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SCHEDULING JOBS ON A SINGLE BPM WITH NON-AGREEABLE RELEASE TIME AND DUE DATES TO MINIMIZE MAKESPAN

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ABSTRACT

This paper proposes a research problem of scheduling jobs on single batch processing machine with non-agreeable release time and due dates with the objective of minimizing makespan. Our aim in the present work is to develop an efficient algorithm from the set of heuristic algorithm for solving the batch processor problem. The efficiency of the developed algorithm is then tested through extensive computational experiments and the results will be presented. Our experimentation shows that the proposed algorithm is giving promising results compared to the best of the available algorithm.

Keywords: Scheduling, Heuristic Algorithm, Batch Processing Machine and Makespan.

SCOPE AND PURPOSE

This paper considers one of the hardest scheduling problems on the heat treatment operation in the steel casting industry. The heat treatment operation is a bottleneck process. This is due to several requirements required to adjust heat treatment operation and is handled with multiple objectives. Thus its scheduling is very important to improve the productivity of the entire manufacturing line. The objective of this paper is to find a solution technique that will find the optimal schedule that minimizes makespan for problems which are found in the heat treatment operation of steel casting industry.

1. INTRODUCTION

The current competitive and globalized market environment is characterized by strong pressure of the customers to supply wide range of products in smaller quantities and to manufacture products with high added value and quality. Increasing demand for complex products with highly added value leads to continuous expansion of product range (in terms of shape and sizes) and reduction of delivery quantity (volume of work orders) (R. Lenort, 2012). This naturally leads to frequent conversion of the production facilities and reduction of capacity exploitation.

Scheduling is a key factor for manufacturing productivity. It can be defined as the allocation of limited resources over time to perform some tasks to satisfy certain conditions. Effective scheduling can improve on time delivery of products, reduce work-in-process inventory, cut lead times, and improve machine utilization. Scheduling and Production Planning problems are typically large in scale and fairly complex. Scheduling problem exists almost everywhere in real-world situations and especially in the manufacturing industries.

Batch processing machines are frequently encountered in many industrial environments such as heat treatment operations in a steel foundry and chemical processes performed in tanks or kilns. The scheduling of batch machines requires the grouping of parts into batches (batch formation) and sequencing of batches. Parts with the same processing requirement belong to a “group”, and parts from different groups cannot be processed in the same batch. Since a batch machine can simultaneously process multiple parts, it may be desirable to form a batch with as many parts as possible. However, parts assigned to a batch may not be available at the same time and the parts available earlier have to wait for processing until all the parts become available. This waiting may cause significant delay of the parts available earlier which results in poor scheduling performance. To overcome the difficulty, it is required to consider batch formation and sequencing in an integrated fashion.

Heat treatment can be defined as the process that is used to alter the physical and mechanical properties of materials without changing the product shape by controlling heating and cooling rates. Heat treating is accomplished in three major stages.

- Stage l – Heating the metal slowly to ensure a uniform temperature
- Stage 2 – Soaking (holding) the metal at a given temperature for a given time
- Stage 3 – Cooling the metal to room temperature

A typical sequence of operations in a heat treatment is given in figure 1.

In the steel industry, determining the optimal heat treatment regime that is required to obtain the desired mechanical properties of the steel is considered as one of the hard and complex processes in the industry. This is because the search space of heat treatment regime is large and it is more complicated in relating the inputs and their outputs. Therefore, it is important to develop a system that is capable of selecting the optimal heat treatment regime so that the required metal properties can be achieved with the least energy consumption and the shortest time. Moreover, scheduling of heat treatment operations jobs are known to have a computationally demanding objective function which could turn to be infeasible when large problems are considered. This has led many researchers who have applied scheduling to heat treatment operations jobs latterly. This is because heat treatment scheduling problems have attracted the attention of researchers due to heavy job that consumes much energy for a longer time. In fact, an efficient algorithm that is able to solve heat treatment jobs scheduling problems is required.

