An Improved Algorithm for Minimizing Makespan on Flowshops with Uncertain Processing Times

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Abstract
We address the four-machine flowshop scheduling problem with the objective of minimizing makespan with uncertain processing times. The problem was investigated in the literature (RAIRO Operations Research 54, 529-553) and different algorithms were proposed. In this paper, we propose a new algorithm for the problem. The new proposed algorithm is compared with the best existing algorithm in the literature by using extensive computational experiments. Computational experiments show that the new proposed algorithm performs much better than the best existing algorithm in the literature in terms of error while both have the same computational time. Specifically, the new proposed algorithm reduces the error of the best existing algorithm in the literature about 40%. This result has been confirmed by using hypotheses testing with a significance level of 0.01.

Key Words
"Makespan, scheduling, algorithm, uncertainty"

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1. Introduction

About seventy percent of the real life of scheduling problems fall in the category of flowshops, Fuchigami and Rangel (2018). There are several real life flowshop scheduling problems with four stages, i.e., with four machines, e.g., Stefansson (2011). In the current paper, we study the flowshop scheduling problem (having four-machine) with makespan performance measure, which helps in decreasing production costs.

One of the assumptions made in the literature is that processing times of jobs are deterministic. On the other hand, often real world manufacturing environments are most of the times subject to an extensive uncertainties, Gonzalez-Neira et al. (2017), Mahjoub et al. (2011). Therefore, the assumption of deterministic processing times is not realistic for all flowshop environments. Moreover, assuming processing times follow certain distributions is not legitimate for some flowshop scheduling environments, e.g., Kouvelis and Yu (1997). Therefore, processing times need to be considered as uncertain.

In an uncertain environment, job processing times are considered to be random variables but their probability distributions are unidentified. If $t_{j,k}$ indicates job $j$’s processing time ($j=1,2,\ldots,n$) on machine $k$ ($k=1,2,\ldots,m$). Similarly, if $LB_{t,j}$ shows the lower bound and $UB_{t,j}$ shows the upper bound of $t_{j,k}$. Then, $t_{j,k}$ satisfies $LB_{t,j} \leq t_{j,k} \leq UB_{t,j}$.

Allahverdi and Sotskov (2003) and Allahverdi and Aydilek (2010a) investigated the problem of $F2|LB_{t,j} \leq t_{j,k} \leq UB_{t,j}|C_{\text{max}}$. Allahverdi and Aydilek (2010a) presented several algorithms and Allahverdi and Sotskov (2003) presented some dominance relations for the problem. Moreover, Allahverdi and Aydilek (2010b) provided different algorithms for the problem of $F2|LB_{t,j} \leq t_{j,k} \leq UB_{t,j}|C_{\text{max}}$. Also, Aydilek and Allahverdi (2010) provided several heuristics while Sotskov et al. (2004) presented several dominance relations for the problem of $F2|LB_{t,j} \leq t_{j,k} \leq UB_{t,j}|\sum C_i$. On the other hand, the problem of $F3|LB_{t,j} \leq t_{j,k} \leq UB_{t,j}|\sum C_i$ was investigated by Sotskov et al. (2004) where they provided few dominance relations for the problem. For other uncertain scheduling environments, the problem was investigated as well in the literature, e.g., Allahverdi and Allahverdi (2018), Aydilek et al. (2013, 2015, 2017), Lai and Sotskov (1999), Lai et al. (1997).

The F4|prmu, $L_{f,j} \leq t_{j,k} \leq U_{f,j}|C_{\text{max}}$ problem was recently investigated by Allahverdi and Allahverdi (2020). They established some dominance relations and presented different algorithms. They indicated that one of their proposed algorithms performs as the best. In the current paper, we propose a new algorithm and indicated that the new algorithm performs better than the best algorithm of Allahverdi and Allahverdi (2020).

The proposed new algorithm is explained in the succeeding section. Next, computational experiments are given in the third section. Finally, conclusions along with some possible extensions to the problem are provided in Section 4.

2. Proposed New Algorithm

The investigated problem was first studied by Allahverdi and Allahverdi (2020). They presented 12 algorithms and compared the 12 algorithms with each other. They showed that one of the algorithms, called Algorithm A7, performed as the best algorithm. We represent their Algorithm A7 by OA. In this section, we propose a new algorithm, which we call it New Algorithm (NA). The steps of NA are given below.

