Development of Approximation Algorithms for Minimizing the Average Flowtime and Maximum Earliness with Zero Release Dates

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Abstract

This paper considers the bicriteria scheduling problem of minimizing the average flowtime and maximum earliness on a single machine with zero release dates. The problem is NP hard, though the Minimum Slack Time (MST) and Shortest Processing Time (SPT) rules yield optimal solutions for the maximum earliness (E_{max}) and average flowtime (F_{avg}) problems, respectively if each criterion were to be applied singly. Thus, in evaluating two proposed heuristics (SAE and EAO), the values of each of the criteria for the two proposed heuristics were compared against the optimal solution of the sub problems. Computational experimental results with job sizes varying from 5 to 200 jobs show that SAE is not significantly different from the optimal F_{avg}. The results also show that for problem sizes, $5 \leq n \leq 30$, SAE is not significantly different from the optimal E_{max}. However, the results of EAO heuristic is significantly different from the optimal for the two criteria except for F_{avg} for problem sizes, $40 \leq n \leq 200$. Therefore, the SAE heuristic is recommended for simultaneously minimizing average flowtime and maximum earliness on a single machine with zero release dates.

Keywords

Average flowtime, maximum earliness, optimal, heuristics, bicriteria

1. Introduction

Multicriteria scheduling relate to two or more performance objectives needing to be optimised. Usually, schedule cost is a function of a number of cost factors including; processing, idle-time, inventory, and tardiness costs amongst others (Oyetunji and Oluleye, 2009). Essentially, schedules obtained using a single criterion have limiting scope (French, 1982). In real life, multiple criteria scheduling problems have great relevance (Nagar, *et al.*, 1995). Tapan, (2012) observed that a necessary condition for a multicriteria scheduling problem is the presence of more than one criterion while a conflict of the criteria is a sufficient condition. Conflicts arise when the solution methods perform differently for considered criteria. Two criteria are considered to be in strict conflict if an increase in satisfaction of one, impairs the other.

Multi-criteria scheduling problems are NP-hard (Rahimi, 2007), with accompanying prohibitive execution time to obtain optimal solutions. The computational complexity is a function of the number of performance measures.

2. Literature Review

Multi-criteria scheduling problems are usually solved using the hierarchical, simultaneous, or pareto-optimal approaches.

The hierarchical approach uses priority to first optimize the most important criterion using others as constraints. The highest priority criterion is optimised terminating with the lowest, (Taha, 2007; Ali, 2016). Rajendran (1995) proposed a multi-criteria scheduling problem for minimizing the weighted sum of machine idle time, total flow time and makespan using the hierarchical method. Two major limitations of the hierarchical approach is that problems are solved in part and solution may be unbalanced if none of the criteria dominates the others.

For the simultaneous optimization method, criteria are aggregated into a Linear Composite Objective Function (LCOF), which can be expressed as:

$$F(X, Y) = \alpha X + \beta Y$$

In general, LCOF can be expressed as:

Optimise $F(Z) = \alpha_1 Z_1 + \alpha_2 Z_2 + \alpha_3 Z +, \dots, +\alpha_m Z_m = \sum_{k=1}^{n} \alpha_k Z_k$

such that $\sum_{k=1}^{n} (\alpha_k) = 1 \quad 0 < \alpha_k < 1$, for all $k = 1, 2, \dots, n$

where:

$\alpha_1, \alpha_2, \dots, \alpha_m$ are the relative weights of criteria $Z, Z_2, \dots, Z_n$ to be optimised, respectively.

F(Z) is the Linear Composite Objective Function (LCOF), and

n is number of the criteria to be optimised.

Tabucanon and Cenna (1991) used simultaneous optimization for minimizing the average flowtime and the maximum tardiness by generating efficient schedules using the Wassenhove and Gelders (1980) algorithm. Also, Farhad and Vahid (2009) explored minimizing the composite function of total machining costs (total completion time), the earliness, tardiness penalties and the makespan. For a single processor with release dates, Oyetunji and Oluleye (2010) proposed two heuristics (HR9 and HR10) for the total completion time and the number of tardy jobs.

The HR7 heuristic proposed by Oyetunji (2010) was used for comparative study. The HR7 heuristic performed better when number of jobs (n) were less than 30 while the HR10 heuristic was better otherwise.