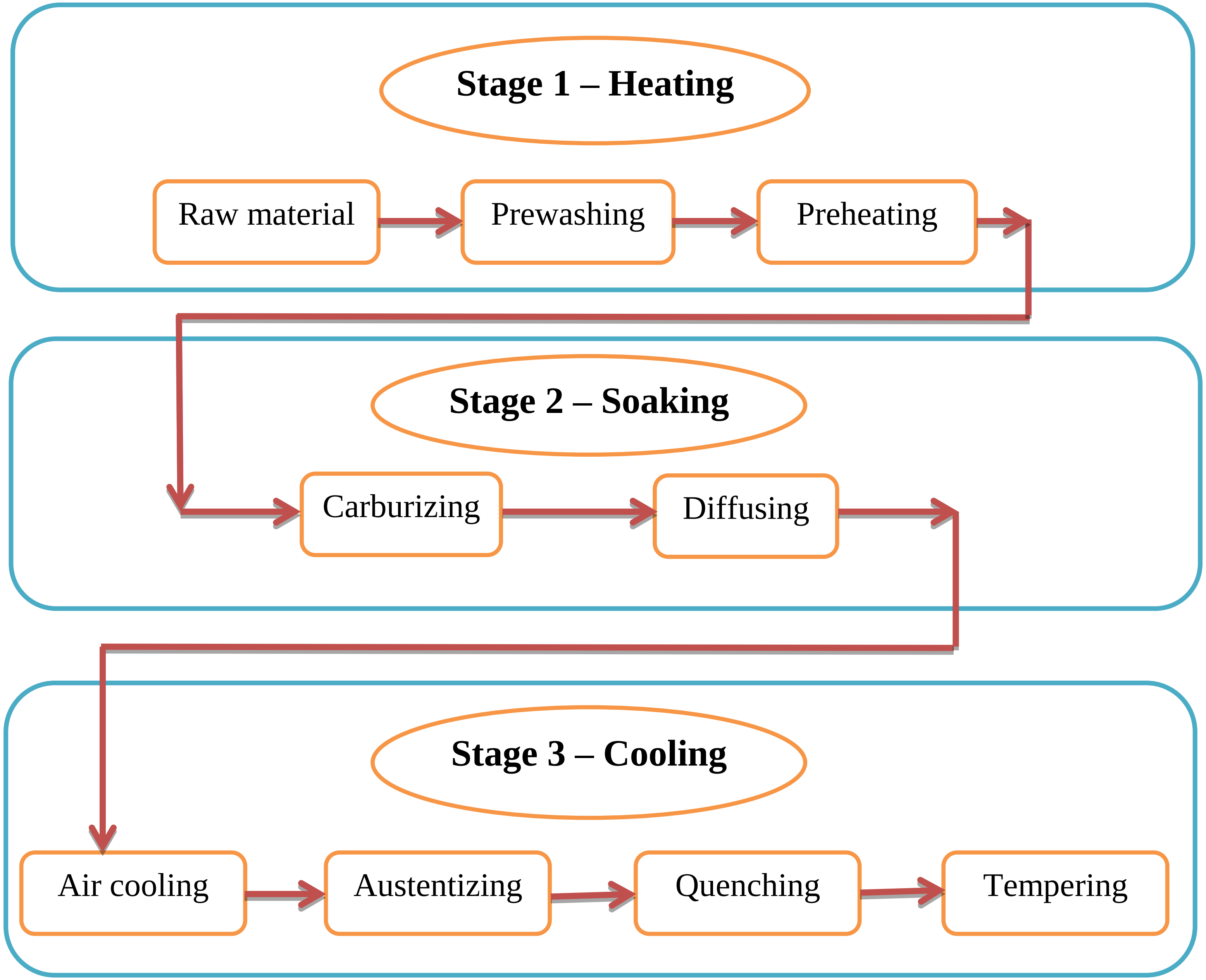

Figure 1: A typical Heat treatment manufacturing process sequence

In theory of scheduling, makespan (C_{max}) is equivalent to the completion time of the last job leaving the system. The smaller makespan usually implies a higher utilization. The utilization of bottleneck station is closely related to the throughput rate of the system. Therefore reducing makespan should also lead to a higher throughput rate. Hence our objective is to minimize makespan.

The paper is organized as follows: Section 1 deals with general introduction. Section 2 deals with reviews related to literature of this paper. Problem statement and assumptions are introduced in sections 3. Section 4 presents briefly the heuristic algorithms proposed for this specific scheduling problem. We then present the computational experiments carried out to compare the performance of the heuristics with the estimated optimal solution and evaluate their relative effectiveness based on various performance measures in section 5. A summary and discussion of future research directions concludes the paper.

2. RELATED WORK

Increasingly in steel industries, customers demand high quality and quick delivery across a wider variety of steel products. Rapidly changing customer requirements and highly dynamic environments are forcing major changes in the production styles and configuration of manufacturing organizations.

Effective production scheduling is at the heart of an efficient manufacturing process and can result in improved on time delivery of products, improved quality, reduced inventory costs and increased productivity. However scheduling is a very complex task due to the need to optimize multiple competing objectives and to react to unpredictable events which can occur during processing. Dynamic scheduling plays an important role in the performance and robustness of production systems with dynamic failure patterns. In such an environment, it is highly desirable to invoke real-time rescheduling in which the schedule modifications are executed concurrently with production.

Recently, many research efforts have been devoted to scheduling problems concerned with batch processing machines. Mathirajan and Sivakumar (2006) have done a quite complete survey on scheduling with batch processing machines. Uzsoy (1994) has examined a problem of scheduling jobs with non-identical size (volume or capacity) specifications on a single burn-in oven to minimize total completion time and makespan. Shuguang Li et al. (2005) considered the problem of scheduling jobs with release times and non-identical job sizes on a single batching machine with the aim of minimizing makespan. The scheduling of parts belonging to multiple groups on a batch machine is considered in Uzsoy (1995). The objectives of makespan, maximum lateness and total weighted completion time are discussed. In the deterministic scheduling literature, the problem of scheduling batch processing machines has also been addressed. Ikura and Gimple (1986) studied the problem of scheduling a single batch processing machine in the presence of release dates and due dates. Batch processing machines are frequently encountered in many industrial environments such as heat treatment operations in a steel foundry and chemical processes performed in tanks or kilns [see M. Mathirajan (2000)].

