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Two single-machine scheduling problems with the effects of deterioration and learning

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Abstract In this paper, we consider two single-machine scheduling problems with the effect of deterioration and learning. In this model, the processing times of jobs are defined as functions of their starting times and positions in a sequence. For the following two objective functions, the weighted sum of completion times and the maximum lateness, this paper gives two heuristics according to the corresponding problems without learning effect. This paper also gives the worst-case error bound for the heuristics and provides computational results to evaluate the performance of the heuristics.

Keywords Scheduling · Single-machine · Deteriorating jobs · Learning effect

1 Introduction

In classical scheduling problems, the processing times of jobs are assumed to be constant values. However, there are many situations where the processing times of jobs may be subject to change due to deterioration and/or learning phenomena. Machine scheduling problems with deteriorating jobs and/or learning effects have been given more attention in recent years. Extensive surveys of research related to scheduling deteriorating jobs can be found in Alidaee and Womer [1] and Cheng et al. [2]. An extensive survey of different scheduling models and problems involving jobs with learning effects can be found in Biskup [3]. More recent papers that have considered scheduling jobs with deteriorating jobs and/or learning effect include Wu et al. [4], Shiau et al. [5], and Eren and Guner [6]. Wu et al. [4] considered a single-machine total weighted completion time scheduling problem under linear deterioration. They proposed a branch-and-bound method and several heuristic algorithms to solve the problem. Shiau et al. [5] considered two-machine flowshop scheduling to minimize mean flow time with simple linear deterioration. Eren and Guner [6] considered the bicriteria parallel machine scheduling with a learning effect. They introduced a mixed nonlinear integer programming formulation for the problem. Lee et al. [7] and Wang et al. [8] developed a new deterioration model where the actual job processing time is a function of jobs already processed. Lee et al. [7] showed that the single-machine makespan problem remains polynomially solvable under the proposed model. Wang et al. [8] showed that the total completion time minimization problem for $a \geq 1$ remains polynomially solvable under the proposed model, where a denotes the deterioration rate. For the case of $0 < a < 1$, they showed that an optimal schedule of the total completion time minimization problem is V-shaped with respect to normal job processing times. They also used the classical smallest-processing-time-first rule as a heuristic algorithm for the case of $0 < a < 1$ and analyze its worst-case bound. However, to the best of our knowledge, apart from the recent papers of Wang et al. [9], Wang et al. [10], Toksar and Guner [11], Lee [12], Wang [13, 14],

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Wang and Cheng [15], Wang and Cheng [16], Toksar and Guner [17], and Wang et al. [18], the scheduling problems with the effects of deterioration and learning have not been investigated. The phenomena of learning effect and deteriorating jobs occurring simultaneously can be found in many real-life situations. For example, as manufacturing becomes increasingly competitive, in order to provide customers with greater product varieties, organizations are moving towards shorter production runs and frequent product changes. The learning and forgetting that workers undergo in this environment have thus become increasingly important as workers tend to spend more time in rotating among tasks and responsibilities prior to becoming fully proficient. These workers are often interrupted by product and process changes, causing deterioration in performance, which we will refer to, for simplicity, as forgetting. Considering learning and forgetting effects in measuring productivity should be helpful in improving the accuracy of production planning and productivity estimation (Nembhard and Osothsilp [19]).

In this paper, we investigate the implications of these phenomena occurring simultaneously for two sing-machine scheduling problems. Specifically, we generalize the results of Wang and Cheng [15] to a more general context.

The remaining part of this paper is organized as follows: In Section 2, we formulate the model. In Sections 3 and 4, we consider two single-machine scheduling problems. In Section 5, we present computational experiments to evaluate the performance of the heuristic algorithms. The last section is the conclusion.

