cdots, n-1$.
Proof. Let $f(x)=\left(b^{r}+1\right)-a x(1-x)^{a-1}-(1-x)^{a}$. Then we have $f^{\prime}(x)=a(a-1) x(1-x)^{a-2} \geq 0$ for $0 \leq x \leq 1, a \geq 1$ and $r=1,2, \cdots, n-1$.

Hence, $f(x)$ is increasing on $0 \leq x \leq 1$. Since $0<b<1$ and $r=1,2, \cdots, n-1$, we have $f(x) \geq f(0)=b^{r}>0$. Thus, the proof is completed.

Lemma 2. $\left(b^{r}+1\right)(\lambda-1)+(1-\lambda x)^{a}-\lambda(1-x)^{a} \geq 0$, for $\lambda \geq 1,0 \leq x \leq 1, a \geq 1,0<b<1$ and $r=1,2, \cdots, n-1$.
Proof. Let $g(\lambda)=\left(b^{r}+1\right)(\lambda-1)+(1-\lambda x)^{a}-\lambda(1-x)^{a}$. Then we have $g^{\prime}(\lambda)=\left(b^{r}+1\right)-a x(1-\lambda x)^{a-1}-(1-x)^{a}$ and $g^{\prime \prime}(\lambda)=a(a-1) x^{2}(1-\lambda x)^{a-2}$.
Since $\lambda \geq 1, a \geq 1,0 \leq x \leq 1$ and $r=1,2, \cdots, n-1$, then the value of $g "(\lambda)$ is a non-negative number. That is, $g "(\lambda) \geq 0$. It implies that $g^{\prime}(\lambda)$ is an increasing function. In addition, from Lemma 1 , we have $g^{\prime}(1)=\left(b^{r}+1\right)-a x(1-x)^{a-1}-(1-x)^{a}>0$. Therefore, $g^{\prime}(\lambda) \geq g^{\prime}(1)>0$ for $\lambda \geq 1, a \geq 1,0 \leq x \leq 1$ and $r=1,2, \cdots, n-1$. Thus, it implies that $g(\lambda)$ is an increasing function for $\lambda \geq 1, a \geq 1,0 \leq x \leq 1$ and $r=1,2, \cdots, n-1$. Since $g(\lambda) \geq g(1)=0$, it is implies that $\left(b^{r}+1\right)(\lambda-1)+(1-\lambda x)^{a}-\lambda(1-x)^{a} \geq 0$, for $\lambda \geq 1, a \geq 1,0 \leq x \leq 1$ and $r=1,2, \cdots, n-1$. Thus, the proof is completed.
Theorem 1. For the minimization of total completion time on a single machine scheduling problem $1 / L E, S_{p s d} / \sum_{i=1}^{n} C_{i}$, there exists an optimal schedule that is obtained by sequencing jobs in non-decreasing order of $p_{i}$.

Proof. For two adjacent jobs $J_{i}$ and $J_{j}$, assuming the processing time $p_{i} \leq p_{j}$. Let $S_{1}=\left[A, J_{i}, J_{j}, B\right]$ and $S_{2}=\left[A, J_{j}, J_{i}, B\right]$ be two job schedules. Where the difference between $S_{1}$ and $S_{2}$ is a pairwise interchange of two adjacent jobs $J_{i}$ and $J_{j}$. A and $B$ are partial schedules and $A$ or $B$ may be empty. We assume that there are $r-1$ jobs in $S_{1}$. Thus, jobs $J_{i}$ and $J_{j}$ are at the positions $r$ th and $(r+1)$ th in $S_{1}$. In other words, $J_{j}$ and $J_{i}$ are at the positions $r$ th and $(r+1)$ th in $S_{2}$. Let $C_{k}\left(S_{1}\right)$ and $C_{k}\left(S_{1}\right)$ denote the completion time of the job $J_{k}$ in the sequence $S_{1}$ and $S_{2}$, respectively. In order to prove the $1 / L E, S_{p s d} / \sum_{i=1}^{n} C_{i}$ the problem is minimized by sequencing the jobs in a SPT order, sufficient to show that (a) $C_{j}\left(S_{1}\right) \leq C_{i}\left(S_{2}\right)$ and (b) $C_{i}\left(S_{1}\right)+C_{j}\left(S_{1}\right) \leq C_{j}\left(S_{2}\right)+C_{i}\left(S_{2}\right)$.