Heat treatment operation job scheduling problems for steel is highly in demand throughout the industry as a result of heavy job that consumes huge amount of energy and takes longer time. Scheduling operations in heat treatment processes has an important meaning for the steel casting production times. Mathirajan et al (2007) proposed problem of task scheduling with the use of parallel, non-identical initial processes in the presence of dynamic job arrivals, non-compatible task series and non-equal task quantities. Recently production planning and scheduling models for a steel foundry, considering the melting furnace of the pre-casting stage as the core foundry operation were proposed by Voorhis et al (2001), Krishnaswamy et al (1998) and Shekar (1998). Scheduling of production orders has been applied in a steel plant in order to find a particular technological operation start and finish times with efficiency limitations and with a purpose to minimize the sum of weighted times of all orders finishing [see L. Tang, G. Liu (2007)].

Recently many researchers have applied scheduling to heat treatment operations jobs. This is because deterministic manufacturing batch scheduling problems has attracted the attention of researchers as a result of heavy product which forced a gradual shift from continues manufacturing to batch manufacturing [see A.E Oluleye (1999)].

Scheduling a batch processing machine with incompatible job can be used in modeling a large number of heat treatment families to minimize number of tardy jobs. Jolai (2005) used a dynamic programming algorithm to solve this problem and this problem has been proved as NP-hard when the number of family and the machine capacity are arbitrary. Mathirajan et al (2007) proposed problem of task scheduling with the use of parallel, non-identical initial processes in the presence of dynamic job arrivals, non-compatible task series and non-equal task quantities. Scheduling of production orders has been applied in a steel plant in order to find a particular technological operation start and finish times with efficiency limitations and with a purpose to minimize the sum of weighted times of all orders finishing (2007). Simulated annealing method is taken from simulation of the physical process of annealing. Annealing can be described as the process of the cooling molten metal after heating this metal to reach the specific crystallite. This process of cooling is used to produce a more optimal solution [see G. Totten (2006)].

Heating treatment operations aim to improve the material properties such as strength and hardness without changing the shape of the products. The properties of most metals and alloys can be affected by heating treatment operation. Furnace designs vary as to its function, heating operations, type of fuel and method of introducing combustion air. In spite of this most process furnaces have some common features. The quality of furnace design depends on fuel type, combustion efficiency, standby losses cycling losses and heat transfer. However, for applying optimization techniques such as scheduling of heating treatment, a furnace model is required N. Yoshitani, A. Hasegawa (1998).

Makespan is the completion time of the last scheduled job and is directly proportional to the production costs. Thus, makespan is a very important scheduling criterion (1999 & 2010), hence, its choice in this study. Jeng and Lin (2004) considered the single-machine scheduling problem of minimizing the maximum completion time (makespan) for a set of independent jobs. They explored the variant in which the processing times of the jobs are non-linear step function of their starting times and due dates. The problem of minimizing the makespan in a single machine with convex decreasing resource dependent processing times was explored by Kaspin and Shabtay (2004). They considered the two cases (where the job release dates are identical and the general case of non-identical job release dates). An O (n) algorithm was proposed for the case of identical job release dates while an O (n2) algorithm was proposed for the case of non-identical job release dates.

Shuguang Li et al. (2005) considered the problem of scheduling jobs with release times and non-identical job sizes on a single batching machine with the aim of minimizing makespan. An approximation algorithm with a worst-case ratio of 2 +was proposed for the problem. Trinder & Watts (1973) indicated that individual centers at the post-casting stage could be scheduled separately. Trinder & Moss (1984) discussed the necessity of real-time systems for foundry production control. These articles provide some broad requirements for production planning and control systems for foundries. Hence, in this paper we have considered the scheduling of heat treatment furnaces in a steel-casting foundry, a special problem of batch processor scheduling, under conditions such as incompatible job families, dynamic job arrivals, non-agreeable release times and due date with the objective of minimizing makespan.

3. PROBLEM STATEMENT AND ASSUMPTIONS

In this section, we present a formal description of the problem. On a single machine, a set of jobs J= {1, 2...N} belongs to one of the family F= {1, 2…f}. Each job j, $1 \le j \le N$, is associated with four parameters: processing time P_f, arrival time A_{jf}, cost/penalty C_{jf} and due date D_{jf}.

All input parameter, including P_f, A_{jf}, C_{jf} and D_{jf}, are integer. No pre-emption is allowed. That is, once the processing of a job is started, it cannot be interrupted until its completion. Jobs belonging to a same family are grouped in to batch. Batch starting time can be arrived from max (largest arrival time of jobs, completion time of previous batch). Batch completion time is the sum of batch start time and processing time. The goal of the problem is to find a schedule (or permutation) of the jobs such that the processing of the jobs can be completed as early as possible.

We shall use the three-field notation of Graham et al (1979) to denote the scheduling of single diffusion furnace problem as 1/batch, incompatible-job-families, non-agreeable release times and due-dates/C_{max}.

To accommodate the problem description as above, we use the following notation.