2 Problem formulation

We formulate the problem as follows: There are n given independent and non-preemptive jobs available for processing on a single machine. All the jobs will be processed starting at time $t_0 \geq 0$ without overlapping and idle time between them. Associated with each job j $(j = 1, 2, ..., n)$, there is a normal processing time p_j, a due date d_j, and a weight w_j. Let $p_{jr}(t)$ be the processing time of job J_j if it is started at time t and scheduled in position r in a sequence. As in Wang and Cheng [15], we assume that the actual processing time of job j if scheduled in position r is given by

$$p_{jr}(t) = \alpha_j(b + ct)r^a, \tag{1}$$

where α_j is the deterioration rate of job J_j; a denotes the learning index with $a < 0, b \geq 0, c \geq 0$. A schedule is a sequence of jobs that specifies the processing order of the jobs on the machine. Under a given schedule $\pi = (1, 2, \ldots, n)$, the completion time of job J_j is given by $C_j = C_j(\pi)$. Let $\sum w_jC_j$ and $L_{\max} = \max\{C_j - d_j | j = 1, 2, \ldots, n\}$ represent the total weighted completion time and the maximum lateness of a given permutation. In the remaining part of the paper, the problem considered will be denoted using the three-field notation schema $\alpha|\beta|\gamma$ introduced by Graham et al. [20].

3 The weighted sum of completion times minimization problem

First, we give some lemmas; they are useful for the following theorems.

Lemma 1 *For a given schedule $\pi = [J_1, J_2, \ldots, J_n]$ of $1|p_j(t) = \alpha_j(b + ct)r^a|\gamma$, if the first job starts at time $t_0 \geq 0$, then the completion time C_j of job J_j is equal to*

$$C_j = \left(t_0 + \frac{b}{c}\right)\prod_{i=1}^{j}(1 + c\alpha_i i^a) - \frac{b}{c}. \tag{2}$$

Lemma 2 (Zhao et al. [21]) *For the problem $1|p_j(t) = \alpha_j(b + ct)|\sum w_jC_j$, an optimal schedule can be obtained by sequencing the jobs in non-decreasing order of $\frac{\alpha_j}{w_j(1+\alpha_j)}$ [i.e., the weighted smallest deterioration rate (WSDR) rule].*

From Lemma 2, we can use WSDR rule as a heuristic algorithm for the general problem $1|p_{jr}(t) = \alpha_j(b + ct)r^a|\sum w_jC_j$.

Theorem 1 *Let S^* be an optimal schedule and S be a WSDR schedule for the problem $1|p_{jr}(t) = \alpha_j(b + ct)r^a|\sum w_jC_j$. Then, $\rho_1 = \sum w_jC_j(S)/\sum w_jC_j(S^*) \leq 1/n^a$, and the bound is tight.*

Proof Without loss of generality, we can suppose that $\frac{\alpha_1}{w_1(1+\alpha_1)} \leq \frac{\alpha_2}{w_2(1+\alpha_2)} \leq \ldots \leq \frac{\alpha_n}{w_n(1+\alpha_n)}$. Then, we have

$$\sum w_jC_j(S) = \sum_{j=1}^{n} w_j\left[\left(t_0 + \frac{b}{c}\right)\prod_{l=1}^{j}(1 + c\alpha_l l^a) - \frac{b}{c}\right]$$
$$\leq \sum_{j=1}^{n} w_j\left[\left(t_0 + \frac{b}{c}\right)\prod_{l=1}^{j}(1 + c\alpha_l) - \frac{b}{c}\right],$$

$$\sum w_j C_j(S^*)$$
$$= \sum_{j=1}^{n} w_j \left[\left(t_0 + \frac{b}{c}\right) \prod_{l=1}^{j} (1 + c\alpha_{[l]} l^a) - \frac{b}{c} \right]$$
$$\geq \sum_{j=1}^{n} w_j \left[\left(t_0 + \frac{b}{c}\right) \prod_{l=1}^{j} (1 + c\alpha_{[l]} n^a) - \frac{b}{c} \right]$$
$$\geq n^a \sum_{j=1}^{n} w_j \left[\left(t_0 + \frac{b}{c}\right) \prod_{l=1}^{j} \left(\frac{1}{n^a} + c\alpha_{[l]}\right) - \frac{b}{cn^a} \right]$$
$$\geq n^a \sum_{j=1}^{n} w_j \left[\left(t_0 + \frac{b}{c}\right) \prod_{l=1}^{j} (1 + c\alpha_{[l]}) - \frac{b}{c} \right]$$
$$\geq n^a \sum_{j=1}^{n} w_j \left[\left(t_0 + \frac{b}{c}\right) \prod_{l=1}^{j} (1 + c\alpha_l) - \frac{b}{c} \right];$$