Erenay *et al.* (2010) proposed two constructive algorithms for the single processor minimization of the number of tardy jobs and the average flowtime. The algorithms provided more efficient schedules compared to existing heuristics.

In simultaneous optimization, criteria domination leads to skewness when a certain criterion is a multiple of another. Also, when units of measure differ, then, dimensional conflict arises. These two effects can be eliminated through normalization (Oyetunji and Oluleye, 2009; Akande *et al* 2015).

When scant information exists as regards the weights of criteria, then the Pareto optimal approach is utilized. Essentially, a set of compromise solutions on the criteria are obtained (Oyetunji, 2011). According to Hoogeveen (2005), obtaining a solution to a bi-criteria scheduling problem in polynomial time first requires that Pareto optimal schedules are found.

A key limitation of the Pareto optimal approach is that the decision maker still needs to select among the set of compromise solutions.

2.1 Bi-criteria Scheduling Problems

Bi-criteria problems are relatively simple compared to multicriteria scheduling problems (Ehrgott and Grandibleux, 2000). Bicriteria considerations offer better affinity to reality when compared to single criteria focus. For an example, minimising the average flowtime while reducing production costs may not have late delivery of goods and services in view. On the other hand, while minimising maximum earliness ensures good inventory management, it may not point the way to how profitable the business is. Combining criteria may better ensure that both vendor and customer benefits are taken care of. The bi-criteria scheduling problem of minimising the average flowtime and the maximum earliness is the focus of this study.

3. Problem definition

The problem $1||F_{avg},E_{max}$ consists of scheduling n jobs in the set $A = \{J_1, J_2, \ldots, J_n\}$ on a single machine. Machine processes a job at a time. Also, neither idle time nor preemption exists. The objective is to minimize the maximum earliness and the average flowtime simultaneously. All jobs are available at the beginning. Notations used include:

Notation	Description
N	Number of jobs
P_i	Processing time of job Ji, i = 1, 2, . . . , n.
d_i	Due date of job Ji, i = 1, 2, . . . , n.
C_i	Completion time of job Ji, i = 1, 2, . . . , n.
F_i	The flowtime, F_i of job is defined by : $F_i = C_i - r_i$
F_t	The total flowtime (F_t) is given by: $F_t = \sum_{i=1}^{n} F_i = \sum_{i=1}^{n} (C_i - r_i)$
F_{avg}	The average flowtime (F_{avg}) is given by: $F_{avg} = \frac{Ft}{N}$
E_i	Job Earliness of job Ji, defined by $E_i = \{ (d_i - C_i) \}$
E_{max}	maximum Earliness defined by $E_{max} = \max(E_1, E_2, \ldots, E_n)$
$\underline{F_{avg}}$	The lower bound of average flowtime
$\overline{F_{avg}}$	The upper bound of average flowtime
$\underline{E_{max}}$	The lower bound of the maximum earliness
$\overline{E_{max}}$	The upper bound of the maximum earliness.

In order to minimize E_{max} and F_{avg} separately, sequence the jobs using the MST rule (Hoogeven. 2005) and the SPT rule (Smith, 1956) respectively. Molaee *et al.* (2010) defined an effective sequence as S with values F_{avg} (S), E_{max} (S), if there does not exist a feasible sequence S′ such that E_{max} (S′) ≤ E_{max} (S) and F_{avg} (S′) ≤ F_{avg} (S) where at least one strict inequality holds. The lower bound of total flowtime in the problem $1||F_{avg}, E_{max}$ is equal to the value of F_{avg} _SPT, i.e. the average flowtime of the SPT order. The upper bound of average flowtime, is equal to F_{avg} _MST. Additionally, the lower bound of the maximum earliness is E_{max}_MST and the upper bound is E_{max}_SPT. Figure 1 shows these values, with the lower and upper bounds of each objective specified.