First, the proof of part (a) is given as follows.

$$
\begin{align*}
& C_{j}\left(S_{1}\right)=\sum_{i=1}^{r-1}\left(1+\sum_{k=i}^{r} b^{k}\right) p_{j[i]}+\left(b^{r}+1\right) p_{i}\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}+p_{j}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{i}}{\sum_{i=1}^{n} p_{i}}\right)^{a}  \tag{3}\\
& C_{i}\left(S_{2}\right)=\sum_{i=1}^{r-1}\left(1+\sum_{k=i}^{r} b^{k}\right) p_{j[i]}+\left(b^{r}+1\right) p_{j}\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}+p_{i}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{j}}{\sum_{i=1}^{n} p_{i}}\right)^{a} \tag{4}
\end{align*}
$$

we have

$$
\begin{equation*}
C_{i}\left(S_{2}\right)-C_{j}\left(S_{1}\right)=\left(b^{r}+1\right)\left(p_{j}-p_{i}\right)\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}-p_{j}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{i}}{\sum_{i=1}^{n} p_{i}}\right)^{a}+p_{i}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{j}}{\sum_{i=1}^{n} p_{i}}\right)^{a} . \tag{5}
\end{equation*}
$$

By substituting $t=\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}, x=\frac{p_{i}}{\sum_{i=r}^{n} p_{[i]}}$ and $\lambda=\frac{p_{j}}{p_{i}}$. Then Equation (5) is equivalent to

$$
C_{i}\left(S_{2}\right)-C_{j}\left(S_{1}\right)=p_{i} t^{a}\left[\left(b^{r}+1\right)(\lambda-1)-\lambda(1-x)^{a}+(1-\lambda x)^{a}\right] .
$$

From Lemma 2, we have $C_{i}\left(S_{2}\right)-C_{j}\left(S_{1}\right) \geq 0$. That is, $C_{j}\left(S_{1}\right) \leq C_{i}\left(S_{2}\right)$ if $p_{i} \leq p_{j}$.
Note the proof of part (a) also shows that the makespan is minimized by the SPT rule. Furthermore, the proof of part (b) is given as follows.

$$
\begin{align*}
& C_{i}\left(S_{1}\right)+C_{j}\left(S_{1}\right)=\sum_{i=1}^{r-1}\left(1+\sum_{k=i}^{r-1} b^{k}\right) p_{j[i]}+p_{i}\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}+\sum_{i=1}^{r-1}\left(1+\sum_{k=i}^{r} b^{k}\right) p_{j[i]} \\
& +\left(b^{r}+1\right) p_{i}\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}+p_{j}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{i}}{\sum_{i=1}^{n} p_{i}}\right)^{a} \tag{6}
\end{align*}
$$

and

$$
\begin{align*}
& C_{j}\left(S_{2}\right)+C_{i}\left(S_{2}\right)=w_{j}\left[\sum_{i=1}^{r-1}\left(1+\sum_{k=i}^{r-1} b^{k}\right) p_{j[i]}+p_{j}\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}\right] \\
& +w_{i}\left[\sum_{i=1}^{r-1}\left(1+\sum_{k=i}^{r} b^{k}\right) p_{j[i]}+\left(b^{r}+1\right) p_{j}\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}+p_{i}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{j}}{\sum_{i=1}^{n} p_{i}}\right)^{a}\right]  \tag{7}\\
& +\left(b^{r}+1\right) p_{j}\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}+p_{i}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{j}}{\sum_{i=1}^{n} p_{i}}\right)^{a}
\end{align*}
$$