hence,

$$\rho_1 = \sum w_j C_j(S) / \sum w_j C_j(S^*) \leq 1/n^a.$$

It is not difficult to see that the bound is tight since, if a=0, we have $\frac{\sum w_j C_j(S)}{\sum w_j C_j(S^*)} = 1$. This result is intuitive because, when $a = 0$, the WSDR schedule is optimal. □

Obviously, $\rho_1 = \sum w_j C_j(S) / \sum w_j C_j(S^*)$ depends on the parameter values.

4 The maximum lateness minimization problem

Lemma 3 (Zhao et al. [21]) *For the problem $1|p_j(t) = \alpha_j(b + ct)|L_{\max}$, an optimal schedule can be obtained by sequencing the jobs in non-decreasing order of d_j [i.e., the smallest due date (EDD) rule].*

Lemma 4 (Wang and Cheng [15]) *For the problem $1|p_{jr}(t) = \alpha_j(b + ct)r^a|C_{\max}$, an optimal schedule can be obtained by sequencing the jobs in non-decreasing order of α_j [i.e., the smallest deterioration rate (SDR) rule].*

In order to solve the problem approximately, from Lemma 3, we can use the EDD rule as a heuristic for the problem $1|p_{jr}(t) = \alpha_j(b + ct)r^a|L_{\max}$. To develop a worst-case performance ratio for the heuristic, we have to avoid cases involving nonpositive $L_{\max}$. Similar to Cheng and Wang [22], the worst-case error bound is defined as follows:

$$\rho_2 = \frac{L_{\max}(S) + d_{\max}}{L_{\max}(S^*) + d_{\max}},$$

where S and $L_{\max}(S)$ denote the heuristic schedule and the corresponding maximum lateness, respectively, while S^* and $L_{\max}(S^*)$ denote the optimal schedule and the minimum maximum lateness value, respectively, and $d_{\max} = \max\{d_j | j = 1, 2, \ldots, n\}$.

Theorem 2 *Let S^* be an optimal schedule and S be an EDD schedule for the problem $1|p_{jr}(t) = \alpha_j(b + ct)r^a|L_{\max}$. Then,*

$$\rho_2 = \frac{L_{\max}(S) + d_{\max}}{L_{\max}(S^*) + d_{\max}} \leq \frac{(t_0 + \frac{b}{c}) \prod_{l=1}^{n} (1 + c\alpha_l) - \frac{b}{c}}{C^*_{\max}},$$

and the bound is tight, where $C^*_{\max}$ is the optimal makespan of the problem $1|p_{jr}(t) = \alpha_j(b + ct)r^a|C_{\max}$.

Proof Without loss of generality, supposing that $d_1 \leq d_2 \leq \ldots \leq d_n$, we have

$$L_{\max}(S) = \max\left\{ \left(t_0 + \frac{b}{c}\right) \prod_{l=1}^{j} (1 + c\alpha_l l^a) - \frac{b}{c} - d_j | j = 1, 2, \ldots, n \right\}$$
$$\leq \max\left\{ \left(t_0 + \frac{b}{c}\right) \prod_{l=1}^{j} (1 + c\alpha_l) - \frac{b}{c} - d_j | j = 1, 2, \ldots, n \right\}$$
$$= L'_{\max}(S),$$

where $L'_{\max}(S)$ is the optimal value of the problem $1|p_j(t) = \alpha_j(b + ct)|L_{\max}$.