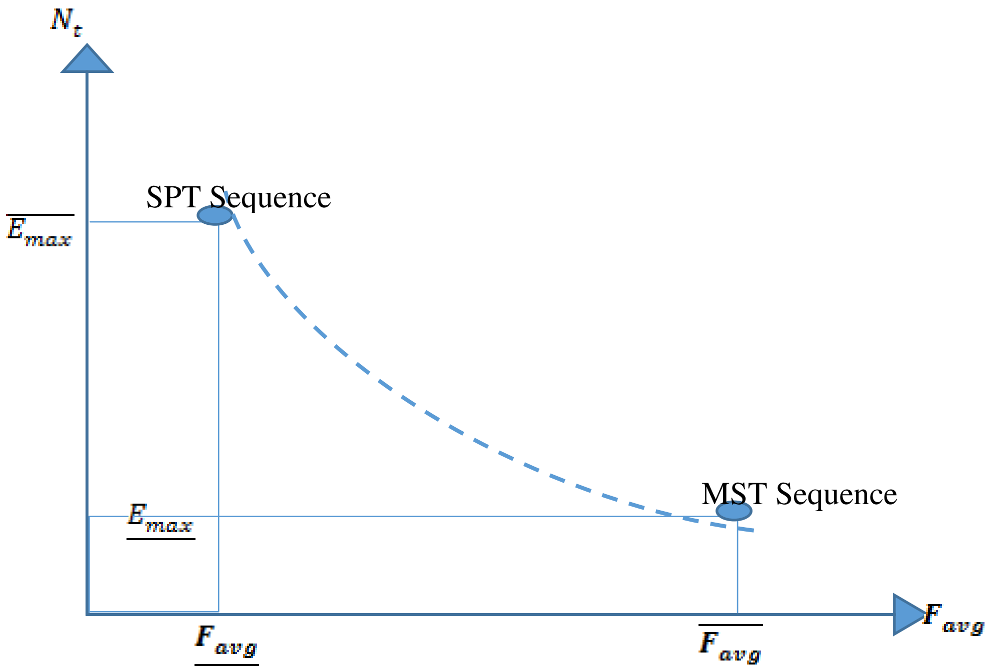

Figure 1. The bounds of maximum earliness and average flowtime

4. Heuristic Development

The two proposed heuristics that utilise dispatching rules as the main framework are now discussed.

4.1 Heuristic SAE

This algorithm is based on the MST and the SPT sequence as follows:

Initialization

JobSet A = [J_1, J_2, J_3, …….J_n], set of given jobs, JobSet B = [0], set of scheduled job

JobSet C = [J_1', J_2', J_3', . . . J_n'], set of unscheduled jobs, $J_j' = J_j$

STEP 1: Form JobSet D by arranging the JobSet A using MST rule. If there is a tie, break the tie using SPT rule.

STEP 2: Compute the optimal E_{max} and F_{avg} from step 1

STEP 3: Form JobSet E by sequencing JobSet A using the SPT rule. If there is a tie break the tie using the EDD rule.

STEP 4: Compute the optimal F_{avg} and E_{max} from step 3

STEP 5: Compute LF1 = $\left(0.5\ E_{max}\ +\ 0.5\ F_{avg}\right)$ for JobSet D and $LF_2 = \left(0.5\ E_{max}\ +\ 0.5FF_{avg}\right)$ for JobSet E

STEP 6: Compute $LF_3 = \min(LF_1, LF_2\ )$. The required sequence is the sequence corresponding to the LF3

STEP 7: STOP.

4.2 Heuristic EAO

The EAO heuristic is based on the variation of two parameters; the due date and the processing time. The steps are as follows:

Initialization

JobSet A = [J_1, J_2, J_3, …….J_n], set of given jobs, JobSet B = [0], set of scheduled job

JobSet C = [J_1', J_2', J_3', …….J_n'], set of unscheduled jobs, $J_j' = J_j$

STEP 1: Form JobSet D by arranging the JobSet A using the schedule index defined by: di + pi

STEP 2: Break any ties using the MST rule index (di - pi). If tie still exists use the EDD rule.

STEP 3: Compute the average flowtime and the maximum earliness of the sequence in step 4

STEP 4: STOP.

In order to amplify understanding, the heuristics are demonstrated with the example in Table 1.