we have

$$
\begin{aligned}
& {\left[C_{j}\left(S_{2}\right)+C_{i}\left(S_{2}\right)\right]-\left[C_{i}\left(S_{1}\right)+C_{j}\left(S_{1}\right)\right]} \\
& =\left(p_{j}-p_{i}\right)\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}+\left(b^{r}+1\right)\left(p_{j}-p_{i}\right)\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}+p_{i}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{j}}{\sum_{i=1}^{n} p_{i}}\right)^{a}-p_{j}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{i}}{\sum_{i=1}^{n} p_{i}}\right)^{a}
\end{aligned}
$$

Since $p_{j}-p_{i} \geq 0$ and $\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}>0$, the first term is non-negative. From (a), the sum of the second to the fourth terms are non-negative as well. Therefore, this implies that $C_{j}\left(S_{2}\right)+C_{i}\left(S_{2}\right) \geq C_{i}\left(S_{1}\right)+C_{j}\left(S_{1}\right)$.

This completes the proof of (b) and thus of the theorem.
Hence, the optimal job-sequence of the single machine scheduling problem $1 / L E, S_{p s d} / \sum_{i=1}^{n} C_{i}$ can be obtained by an algorithm which sequences the jobs in a SPT order. That is, the problem $1 / L E, S_{p s d} / \sum_{i=1}^{n} C_{i}$ can be solved in polynomial time.

## 4. The Total Weighted Completion Time Problem

For the problem to minimize the total weighted completion time, we show that an optimal solution if the processing times and the weights are agreeable, i.e., $p_{i} \leq p_{j}$ implies $w_{i} \geq w_{j}$ for all the jobs $J_{i}$ and $J_{j}$. The result is stated in the following theorem. Before proving Theorem 2, two lemmas are introduced as follows. Lemma 3. $1-\lambda_{1} a x(1-\alpha x)^{a-1}-\lambda_{2}(1-x)^{a} \geq 0$ for $a \geq 1,0 \leq \lambda_{2} \leq 1, \alpha \geq 1$ and $0 \leq x \leq 1$.

Proof. Let $f(x)=1-\lambda_{1} a x(1-\alpha x)^{a-1}-\lambda_{2}(1-x)^{a}$. Then we have $f^{\prime}(x)=-\lambda_{1} a(1-\alpha x)^{a-1}+\lambda_{1} a(a-1) \alpha x(1-\alpha x)^{a-2}+\lambda_{2} a(1-x)^{a-1} \geq 0$ for $a \geq 1,0 \leq \lambda_{2} \leq 1, \quad \alpha \geq 1$ and $0 \leq x \leq 1$.

Hence, $f(x)$ is increasing on the value of $x$.
Since $f(x) \geq f(0)=1-\lambda_{2} \geq 0$, for $a \geq 1, \quad 0 \leq \lambda_{1} \leq \lambda_{2} \leq 1, \alpha \geq 1$ and $0 \leq x \leq 1$. Thus, completes the proof.