N: Number of Jobs

F: Number of family

K: Batch capacity

P_f: Processing time of family f Ɛ F

D_{jf}: Due date of job j Ɛ N in family f Ɛ F

A_{jf}: Arrival time of job j Ɛ N in family f Ɛ F

C_{jf}: Cost/Penalty job j Ɛ N in family f Ɛ F

The following assumptions are made for the above considered scheduling problem:

1. Machine is available from the beginning
2. Machine is identical and is able to perform all operations.
3. Machine breakdown is not considered and manpower of uniform skill is continuously available
4. Dynamic arrival of jobs. The processing times of all jobs are integer
5. Job processing time is deterministic and known in advance
6. Jobs of the same family have the same processing times
7. Setup times are independent of job sequence and are included in the processing times.
8. Neither job splitting nor pre-emption is allowed
9. The batch processing time equals the processing time of the corresponding family
10. Processing time of job-families is considered constant and independent of the number of jobs in a batch
11. All jobs in a batch start and finish at the same time
12. The batch size of the BP is dependent on the capacity of the BP

4. DEVELOPMENT OF ALGORITHM

In industry and manufacturing, scheduling is very important especially when several jobs have to be processed on limited resources. Minimizing the time or resources will first benefit from scheduling jobs.

The makespan or schedule length is an important scheduling criterion as it has direct correlation with the production costs. Because of the release dates constraints, the problem is NP-Hard. So approximation algorithms are desired to solve this important scheduling problem. Based on the analysis carried below and our observation of the effects of idle time on the machine with respect to the scheduling problem being considered, an algorithm is proposed for solving this problem.

The principle of GH algorithm just outlined is illustrated in Figure 2. The systematic procedure of variants to schedule jobs in heat treatment furnace is as follows.

1. Initialize: N, BC, BST and BCT
   1.1. For i=1 to N
   1.2. If f= =1
      1.2.1. $J_{1j}=J_i$
      1.2.2. j++
   1.3. Else if f= =2
      1.3.1. $J_{2k}=J_i$
      1.3.2. k++
   1.4. Else
      1.4.1. $J_{3l}=J_i$
      1.4.2. l++
   1.5. Calculate $Index_i$, $C_{f1}=j$, $C_{f2}=k$, $C_{f3}=l$
2. While (AJ≠N)
   2.1. Sort J_{1i} , i=1 to C_{f1}
   2.2. Sort J_{2j} , j=1 to C_{f2}
   2.3. Sort J_{3k} , k=1 to C_{f3}
   2.4. $Batch_1 = J_{1i}$, i=1 to BC

2.5. $Batch_2 = J_{2i}$, i=1 to BC

2.6. $Batch_3 = J_{3i}$, i=1 to BC

2.7. For i=1 to 3

2.7.1. BST_i= max(RT of $batch_i$, BCT_{i-1})

2.7.2. $BCT_i=BST_i+PRT_i$

2.8. New batch= max($Batch_i$ (TWT_i))

2.9. Remove allocated job

3. Compute C_{max}

The variables used for the Heuristics algorithm are summarized as follows:

BC – Batch capacity

BST – Batch start time

BCT – Batch completion time

C_{f1} – Number of jobs in family 1

C_{f2} – Number of jobs in family 2

C_{f3} – Number of jobs in family 3

AJ – Allocated job

N – Number of jobs

RT – Release time

PRT – Process time

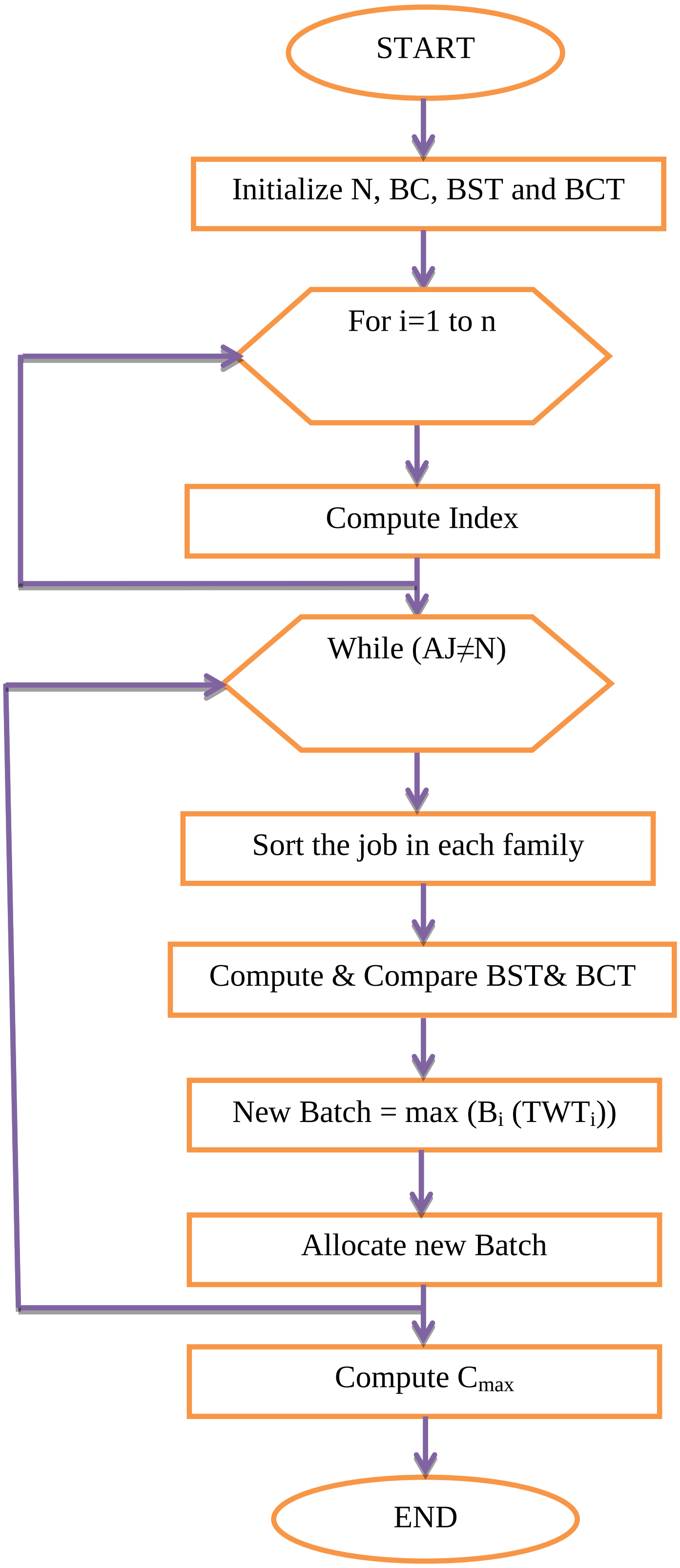

Figure 2: Program flow chart

The proposed 13 variants of the above GHM differ compared with the other variants. For first 10 variants we used ten different *k*-values from 0.5 and 5 in increments of 0.5. The remaining variants (CR, ST and EDD) index is calculated based on below stated expressions. The methods of computing this index for each of these 13 variants are given below. All the 13 variants of the GHM are implemented using Turbo c++.

FORMULA FOR CALCULATING INDEX

Variants 1 to 10: ATC with *K* value

$$Index = \left(\left(1 \big/ \left(p_f * d_{jf} \right) \right) \exp^{-\left(\max\left(0, d_{jf} - \left(p_f + \max\left(p_f + t\right)\right)\right)\right)} \right) \Big/ \left(\bar{p}_f * K \right)$$

Variant 11: CR

$$Index = \left(d_{jf} - today\_date \right) / \, p_f$$

Variant 12: ST

$$Index = d_{jf} - today\_date$$

Variant 13: EDD

Index is Earliest Due-date (EDD)

5. RESULTS AND DISCUSSIONS

To determine how well the proposed variants of the GHM perform is, we carried out computational experiments using an experimental approach. An experimental approach relies on two elements and they are a) experimental design b) measure of effectiveness.

Experimental design

The experimental design is the process of planning an experiment to ensure that the appropriate data will be generated to evaluate the performance of the proposed variants of the GHM.

In this section, we describe our experiments to evaluate the performance of the proposed heuristic. There are 3 levels of jobs for which the number of jobs (N) is equal to 25, 50 and 100. Their corresponding release times and due dates are uniformly generated from the sets {[1, 8], [1, 16], [1, 24]} & {[1, 40], [1, 60], [1, 80]} respectively and the penalty is uniformly distributed from [1, 10]. Each level of jobs have 3 families, f = 1, 2 & 3 and the processing times of family 1, 2, & 3 are 3, 6, & 9 respectively. We are considering 27 problem configurations for each class. 10 instances are generated which result in 270 test problems for our proposed GHM.

Measure of effectiveness

Since the performance of the proposed variants of the GHM may vary over a range of problem instances, the performances of the proposed variants of the GHM are compared using the following two standard measures:

(a) Average relative percentage deviation (ARPD): For each problem instance, we compute the relative percentage deviation (RPD) with respect to estimated optimal solution.

$$RPD = \left(\frac{\left(TWT\left(Heuristic\_Method\right) - TWT\left(Estimated\_Optimal\_\Pr ocedure\right)\right)}{TWT\left(Estimated\_Optimal\_\Pr ocedure\right)} \right) * 100$$

Further, we compute the average of RPD (ARPD) obtained for different heuristics over the number of problem instances planned in the problem configurations. This measure provides the average performance of the heuristics.

(b) Maximum relative percentage deviation (MRPD): We compute the maximum of RPD (MRPD) which is obtained for different heuristics, over the number of problem instances planned in the problem configurations. This measure provides the worst case performance of the heuristics.

ANALYSIS

For each of the problem instance there are 13 feasible solutions. Using each of the 13 variants of the proposed GHM, minimizing C_{max} is obtained. For each of the 270 problem instances, 13 feasible solutions obtained are given as and input to the estimates as an optimal solution. And then for each of the 270 problem instances, the RPD of 13 variants of the GHM is computed in comparison with estimated optimal solution.

The average of RPD (ARPD) for various problem configurations over 10 instances and for each of the 13 variants of the proposed GHM are computed and given in Table 1.

Similarly to the ARPD, the maximum of RPD (MRPD) are computed for each problem configuration and presented in Table 2. Irrespective of the problem configurations, the ARPD and MRPD over 270 instances for each of the 13 variants of the proposed GHM is computed and shown in Figures 1 and 2 respectively.