Table 1 : A 5x1 problem size as a case study

Job j	1	2	3	4	5
Pj	4	3	7	2	2
Dj	5	6	8	8	17

Source : Baker and Trietsch, (2013)

Sub-Problem Optimal

Job j	1	2	3	4	5
Pj	4	3	7	2	2
Dj	5	6	8	8	17
$D_j – P_j$	1	3	1	6	15

MST for maximum earliness yields the sequence 1 ,3 , 2, 4, 5. Or 3, 1, 2, 4, 5

Optimal E_{max} (1 ,3 , 2, 4, 5) = max{(d_1 - C_1), (d_2 - C_2), …, (d_n - C_n)}

$$E_{max} = \max((5\text{-}4), (8\text{-}11), (6\text{-}14), (8\text{-}16), 17\text{-}18) = 1$$

Optimal E_{max} (3, 1, 2, 4, 5) = max{(d_1 - C_1), (d_2 - C_2), …, (d_n - C_n)}

$$E_{max} = \max((8\text{-}7), (5\text{-}11), (6\text{-}14), (8\text{-}16), 17\text{-}18) = 1$$

SPT for average flowtime yields the sequence 4, 5, 2,1,3

The F_T = 2 + 4 + 7 + 11 + 18 = 42

The average flowtime (F_{avg}) is given by: $F_{avg} = \frac{Ft}{N} = \frac{42}{5} = 8.4$

SAE HEURISTIC

STEP 1: JobSet D = 1 ,3, 2, 4, 5

STEP 2 : JobSet D $F_{avg} = \frac{4+11+14+16+18}{5} = 12.6$, Optimal E_{max} = 1

STEP 3: JobSet E = 4, 5, 2,1,3

STEP 4 : Optimal average flowtime (F_{avg}) is given by: $F_{avg} = \frac{Ft}{N} = \frac{42}{5} = 8.4$

E_{max} = max ((8-2), (17-4), (6-7), (5-11), (8-18)) = 13

STEP 5: LF1 = 6.3 + 0.5 = 6.8 $LF_2 = (6.5 + 4.2)$ = 10.7

STEP 6: LF_3 = 6.8. The JobSetD (required sequence) is the sequence corresponding to the LF1

Table 2 : EAO Heuristic

Job j	1	2	3	4	5
P_j	4	3	7	2	2
D_j	5	6	8	8	17
$P_j + D_j$	9	9	15	10	19

EAO heuristic sequence = 1,2. 4, 3, 5, F_T = 4 + 7 + 9 + 16 + 18 =54, $F_{avg} = \frac{54}{5} = 10.8$

E_{max}= max{ (5-4), (6-7), (8-9), 8-(16) (17-18 } = 1

The results summary is as in Table 3.

Table 3: Results Summary

Optimal Sub problem		SAE		EAO	
E_{max}	F_{avg}	E_{max}	F_{avg}	E_{max}	F_T
1	8.4	1	12.6	1	10.8

5. Computational Experiments

In evaluating the performance of the proposed heuristics, problem instances were implemented in MATLAB 2017 version and run on a PC with a 3.6 GHz Intels AMD-E2 1800 APU processor with 4GB RAM memory. Randomly generated problems ranging from 5-200 jobs, with 50 instances of each of the problem size were used in experimentation. The Gursel *et al.* (2010) concept was adopted to generate scheduling variables. The relations are given as follows:

i. The processing time P follows the uniform distribution U(1,10).
ii. The due date D_i is given by the equation; $Di = kP_i$. where k is uniformly distributed between U(1,4).

5.1 Performance measures

Comparison of the solution methods was made resulting from 50 instances for each combination of job size, due date, and processing time distribution. These problems were solved using the solution methods (i.e., MST for E_{max}, SPT for F_{avg}, and the proposed heuristics SAE and EAO) . A number of measures were considered.

(a) The Percentage Deviation (P.D) test: The deviation of each of the solution methods with respect to the optimal were measured. The P.D of SAE heuristic with respect to the optimal value (OPT_{value}) is given by

$$P.D = \frac{SAE\ value - OPT_{value}}{OPT_{value}} \times 100$$

(b) The Approximation Ratio (A.R) : The A.R is the ratio of the value of the objective function obtained to the benchmark value (BM_{value}). The A.R of a given SAE heuristic is given by:

A.R of SA = $\frac{SAE\ value}{BM_{value}}$

(c)Test of mean (t-test): T-test is used to determine if the values of the objective functions obtained for different solution methods are statistically different. An independent t-test with 95% confidence level was adopted.