**NA Statements**

The $LB_{t,j}$ and $UB_{t,j}$ values are given where $i$ denotes the number of jobs and $k$ denotes the number of machine

**For** for $i=1,\ldots,n$ let $pfm_i=l_i((LB_{t,j}+UB_{t,j})/2)+l_i((LB_{t,j}+UB_{t,j})/2)$

$p sm_i=l_i((LB_{t,j}+UB_{t,j})/2)+l_i((LB_{t,j}+UB_{t,j})/2)$

**End For**

Let $s_0$ and $s_n$ denote unassigned and assigned sequences where initially, $s_0=\{1,2,\ldots,n\}$ and $s_n=\phi$

Let $poz_1=1$, and $poz_2=poz_3=zero$

**While** $poz_3 < n$

Let $pfm_{in}=\min\{pfm_i\}$ and $psm_{in}=\min\{psm_i\}$ where $i \in s_u$

**If** $pfm_{in} \leq p sm_{in}$, put that job in the sequence $s_{iu}$, in position $poz_1$

and let $poz_1=poz_1+1$

**Else** put that job in the sequence $s_{iu}$, in position $n-poz_2$

and let $poz_2=poz_2+1$

Delete the job from the sequence $s_u$

Let $poz_3=poz_3+1$

**End While**

Assign the only job remaining in $s_u$ to the last remaining position in $s_n$. The sequence $s_n$ is the solution of the algorithm NA.
The values of \( l_1, l_2, l_3 \) and \( l_4 \) used to compute \( p_{fm} \) and \( p_{sm} \) in the algorithm NA, are investigated by fine-tuning their values. The values from 0 to 1 with the increments of 0.1 were investigated for each of \( l_1, l_2, l_3 \) and \( l_4 \). It was found that the values of \( l_1=0.8, l_2=0.2, l_3=0.2 \) and \( l_4=0.8 \) were the best for the algorithm. Hence, these values are used for the NA algorithm in the computational section.

3. Algorithm Evaluations

Our newly proposed algorithm NA and the best existing algorithm OA are compared in this section. For the computational experiments, we use the same parameters that were used in evaluating algorithm OA for a fair comparison. Aydilek et al. (2017) used similar experimental parameters that we use in this paper.

The next hypotheses were performed to compare the performances of the both algorithms OA and NA. Moreover, there are four considered distributions. Hence, \( w_1, w_2, w_3, w_4 \) are the best for the \( D \) range of 40, 30, 20, or 10. \( D \) indicates the difference between bounds (lower and upper) on processing times. These four values of gaps were also used in the evaluation of OA. Once the lower bounds and upper bounds are generated, instances of processing times are required to be generated for computational purposes. To generate instances of processing times only using a single distribution is misleading since processing times are uncertain. Therefore, they are generated using normal, positive linear, uniform, and negative linear distributions. The uniform and normal distributions are representative for symmetric distributions while the other two distributions are representative for skewed distributions.

We consider six values for \( n \) as 300, 400, 500, 600, 700, 800. Furthermore, we consider four values of 40, 30, 20, and 10 for \( D \). Moreover, there are four considered distributions. Hence, we have in total 96 (4*4*6) combinations. 1000 replications were generated for each combination, which resulted in a total of 96,000 generated problems.

The algorithms OA and NA were compared by both performance measures of Error (average error) and Std (standard deviation). The error was expressed as (algorithm’s makespan – minimum makespan) / minimum makespan. The computational results are provided in Table 1-4, for uniform, normal, negative linear, and positive linear distributions. In the tables, the first column indicates the number of jobs, the second column denotes the difference between the upper and lower bounds of processing time, the third and fourth columns show the errors of OA and NA, respectively. The fifth and sixth columns represent the standard deviations of the OA and NA. Finally, the last column shows the percentage improvement in error of NA over OA.

The summarized computational results are presented in Figure 1-4. It is clear from the figures that the new algorithm NA performs much better than the existing algorithm OA. The overall percentage improvement of the proposed algorithm NA over the existing algorithm OA is 38.61 %. It is clear from the figures that the algorithm’s performance does not alter much either with the number of jobs or the difference of the upper and lower bounds of job processing times. Figure 5 summarizes the results in terms of the distributions and delta while Figure 6 summarizes the results in terms of the distributions and job numbers.

The new algorithm NA and the existing algorithm in the literature were also statistically compared by utilizing a two-sample t test. The next hypotheses were performed to compare the performances of the both algorithms OA and NA.

\[
H_0: \mu(NA) = \mu(OA) \\
H_1: \mu(NA) < \mu(OA)
\]

where \( \mu(\text{Algorithm-h}) \) symbolizes Algorithm-h’s average error. The null hypothesis \( H_0 \) was rejected at a significance level (\( \alpha \)) of 0.01 for all \( n \) and \( \Delta \) combinations.