$$L_{\max}(S^*)$$
$$= \max\left\{ \left(t_0 + \frac{b}{c}\right) \prod_{l=1}^{j} (1 + c\alpha_{[l]} l^a) - \frac{b}{c} - d_{[j]} | j = 1, 2, \ldots, n \right\}$$
$$= \max\left\{ \left(t_0 + \frac{b}{c}\right) \prod_{l=1}^{j} (1 + c\alpha_{[l]}) - \frac{b}{c} - d_{[j]} - \left(t_0 + \frac{b}{c}\right) \prod_{l=1}^{j} (1 + c\alpha_{[l]}) + \frac{b}{c} + \left(t_0 + \frac{b}{c}\right) \times \prod_{l=1}^{j} (1 + c\alpha_{[l]} l^a) - \frac{b}{c} | j = 1, 2, \ldots, n \right\}$$

$$\geq \max\left\{\left(t_0+\frac{b}{c}\right)\prod_{l=1}^{j}(1+c\alpha_{[l]})-\frac{b}{c}\right.$$

$$\left.-d_{[j]}\,|\,j=1,2,\ldots,n\right\}-\left(t_0+\frac{b}{c}\right)$$

$$\times\prod_{l=1}^{j}(1+c\alpha_{[l]})+\frac{b}{c}+\left(t_0+\frac{b}{c}\right)$$

$$\times\prod_{l=1}^{j}(1+c\alpha_{[l]}l^a)-\frac{b}{c}$$

$$\geq L'_{\max}(S)-\left(t_0+\frac{b}{c}\right)\prod_{l=1}^{n}(1+c\alpha_l)+\frac{b}{c}+C^*_{\max};$$

hence,

$$L_{\max}(S)-L_{\max}(S^*)\leq\left(t_0+\frac{b}{c}\right)\prod_{l=1}^{n}(1+c\alpha_l)-\frac{b}{c}-C^*_{\max},$$

and so,

$$\rho_2=\frac{L_{\max}(S)+d_{\max}}{L_{\max}(S^*)+d_{\max}}$$

$$\leq 1+\frac{(t_0+\frac{b}{c})\prod_{l=1}^{n}(1+c\alpha_l)-\frac{b}{c}-C^*_{\max}}{L_{\max}(S^*)+d_{\max}}$$

$$\leq 1+\frac{(t_0+\frac{b}{c})\prod_{l=1}^{n}(1+c\alpha_l)-\frac{b}{c}-C^*_{\max}}{C^*_{\max}}$$

$$\leq\frac{(t_0+\frac{b}{c})\prod_{l=1}^{n}(1+c\alpha_l)-\frac{b}{c}}{C^*_{\max}},$$

where $C^*_{\max}$ can be obtained by the SDR rule (see Lemma 4).

It is not difficult to see that the bound is tight, since, if a=0, we have $C_{\max}=(t_0+\frac{b}{c})\prod_{l=1}^{n}(1+c\alpha_l)-\frac{b}{c}$ and $\rho_2=\frac{L_{\max}(S)+d_{\max}}{L_{\max}(S^*)+d_{\max}}=1$. This result is intuitive because when $a=0$, the EDD schedule is optimal. □

5 Computational experiments

Computational experiments were conducted to evaluate the effectiveness of the heuristics of WSDR and EDD. The heuristic algorithms were coded in VC++ 6.0 and ran the computational experiments on a Pentium 4-2.4G personal computer with a RAM size of 1 G. For all the tests, the values $t_0=0$. In addition, the learning curves were taken to be 90%, 80%, and 70%, which yielded $a=-0.152$, -0.322, and -0.515, respectively, according to Biskup [23]. For each job J_j, the job deterioration rate α_j was generated from a uniform distribution over [1, 100], and the weight w_j was generated from a uniform distribution over [1, 10]. For each job J_j, the due date d_j was generated from a uniform distribution over $\left[1, \tau\frac{b}{c}\prod_{l=1}^{n}(1+c\alpha_l)-1\right]$,