The result in Tables 1 & 2 and Figures 3 & 4 shows that the best C_{max} is obtained from the Variants 13.

Table 1: Performance of proposed heuristic methods in comparison with average relative percentage deviation (ARPD)

S.No	Problem Configuration	V 1	V 2	V 3	V 4	V 5	V 6	V 7	V 8	V 9	V 10	V 11	V 12	V 13
1	1	0.63	2.14	0.63	2.14	0.63	2.14	0.63	2.14	0.63	3.56	0.63	3.56	0.63
2	2	2.50	0.00	2.50	2.50	2.50	0.00	2.50	2.50	2.50	0.00	2.50	0.00	0.00
3	3	2.33	2.33	2.33	2.33	2.33	2.33	2.33	2.33	2.33	0.00	2.33	0.00	2.33
4	4	2.73	3.22	2.73	3.22	2.73	3.22	2.73	3.22	2.73	1.84	2.73	1.84	2.73
5	5	1.75	0.61	1.75	0.61	1.75	0.61	1.75	0.61	1.75	6.27	1.75	6.27	1.75
6	6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.65	0.00	5.65	0.00
7	7	2.41	1.49	2.41	1.51	2.41	1.49	2.41	1.51	2.41	1.49	2.41	1.49	2.41
8	8	1.11	5.01	1.11	5.01	1.11	5.01	1.11	5.01	1.11	5.83	1.11	5.83	1.11
9	9	1.25	1.63	1.25	1.63	1.25	1.63	1.25	1.63	1.25	4.36	1.25	4.36	1.25
10	10	1.14	1.10	1.14	0.54	1.99	1.10	1.14	0.54	1.14	2.38	1.14	2.38	1.14
11	11	0.22	0.67	0.22	0.67	0.22	0.23	0.22	0.67	0.22	1.63	0.22	1.63	0.22
12	12	1.55	0.76	1.55	0.76	1.55	0.76	1.55	0.76	1.55	0.00	1.55	0.00	1.55
13	13	0.91	2.10	0.91	1.39	0.91	2.10	0.91	1.39	0.91	4.00	0.91	4.00	0.91
14	14	4.35	1.75	4.35	1.75	4.35	1.75	4.35	1.75	4.35	3.95	4.35	3.95	4.35
15	15	3.90	0.25	3.90	0.25	3.90	0.25	3.90	0.25	3.90	3.07	3.90	3.07	3.90
16	16	0.00	5.97	0.00	3.17	0.00	5.97	0.00	3.17	0.00	6.54	0.00	6.54	0.00
17	17	1.72	3.07	1.72	2.76	1.72	3.07	1.72	2.76	1.72	4.21	1.72	4.21	1.72
18	18	0.91	3.32	0.91	3.32	0.91	3.32	0.91	3.32	0.91	2.70	0.91	2.70	0.91
19	19	0.71	0.30	0.71	0.30	0.71	0.58	0.71	0.30	0.71	1.43	0.71	1.43	0.71
20	20	1.47	0.29	1.47	0.73	1.47	0.00	1.47	0.73	1.47	0.90	1.47	0.90	1.47
21	21	0.44	0.44	0.44	0.29	0.44	0.44	0.44	0.29	0.44	1.17	0.44	1.17	0.44
22	22	0.26	1.87	0.26	1.26	0.26	1.87	0.26	1.26	0.26	3.07	0.26	3.07	0.26
23	23	0.75	1.51	0.75	1.14	0.75	1.51	0.75	1.14	0.75	2.99	0.75	2.99	0.75
24	24	1.28	1.39	1.28	1.40	1.28	1.18	1.28	1.82	1.28	1.07	1.28	1.07	1.28
25	25	0.48	1.95	0.48	1.41	0.48	1.95	0.48	1.41	0.48	3.08	0.48	3.08	0.48
26	26	1.43	2.96	1.43	2.96	1.43	2.96	1.43	2.96	1.43	2.44	1.43	2.44	1.43
27	27	0.90	1.57	0.90	1.75	0.90	1.57	0.90	1.75	0.90	2.53	0.90	2.53	0.90
Average		1.37	1.77	1.37	1.66	1.41	1.74	1.37	1.68	1.37	2.82	1.37	2.82	1.28

Table 2: Performance of proposed heuristic algorithms in comparison with maximum relative percentage deviation (MRPD)