### Table 1. Experimental results - Normal Distribution

| \( n \) | \( D \) | Error of OA | Error of NA | Std of OA | Std of NA | % Improvement |
|-------|-----|------------|------------|----------|----------|--------------|
| 300   | 10  | 0.1048     | 0.0639     | 0.0021   | 0.0015   | 39.0115      |
| 300   | 20  | 0.1000     | 0.0596     | 0.0020   | 0.0014   | 40.4189      |
| 300   | 30  | 0.0757     | 0.0469     | 0.0016   | 0.0011   | 38.0926      |
| 300   | 40  | 0.0765     | 0.0464     | 0.0016   | 0.0011   | 39.2996      |
| 400   | 10  | 0.0855     | 0.0487     | 0.0017   | 0.0011   | 43.0434      |
| 400   | 20  | 0.0717     | 0.0421     | 0.0015   | 0.0010   | 41.2755      |
| 400   | 30  | 0.0667     | 0.0398     | 0.0013   | 0.0010   | 40.2993      |
| 400   | 40  | 0.0605     | 0.0397     | 0.0011   | 0.0009   | 34.3207      |
### Table 1 (cont). Experimental results - Normal Distribution

| n   | D  | Error of OA | Error of NA | Std of OA | Std of NA | % Improvement |
|-----|----|--------------|-------------|-----------|-----------|---------------|
| 500 | 10 | 0.0711       | 0.0474      | 0.0016    | 0.0011    | 33.3315       |
| 500 | 20 | 0.0640       | 0.0330      | 0.0013    | 0.0008    | 48.3936       |
| 500 | 30 | 0.0624       | 0.0340      | 0.0012    | 0.0008    | 45.4520       |
| 500 | 40 | 0.0538       | 0.0330      | 0.0011    | 0.0007    | 38.6690       |
| 600 | 10 | 0.0748       | 0.0386      | 0.0015    | 0.0009    | 48.3881       |
| 600 | 20 | 0.0633       | 0.0317      | 0.0012    | 0.0008    | 49.9877       |
| 600 | 30 | 0.0532       | 0.0312      | 0.0011    | 0.0008    | 41.4104       |
| 600 | 40 | 0.0486       | 0.0290      | 0.0010    | 0.0007    | 40.3749       |
| 700 | 10 | 0.0592       | 0.0374      | 0.0013    | 0.0008    | 36.8286       |
| 700 | 20 | 0.0504       | 0.0322      | 0.0010    | 0.0007    | 36.1635       |
| 700 | 30 | 0.0480       | 0.0286      | 0.0010    | 0.0007    | 40.3868       |
| 700 | 40 | 0.0485       | 0.0294      | 0.0010    | 0.0007    | 39.3579       |
| 800 | 10 | 0.0557       | 0.0293      | 0.0012    | 0.0007    | 47.3078       |
| 800 | 20 | 0.0512       | 0.0275      | 0.0011    | 0.0007    | 46.3253       |
| 800 | 30 | 0.0447       | 0.0235      | 0.0009    | 0.0006    | 47.4913       |
| 800 | 40 | 0.0423       | 0.0225      | 0.0008    | 0.0005    | 46.7650       |

### Table 2. Experimental results - Uniform Distribution

| n   | D  | Error of OA | Error of NA | Std of OA | Std of NA | % Improvement |
|-----|----|--------------|-------------|-----------|-----------|---------------|
| 300 | 10 | 0.1113       | 0.0683      | 0.0023    | 0.0015    | 38.5890       |
| 300 | 20 | 0.1012       | 0.0863      | 0.0021    | 0.0020    | 14.7158       |
| 300 | 30 | 0.0986       | 0.0826      | 0.0020    | 0.0018    | 16.1901       |
| 300 | 40 | 0.1049       | 0.0953      | 0.0019    | 0.0020    | 9.1123        |
| 400 | 10 | 0.0883       | 0.0544      | 0.0017    | 0.0013    | 38.4200       |
| 400 | 20 | 0.0913       | 0.0516      | 0.0019    | 0.0011    | 43.5368       |
| 400 | 30 | 0.0805       | 0.0545      | 0.0016    | 0.0012    | 32.2359       |
| 400 | 40 | 0.0909       | 0.0661      | 0.0016    | 0.0014    | 27.2762       |
| 500 | 10 | 0.0831       | 0.0439      | 0.0017    | 0.0011    | 47.2228       |
| 500 | 20 | 0.0757       | 0.0470      | 0.0015    | 0.0011    | 37.9654       |
| 500 | 30 | 0.0727       | 0.0455      | 0.0015    | 0.0010    | 37.3814       |
| 500 | 40 | 0.0753       | 0.0592      | 0.0014    | 0.0012    | 21.3773       |
| 600 | 10 | 0.0727       | 0.0416      | 0.0014    | 0.0010    | 42.8160       |
| 600 | 20 | 0.0671       | 0.0412      | 0.0013    | 0.0010    | 38.6796       |
| 600 | 30 | 0.0646       | 0.0474      | 0.0013    | 0.0011    | 26.6545       |
| 600 | 40 | 0.0721       | 0.0414      | 0.0014    | 0.0009    | 42.6536       |
| 700 | 10 | 0.0674       | 0.0349      | 0.0014    | 0.0009    | 48.2614       |
| 700 | 20 | 0.0627       | 0.0344      | 0.0013    | 0.0008    | 45.1832       |
| 700 | 30 | 0.0698       | 0.0359      | 0.0013    | 0.0008    | 48.5508       |
| 700 | 40 | 0.0615       | 0.0401      | 0.0012    | 0.0009    | 34.7529       |
Table 2 (cont.). Experimental results - Uniform Distribution