Lemma 4. $(\alpha-1)+\lambda_{1}(1-\alpha x)^{a}-\lambda_{2} \alpha(1-x)^{a} \geq 0$, for $0 \leq \lambda_{1} \leq \lambda_{2} \leq 1,0 \leq x \leq 1, \alpha \geq 1$ and $\alpha \geq 1$.
Proof. Let $f(\alpha)=(\alpha-1)+\lambda_{1}(1-\alpha x)^{a}-\lambda_{2} \alpha(1-x)^{a}$. Then we have $f^{\prime}(\alpha)=1-\lambda_{1} a x(1-\alpha x)^{a-1}-\lambda_{2}(1-x)^{a}$, and $f^{\prime \prime}(\alpha)=\lambda_{1} a(a-1) x^{2}(1-\alpha x)^{a-2} \geq 0$. Since $a \geq 1,0 \leq \lambda_{1} \leq \lambda_{2} \leq 1, \alpha \geq 1,0 \leq x \leq 1$, the value of $f^{\prime \prime}(\alpha)$ is a non-negative number. That is, $f^{\prime \prime}(\alpha) \geq 0$. It implies that $f^{\prime}(\alpha)$ is an increasing function. In addition, from Lemma 3, we have $f^{\prime}(1)=1-\lambda_{1} a x(1-x)^{a-1}-\lambda_{2}(1-x)^{a} \geq 0$. Therefore, $f^{\prime}(\alpha) \geq f^{\prime}(1) \geq 0$ for $a \geq 1$, $0 \leq \lambda_{1} \leq \lambda_{2} \leq 1, \alpha \geq 1$ and $0 \leq x \leq 1$. Hence, $f(\alpha)$ is an increasing function for $a \geq 1$ $0 \leq \lambda_{1} \leq \lambda_{2} \leq 1, \alpha \geq 1,0 \leq x \leq 1$. Also, $f(\alpha) \geq f(1)=\left(\lambda_{1}-\lambda_{2}\right)(1-x)^{a} \geq 0$ for $0 \leq \lambda_{1} \leq \lambda_{2} \leq 1,0 \leq x \leq 1$, $a \geq 1$ and $a \geq 1$. Thus, the proof is completed.
Theorem 2. For minimization of the total weighted completion time on a single machine scheduling problem $1 / L E, S_{p s d} / \sum_{i=1}^{n} w_{i} C_{i}$, if the jobs have agreeable weights, i.e., $p_{i} \leq p_{j}$ implies $w_{i} \geq w_{j}$ for all the jobs $J_{i}$ and $J_{j}$, where an optimal schedule is obtained by sequencing jobs in a non-decreasing order of $p_{i} / w_{i}$.

Proof. Since $p_{i} \leq p_{j}$, is observed from Theorem 1 where $C_{j}\left(S_{1}\right) \leq C_{i}\left(S_{2}\right)$. We only need to show that $w_{i} C_{i}\left(S_{1}\right)+w_{j} C_{j}\left(S_{1}\right) \leq w_{j} C_{j}\left(S_{2}\right)+w_{i} C_{i}\left(S_{2}\right)$. From Equations (6)-(7), we have

$$
\begin{aligned}
& w_{j} C_{j}\left(S_{2}\right)+w_{i} C_{i}\left(S_{2}\right)-w_{i} C_{i}\left(S_{1}\right)-w_{j} C_{j}\left(S_{1}\right) \\
& =w_{j}\left[\sum_{i=1}^{r-1}\left(1+\sum_{k=i}^{r-1} b^{k}\right) p_{j[i]}+p_{j}\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}\right]+w_{i}\left[\sum_{i=1}^{r-1}\left(1+\sum_{k=i}^{r} b^{k}\right) p_{j[i]}+\left(b^{r}+1\right) p_{j}\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}\right. \\
& \left.+p_{i}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{j}}{\sum_{i=1}^{n} p_{i}}\right)^{a}\right]-w_{i}\left[\sum_{i=1}^{r-1}\left(1+\sum_{k=i}^{r-1} b^{k}\right) p_{j[i]}+p_{i}\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}\right] \\
& -w_{j}\left(\sum_{i=1}^{r-1}\left(1+\sum_{k=i}^{r} b^{k}\right) p_{j[i]}+\left(b^{r}+1\right) p_{i}\left(\frac{\sum_{i=r}^{n} p_{i i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}+p_{j}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{i}}{\sum_{i=1}^{n} p_{i}}\right)^{a}\right] \\
& =b^{r}\left(w_{i}-w_{j}\right) \sum_{i=1}^{r-1} p_{j[i]}+b^{r}\left(w_{i} p_{j}-w_{j} p_{i}\right)\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}+\left(w_{i}+w_{j}\right)\left(p_{j}-p_{i}\right)\left(\frac{\sum_{i=r}^{n} p_{i[]}}{\sum_{i=1}^{n} p_{i}}\right)^{a} \\
& +w_{i} p_{i}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{j}}{\sum_{i=1}^{n} p_{i}}\right)^{a}-w_{j} p_{j}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{i}}{\sum_{i=1}^{n} p_{i}}\right)^{a} .
\end{aligned}
$$