6. Results and Discussion

The results of the computational experiment are as in table 4. The results involve the optimal value of the sub problems and the results of the two proposed heuristics for the problem.

Table 4: Mean values of Performance measures

Optimal Sub Problem			SAE		EAO	
Size	F_{avg} (SPT)	E_{max} (MST)	F_{avg}	E_{max}	F_{avg}	E_{max}
5	11.89	13.12	12.47	13.23	12.13	14.12
10	20.79	12.38	22.15	12.48	21.38	14.74
20	39.18	14.96	40.7	15.24	40.5	18.5
30	55.99	14.32	57.37	15.35	57.91	19.06
40	72.74	14.66	73.09	15.66	75.48	19.18
60	108.4	14.42	108.76	20.26	112.31	20.66
80	142.94	13.78	142.95	20.1	148.1	19.98
100	180.86	13.98	180.86	21.02	187.56	20.9
150	266.51	14.86	266.51	21.7	276.57	21.66
200	3526.6	14.28	3526.6	20.54	3659.7	20.54

The P.D test was carried out by testing the value of each of the criterion from the two proposed solution methods against the respective optimal sub problem solution method. The E_{max} values from the two proposed heuristics were tested against the optimal E_{max} while the F_{avg} values were tested against the optimal F_{avg}. Table 5 shows the result

Table 5: The Percentage Deviation table

Optimal Sub Problem			SAE		EAO	
Size	F_{avg} (SPT)	E_{max} (MST)	P.D (F_{avg})	P.D (E_{max})	P.D (F_{avg})	P.D (E_{max})
5	11.89	13.12	4.88	0.84	2.02	7.62
10	20.79	12.38	6.54	0.81	2.84	19.06
20	39.18	14.96	3.88	1.87	3.37	23.66
30	55.99	14.32	2.47	7.2	3.443	33.1
40	72.74	14.66	0.48	6.82	3.77	30.83
60	108.4	14.42	0.33	40.5	3.61	43.27
80	142.94	13.78	0.007	45.86	3.62	44.99
100	180.86	13.98	Optimal	50.36	3.71	49.5
150	266.51	14.86	Optimal	46.03	3.78	45.76
200	3526.6	14.28	Optimal	43.84	3.77	43.84

The F_{avg} obtained from the two proposed heuristics were also subject to A.R test against the optimal F_{avg} from the SPT method. The E_{max} values were compared against the optimal E_{max} from the MST rule. Figure 1 shows the plot of F_{avg} for the two proposed heuristics against the optimal value. The plot shows that the SAE heuristic performed better than EAO. The plot also shows that SAE converges towards optimal for problem sizes not less than 80 ($n \geq 80$).

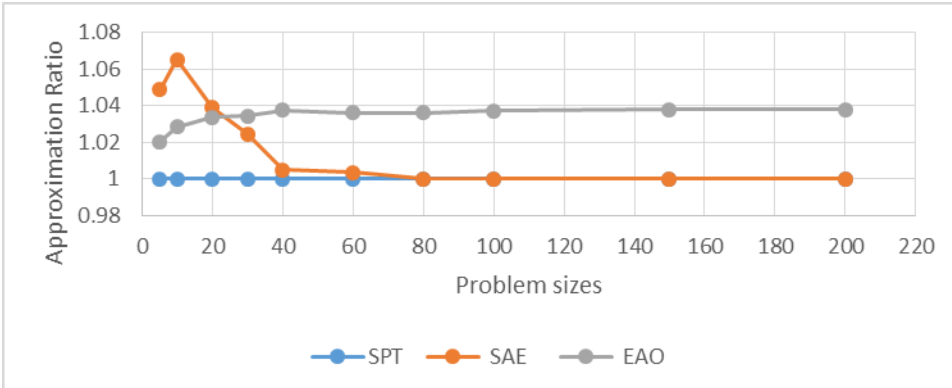

Figure 1. The plot of Approximation ratio for the total flowtime performance measure

The Figure 2 show the plot of the E_{max} for the two proposed heuristics against the optimal value. The plot shows that SAE performed better for job sizes not greater than 40 ($n \leq 40$). For higher job sizes, ($n \geq 80$), even though the two proposed heuristics converge they are far away from the optimal plot.