S.No	Problem Configuration	V 1	V 2	V 3	V 4	V 5	V 6	V 7	V 8	V 9	V 10	V 11	V 12	V 13
1	1	2.50	8.57	2.50	8.57	2.50	8.57	2.50	8.57	2.50	9.38	2.50	9.38	2.50
2	2	2.50	0.00	2.50	2.50	2.50	0.00	2.50	2.50	2.50	0.00	2.50	0.00	0.00
3	3	2.33	2.33	2.33	2.33	2.33	2.33	2.33	2.33	2.33	0.00	2.33	0.00	2.33
4	4	12.20	12.20	12.20	12.20	12.20	12.20	12.20	12.20	12.20	7.14	12.20	7.14	12.20
5	5	4.55	2.44	4.55	2.44	4.55	2.44	4.55	2.44	4.55	16.67	4.55	16.67	4.55
6	6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	7.69	0.00	7.69	0.00
7	7	3.92	3.85	3.92	3.92	3.92	3.85	3.92	3.92	3.92	3.85	3.92	3.85	3.92
8	8	5.56	19.51	5.56	19.51	5.56	19.51	5.56	19.51	5.56	19.51	5.56	19.51	5.56
9	9	6.25	6.25	6.25	6.25	6.25	6.25	6.25	6.25	6.25	11.11	6.25	11.11	6.25
10	10	3.70	3.33	3.70	1.69	5.08	3.33	3.70	1.69	3.70	5.66	3.70	5.66	3.70
11	11	1.56	1.67	1.56	1.67	1.56	1.67	1.56	1.67	1.56	5.08	1.56	5.08	1.56
12	12	1.61	1.56	1.61	1.56	1.61	1.56	1.61	1.56	1.61	0.00	1.61	0.00	1.61
13	13	4.05	8.33	4.05	4.29	4.05	8.33	4.05	4.29	4.05	11.43	4.05	11.43	4.05
14	14	10.14	7.81	10.14	7.81	10.14	7.81	10.14	7.81	10.14	12.90	10.14	12.90	10.14
15	15	9.38	1.52	9.38	1.52	9.38	1.52	9.38	1.52	9.38	8.57	9.38	8.57	9.38
16	16	0.00	10.29	0.00	10.29	0.00	10.29	0.00	10.29	0.00	11.76	0.00	11.76	0.00
17	17	8.33	10.77	8.33	8.33	8.33	10.77	8.33	8.33	8.33	14.49	8.33	14.49	8.33
18	18	5.48	6.85	5.48	6.85	5.48	6.85	5.48	6.85	5.48	6.17	5.48	6.17	5.48
19	19	2.73	0.98	2.73	1.82	2.73	1.63	2.73	1.82	2.73	3.92	2.73	3.92	2.73
20	20	2.68	1.75	2.68	2.61	2.68	0.00	2.68	2.61	2.68	1.82	2.68	1.82	2.68
21	21	2.65	0.92	2.65	0.92	2.65	0.92	2.65	0.92	2.65	2.65	2.65	2.65	2.65
22	22	1.74	4.46	1.74	4.46	1.74	4.46	1.74	4.46	1.74	6.96	1.74	6.96	1.74
23	23	2.59	3.57	2.59	3.57	2.59	3.57	2.59	3.57	2.59	5.31	2.59	5.31	2.59
24	24	2.61	5.22	2.61	5.22	2.61	5.22	2.61	5.22	2.61	3.45	2.61	3.45	2.61
25	25	1.67	6.19	1.67	5.88	1.67	6.19	1.67	5.88	1.67	6.72	1.67	6.72	1.67
26	26	4.27	5.13	4.27	5.13	4.27	5.13	4.27	5.13	4.27	10.66	4.27	10.66	4.27
27	27	0.90	1.57	0.90	1.75	0.90	1.57	0.90	1.75	0.90	2.53	0.90	2.53	0.90
Maximum		12.20	19.51	12.20	19.51	12.20	19.51	12.20	19.51	12.20	19.51	12.20	19.51	12.20