By substituting $\lambda_{1}=\frac{w_{i}}{w_{i}+w_{j}}, \quad \lambda_{2}=\frac{w_{j}}{w_{i}+w_{j}}, \quad t=\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}, \quad x=\frac{p_{i}}{\sum_{i=r}^{n} p_{[i]}}$ and $\alpha=\frac{p_{j}}{p_{i}}$. Then $\left(w_{i}+w_{j}\right)\left(p_{j}-p_{i}\right)\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}+w_{i} p_{i}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{j}}{\sum_{i=1}^{n} p_{i}}\right)^{a}-w_{j} p_{j}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{i}}{\sum_{i=1}^{n} p_{i}}\right)^{a}$ can be rewritten as $\left(w_{i}+w_{j}\right)\left(p_{j}-p_{i}\right)\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a}+w_{i} p_{i}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{j}}{\sum_{i=1}^{n} p_{i}}\right)^{a}-w_{j} p_{j}\left(\frac{\sum_{i=r}^{n} p_{[i]}-p_{i}}{\sum_{i=1}^{n} p_{i}}\right)^{a} \quad$ (from Lemma 4). $=\left(w_{i}+w_{j}\right) t^{a} p_{i}\left[(\alpha-1)+\lambda_{1}(1-\alpha x)^{a}-\lambda_{2} \alpha(1-x)^{a}\right] \geq 0$
From $p_{i} / w_{i}<p_{j} / w_{j}$, we have $b^{r}\left(w_{i} p_{j}-w_{j} p_{i}\right)\left(\frac{\sum_{i=r}^{n} p_{[i]}}{\sum_{i=1}^{n} p_{i}}\right)^{a} \geq 0$. In addition, from $p_{i} \leq p_{j}$ which implies $w_{i} \geq w_{j}$, we have $b^{r}\left(w_{i}-w_{j}\right) \sum_{i=1}^{r-1} p_{j i \mathrm{i}]} \geq 0$.

Hence, $w_{j} C_{j}\left(S_{2}\right)+w_{i} C_{i}\left(S_{2}\right)-w_{i} C_{i}\left(S_{1}\right)-w_{j} C_{j}\left(S_{1}\right) \geq 0$. That is, $w_{j} C_{j}\left(S_{2}\right)+w_{i} C_{i}\left(S_{2}\right) \geq w_{i} C_{i}\left(S_{1}\right)+w_{j} C_{j}\left(S_{1}\right)$
Thus, the proof is completed.
Hence, the optimal job-sequence of the scheduling problem $1 / L E, S_{p s d} / \sum_{i=1}^{n} w_{i} C_{i}$ can be obtained by an algorithm which sequences the jobs in a SPT order. That is, the problem of $1 / L E, S_{p s d} / \sum_{i=1}^{n} w_{i} C_{i}$ can besolved in polynomial time.

## 5. Conclusion

In this study, we analyzed a single machine scheduling problem with time-dependent learning and setup times. Time-dependent learning means that the actual processing time of a job is a function of the sum of the normal processing times of the jobs already scheduled. The setup time of a job is proportional to the length of the already processed jobs, that is, past-sequence-dependent (psd) setup time. The problem addressed with the two objectives, i.e., minimization of the total completion time and total weighted completion time, was studied in depth. We proved that the SPT rule can provide the optimal schedule for both the total completion time and total weighted completion time objectives. We also show that both the total completion time problem remains poly-
nomially solvable, as does the total weighted completion time problem, under certain agreeable conditions.

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