| n  | D | Error of OA | Error of NA | Std of OA | Std of NA | % Improvement |
|----|---|-------------|-------------|-----------|-----------|--------------|
| 800| 10| 0.0579      | 0.0382      | 0.0013    | 0.0009    | 34.0963      |
| 800| 20| 0.0589      | 0.0306      | 0.0011    | 0.0007    | 48.0392      |
| 800| 30| 0.0555      | 0.0312      | 0.0010    | 0.0007    | 43.7571      |
| 800| 40| 0.0589      | 0.0353      | 0.0011    | 0.0008    | 40.1509      |

Table 3. Experimental results - Positive Linear Distribution

| n  | D | Error of OA | Error of NA | Std of OA | Std of NA | % Improvement |
|----|---|-------------|-------------|-----------|-----------|--------------|
| 300| 10| 0.0909      | 0.0599      | 0.0020    | 0.0014    | 34.1019      |
| 300| 20| 0.0787      | 0.0568      | 0.0016    | 0.0013    | 27.8308      |
| 300| 30| 0.0815      | 0.0584      | 0.0016    | 0.0012    | 28.3393      |
| 300| 40| 0.0801      | 0.0542      | 0.0016    | 0.0012    | 32.3999      |
| 400| 10| 0.0723      | 0.0513      | 0.0016    | 0.0012    | 29.0390      |
| 400| 20| 0.0751      | 0.0431      | 0.0015    | 0.0010    | 42.5667      |
| 400| 30| 0.0615      | 0.0390      | 0.0011    | 0.0008    | 36.6554      |
| 400| 40| 0.0630      | 0.0418      | 0.0012    | 0.0010    | 33.7081      |
| 500| 10| 0.0641      | 0.0431      | 0.0014    | 0.0011    | 32.7232      |
| 500| 20| 0.0676      | 0.0392      | 0.0013    | 0.0009    | 41.9713      |
| 500| 30| 0.0581      | 0.0408      | 0.0012    | 0.0009    | 29.7391      |
| 500| 40| 0.0650      | 0.0318      | 0.0012    | 0.0007    | 51.0430      |
| 600| 10| 0.0651      | 0.0361      | 0.0014    | 0.0009    | 44.5162      |
| 600| 20| 0.0634      | 0.0340      | 0.0012    | 0.0008    | 46.3306      |
| 600| 30| 0.0507      | 0.0363      | 0.0010    | 0.0008    | 28.4212      |
| 600| 40| 0.0533      | 0.0300      | 0.0010    | 0.0007    | 43.6218      |
| 700| 10| 0.0567      | 0.0320      | 0.0012    | 0.0008    | 43.5140      |
| 700| 20| 0.0502      | 0.0311      | 0.0011    | 0.0007    | 38.1106      |
| 700| 30| 0.0451      | 0.0277      | 0.0009    | 0.0006    | 38.5470      |
| 700| 40| 0.0448      | 0.0281      | 0.0008    | 0.0006    | 37.1593      |
| 800| 10| 0.0607      | 0.0312      | 0.0012    | 0.0008    | 48.6142      |
| 800| 20| 0.0510      | 0.0265      | 0.0010    | 0.0006    | 48.0716      |
| 800| 30| 0.0474      | 0.0217      | 0.0009    | 0.0005    | 54.3399      |
| 800| 40| 0.0406      | 0.0247      | 0.0007    | 0.0005    | 39.2330      |