Table 1 Computational results of the heuristics for $\tau=0.25$

a	n	ρ_1		$\frac{1}{n^a}$	ρ_2		$\frac{\prod_{l=1}^{n}(1+\alpha_l)-1}{C^*_{\max}}$
		Mean	Max		Mean	Max	Mean
−0.152	6	1.0002	1.0045	1.3130	1.0001	1.0014	1.0157
	7	1.0005	1.0017	1.3442	1.0005	1.0057	1.0255
	8	1.0015	1.0026	1.3717	1.0007	1.0214	1.2459
	9	1.0004	1.0047	1.3965	1.0006	1.0014	1.2543
	10	1.0013	1.0142	1.4191	1.0023	1.0547	2.3541
	11	1.0017	1.0067	1.4398	1.0042	1.0746	3.1269
	12	1.0067	1.1004	1.4589	1.0056	1.1476	4.2785
−0.322	6	1.0012	1.0035	1.7806	1.0000	1.0001	1.1452
	7	1.0013	1.0045	1.8712	1.0013	1.0045	1.6748
	8	1.0015	1.0672	1.9534	1.0019	1.0267	2.3587
	9	1.0017	1.0369	2.0289	1.0016	1.0287	4.1254
	10	1.0013	1.0268	2.0989	1.0013	1.0534	6.3248
	11	1.0019	1.0216	2.1644	1.0035	1.0654	12.3645
	12	1.0095	1.0324	2.2259	1.0125	1.0961	24.9564
−0.515	6	1.0011	1.0128	2.5162	1.0007	1.0658	1.3026
	7	1.0012	1.0394	2.7241	1.0026	1.0086	2.2547
	8	1.0015	1.0523	2.9180	1.0037	1.0095	3.9564
	9	1.0027	1.0025	3.1005	1.0032	1.0098	9.9835
	10	1.0029	1.0169	3.2734	1.0059	1.0123	26.3248
	11	1.0041	1.0093	3.4381	1.0046	1.0267	66.0234
	12	1.0102	1.0125	3.5957	1.0014	1.0054	158.1248

Table 2 Computational results of the heuristics for $\tau = 0.5$

a	n	ρ_1		$\frac{1}{n^a}$	ρ_2		$\frac{\prod_{l=1}^{n}(1+\alpha_l)-1}{C^*_{\max}}$
		Mean	Max		Mean	Max	Mean
−0.152	6	1.0003	1.0154	1.3130	1.0007	1.0137	1.2376
	7	1.0007	1.0245	1.3442	1.0012	1.0113	1.3579
	8	1.0011	1.0243	1.3717	1.0019	1.0123	1.5678
	9	1.0038	1.0398	1.3965	1.0023	1.0159	2.0345
	10	1.0025	1.0565	1.4191	1.0029	1.0985	2.3654
	11	1.0037	1.0755	1.4398	1.0036	1.0132	3.2670
	12	1.0074	1.0856	1.4589	1.0045	1.0254	4.2540
−0.322	6	1.0004	1.0019	1.7806	1.0068	1.0269	1.1657
	7	1.0005	1.0043	1.8712	1.0124	1.0789	1.9854
	8	1.0010	1.0087	1.4121	1.0089	1.0885	2.6845
	9	1.0020	1.0096	2.0289	1.0027	1.0138	4.6120
	10	1.0034	1.0098	2.0989	1.0065	1.0241	7.2587
	11	1.0047	1.0189	2.1644	1.0000	1.0000	12.6523
	12	1.0114	1.0241	2.2259	1.0000	1.0000	25.1212
−0.515	6	1.0008	1.0031	2.5162	1.0127	1.0245	1.3017
	7	1.0018	1.0056	2.7241	1.0005	1.0028	2.1577
	8	1.0035	1.9857	2.9180	1.0035	1.0076	4.0245
	9	1.0007	1.0087	3.1005	1.0038	1.0103	9.2256
	10	1.0097	1.0099	3.2734	1.0018	1.0029	22.3578
	11	1.0106	1.0155	3.4381	1.0000	1.0000	62.1312
	12	1.0138	1.0208	3.5957	1.0000	1.0000	160.3542

where $\tau \in \{0.25, 0.5, 1\}$ and $b = c = 1$. For each heuristic, seven different job sizes, $n = 6, 7, 8, 9, 10, 11$, and 12, were used. As a consequence, 42 experimental conditions were examined and 20 replications were randomly generated for each condition. A total of 840 problems were tested.