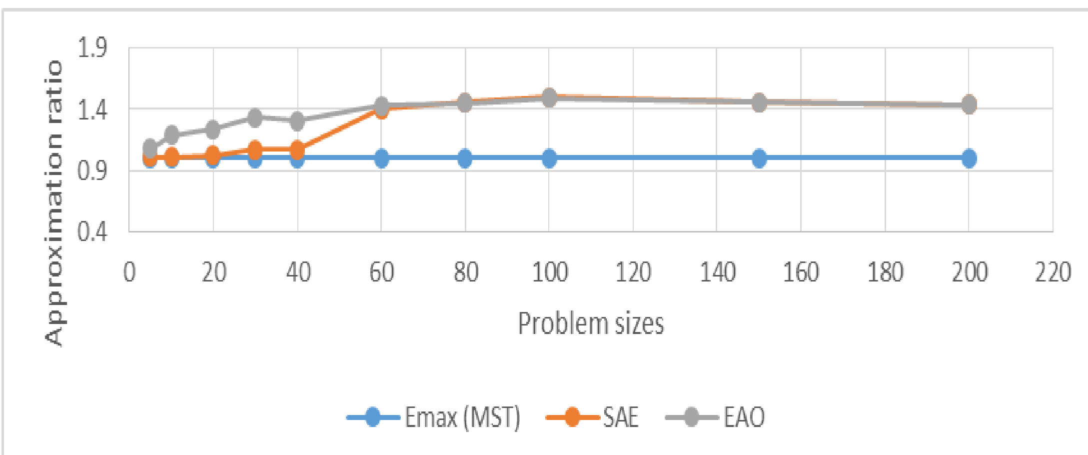

Figure 2. The plot of Approximation ratio for the maximum earliness performance measure

Table 6: Test of means of average flowtime time for 5 ≤n ≤ 30 problems

Solution Method	SAE	EAO	SPT
SAE	----	>0.05	>0.05
AEO	>0.05	-------	<0.05*
SPT	>0.05	<0.05*	------

Table 7: Test of means of average flowtime for 40 ≤n ≤ 200 problems

Solution Method	SAE	EAO	SPT
SAE	----	>0.05	>0.05
AEO	>0.05	-------	>0.05
SPT	>0.05	>0.05	------

Table 8: Test of means of maximum earliness for 5 ≤n ≤ 30 problems

Solution Method	SAE	EAO	MST
SAE	----	<0.05*	>0.05
AEO	<0.05*	-------	<0.05*
MST	> 0.05	<0.05*	------

Table 9: Test of means of maximum earliness for 40 ≤n ≤ 200 problems

Solution Method	SAE	EAO	MST
SAE	----	<0.05*	<0.05*
AEO	<0.05*	-------	<0.05*
MST	<0.05*	<0.05*	------

Note: *indicates significant result at 5% level; Sample size = 50; -----indicates not necessary

The t-tests results show that for the average flowtime, the SAE heuristic result is not significantly different from the optimal for all the considered problem sizes. For the maximum earliness, the SAE result is not significantly different from the optimal for problem sizes, 5 ≤n ≤ 30 while for 40 ≤n ≤ 200, the result is significantly different from the optimal. The EAO heuristic is significantly different from the optimal for the two criteria except for F_{avg} for problem sizes, 40 ≤n ≤ 200.

7. Conclusion and Recommendation

This paper proposed two direct heuristics for minimizing the average flowtime and maximum earliness on a single machine with zero release dates. Results of the simulation in terms of effectiveness shows that the SAE heuristic yielded results that are not significantly different from the optimal solution (SPT) for the average flowtime for all the considered problem sizes (5 ≤n ≤ 200). Also for problem sizes, 5 ≤n ≤ 30, the SAE heuristic is not significantly different from the optimal (obtained from the MST heuristic) for maximum earliness**.** Thus, the SAE heuristic is recommended for simultaneously minimizing average flowtime and maximum earliness on a single machine with zero release date especially for job sizes not greater than 30.

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