Table 4. Experimental results - Negative Linear Distribution

| n  | D | Error of OA | Error of NA | Std of OA | Std of NA | % Improvement |
|----|---|-------------|-------------|-----------|-----------|--------------|
| 300| 10| 0.1242      | 0.0744      | 0.0026    | 0.0017    | 40.0813      |
| 300| 20| 0.1118      | 0.0720      | 0.0022    | 0.0016    | 35.6125      |
| 300| 30| 0.1132      | 0.0787      | 0.0021    | 0.0018    | 30.4638      |
| 300| 40| 0.1127      | 0.0819      | 0.0021    | 0.0017    | 27.2850      |
Table 4 (cont.). Experimental results - Negative Linear Distribution

| n   | D | Error of OA | Error of NA | Std of OA | Std of NA | % Improvement |
|-----|---|-------------|-------------|-----------|-----------|---------------|
| 400 | 10| 0.0998      | 0.0550      | 0.0021    | 0.0014    | 44.8716       |
| 400 | 20| 0.1063      | 0.0525      | 0.0021    | 0.0012    | 50.5669       |
| 400 | 30| 0.0880      | 0.0610      | 0.0017    | 0.0013    | 30.6426       |
| 400 | 40| 0.0999      | 0.0637      | 0.0017    | 0.0015    | 36.2614       |
| 500 | 10| 0.0864      | 0.0418      | 0.0017    | 0.0010    | 51.5902       |
| 500 | 20| 0.0761      | 0.0493      | 0.0016    | 0.0011    | 35.1628       |
| 500 | 30| 0.0748      | 0.0560      | 0.0014    | 0.0012    | 25.1616       |
| 500 | 40| 0.0804      | 0.0651      | 0.0015    | 0.0014    | 19.1128       |
| 600 | 10| 0.0807      | 0.0449      | 0.0017    | 0.0011    | 44.4261       |
| 600 | 20| 0.0805      | 0.0431      | 0.0016    | 0.0011    | 46.5258       |
| 600 | 30| 0.0851      | 0.0427      | 0.0016    | 0.0010    | 49.8085       |
| 600 | 40| 0.0754      | 0.0524      | 0.0014    | 0.0011    | 30.5661       |
| 700 | 10| 0.0792      | 0.0419      | 0.0016    | 0.0010    | 47.0908       |
| 700 | 20| 0.0670      | 0.0375      | 0.0013    | 0.0009    | 44.1186       |
| 700 | 30| 0.0826      | 0.0395      | 0.0015    | 0.0010    | 52.2542       |
| 700 | 40| 0.0712      | 0.0456      | 0.0015    | 0.0010    | 35.9916       |
| 800 | 10| 0.0640      | 0.0398      | 0.0013    | 0.0010    | 37.7042       |
| 800 | 20| 0.0582      | 0.0364      | 0.0012    | 0.0008    | 37.4284       |
| 800 | 30| 0.0574      | 0.0373      | 0.0011    | 0.0008    | 34.9051       |
| 800 | 40| 0.0627      | 0.0382      | 0.0011    | 0.0009    | 39.1360       |

Figure 1. Percentage improvement of NA over OA – Normal Distribution
**Figure 2.** Percentage improvement of NA over OA – Uniform Distribution

**Figure 3.** Percentage improvement of NA over OA – Positive Linear Distribution
Figure 4. Percentage improvement of NA over OA – Negative Linear Distribution

Figure 5. Percentage improvement of NA over OA over Distributions and Delta
4. Conclusion

The flowshop scheduling problem with four-machine where processing times are uncertain is addressed. The objective is to minimize makespan. This problem was earlier investigated in the scheduling literature and several algorithms were presented. It was shown that the algorithm OA in the literature was the best. In the current paper, we propose a new algorithm (NW). We show that the proposed new algorithm NW significantly reduces the error of the best existing algorithm OA. In other words, the algorithm NW reduces the error of the best existing algorithm OA about 40%. It should be noted that both algorithms OA and NW have the same computational times. This result was statistically verified by conducting test of hypothesis with a significance level of 0.01. Therefore, the newly proposed algorithm NW is recommended.

One of the assumptions made in this paper is that there are no setup times. This may be true for majority of manufacturing systems while it may not be appropriate for some other manufacturing systems. Thus, an extension of the addressed problem is to consider the flowshop scheduling problem with four-machine for minimizing makespan where setup times are separate from processing times and processing times are uncertain. Another extension is to investigate the considered problem with a due date related performance measure such as total tardiness or number of tardy jobs.

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