In order to study the effects of these parameters, as well as to construct accurate and easily implemented algorithms, two heuristic algorithms are presented in this section. Each algorithm consists of two phases; the first phase involves generating an initial solution in a simple way, and the second phase further improves the quality of the solution by a neighborhood search, which provides good solutions and offers possibilities to be enhanced [24]. In the first step, jobs are sorted in non-decreasing order of the ratio $\frac{\alpha_j}{w_j(1+\alpha_j)}$ and d_j to obtain

Table 3 Computational results of the heuristics for $\tau = 1$

a	n	ρ_1		$\frac{1}{n^a}$	ρ_2		$\frac{\prod_{l=1}^{n}(1+\alpha_l)-1}{C^*_{\max}}$
		Mean	Max		Mean	Max	Mean
−0.152	6	1.0000	1.0000	1.3130	1.0013	1.0045	1.1234
	7	1.0005	1.0027	1.3442	1.0021	1.0100	1.2755
	8	1.0012	1.0103	1.3717	1.0013	1.0114	1.3245
	9	1.0023	1.0523	1.3965	1.0020	1.0466	2.1128
	10	1.0017	1.0571	1.4191	1.0011	1.0215	2.4573
	11	1.0039	1.0455	1.4398	1.0030	1.0221	3.2314
	12	1.0082	1.0492	1.4589	1.0022	1.0119	4.2359
−0.322	6	1.0000	1.0000	1.7806	1.0002	1.0011	1.2453
	7	1.0013	1.0056	1.8712	1.0015	1.0214	1.6547
	8	1.0025	1.0059	1.9534	1.0019	1.0324	2.7842
	9	1.0033	1.0109	2.0289	1.0015	1.0128	4.3549
	10	1.0097	1.0234	2.0989	1.0019	1.0391	7.4785
	11	1.0117	1.0359	2.1644	1.0000	1.0000	12.5897
	12	1.0187	1.0721	2.2259	1.0000	1.0000	27.1246
−0.515	6	1.0006	10034	2.5162	1.0000	1.0000	1.3547
	7	1.0059	1.0246	2.7241	1.0003	1.0087	2.5412
	8	1.0105	1.0227	2.9180	1.0019	1.0103	4.3248
	9	1.0112	1.0564	3.1005	1.0021	1.0126	10.8759
	10	1.0096	1.0376	3.2734	1.0000	1.0000	22.4457
	11	1.0109	1.0447	3.4381	1.0000	1.0000	61.2247
	12	1.0201	1.0924	3.5957	1.0000	1.0000	180.2457

an initial solution. The second step is to improve the initial solution by using pairwise interchanges. In order to study the impact of the parameters, the mean and maximum of the ratio of the optimal solution and the WSDR (EDD) solution and the worst-case error bound are reported in Tables 1, 2, and 3. It is observed from Tables 1, 2, and 3 that the mean and maximum of the ratio of the optimal solution and the WSDR solution and the worst-case error bound for WSDR algorithm increase as the learning effect is stronger. It is noticed from Tables 1, 2, and 3 that the mean and maximum of the ratio of the optimal solution and the EDD solution decrease as the tardiness factor τ becomes larger. It is also found that the minimum and mean ratios equal one for some cases. In these cases, it is very easy to find a schedule such that all jobs can be finished before their due dates, yielding zero maximum tardiness. In addition, the ratio of the two solutions increases as the job size increases. This phenomenon is due to the fact that the learning effect becomes even stronger as the number of processed jobs grows.

6 Conclusions

We have considered in this paper two single-machine scheduling problems with the effect of deterioration and learning. For the weighted sum of completion times minimization problem and the maximum lateness minimization problem, we gave two heuristics according to the corresponding problems without learning effect. We also gave the worst-case error bound for the heuristics. Computational results show that the heuristic algorithms are very effective and efficient in obtaining near-optimal solutions. Future research may focus on determining the computational complexity of these two problems as they remain open, or proposing more sophisticated heuristics.

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