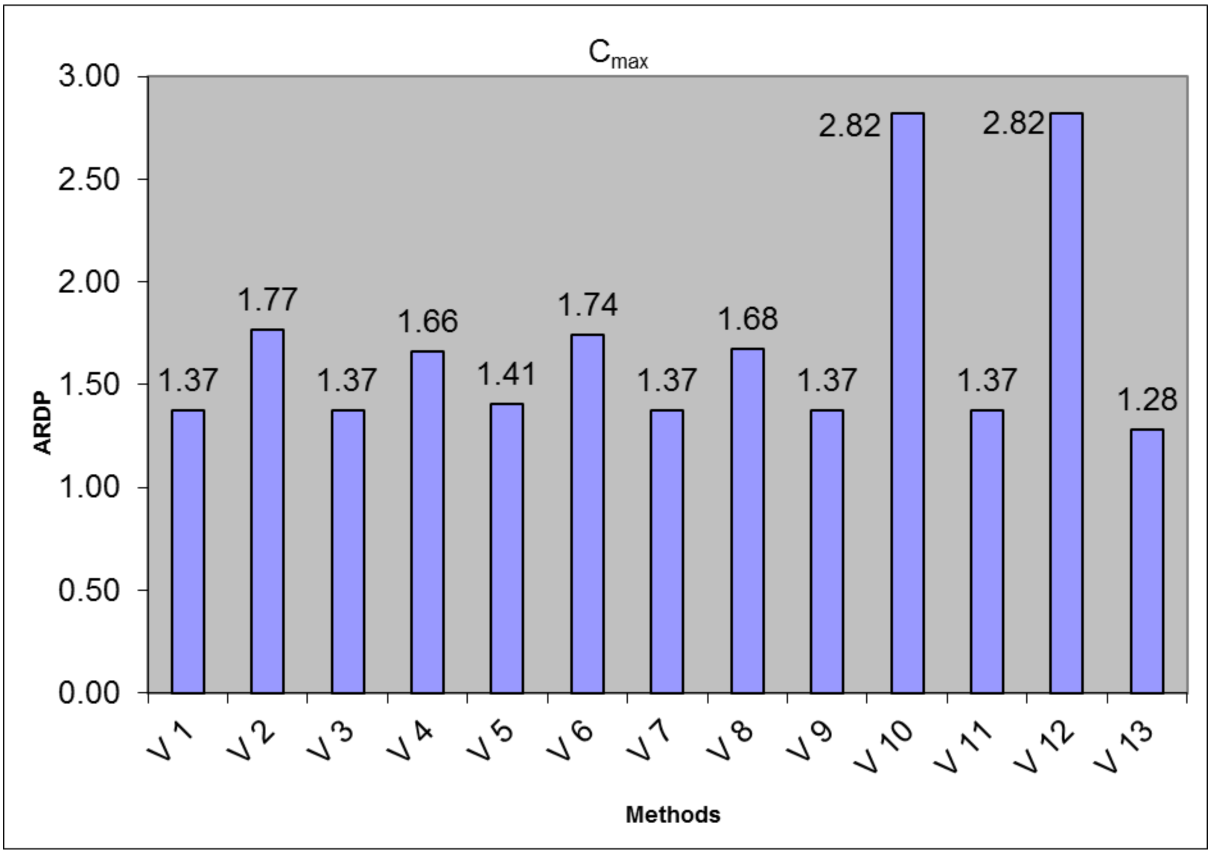

Figure 3: Performance of proposed heuristic methods w.r.t ARPD over 270 problem instances

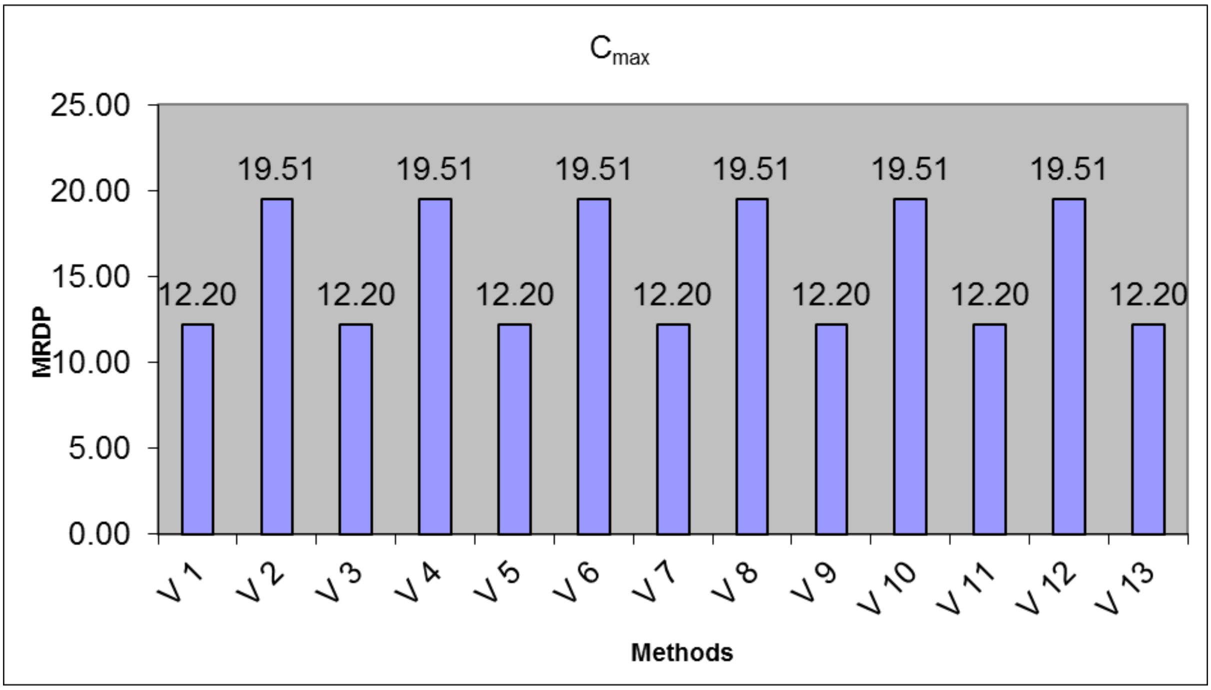

Figure 4: Performance of proposed heuristic methods w.r.t. MRPD over 270 problem instances

6. CONCLUSION

The problem of scheduling in Heat Treatment plant is large scale and complex. This paper considers one of the hardest scheduling problems on the heat treatment operation in the steel casting industry. We consider the problem of minimizing the total completion time on a single-batch processing machine with non-agreeable release time and due dates, where the machine capacity restrictions are considered. A batch processing machine (BPM) or batching machine is a machine that can process several jobs simultaneously as a batch with common starting and ending times. It has been observed that the idleness on the machine is one of the factors that prolong the makespan.

This paper provides a few greedy heuristics method for the problem of minimizing the maximum completion time on a single-batch processing machine. The performance of the proposed heuristic is evaluated over a large number of randomly generated problem instances and it was tested on small size problems up to 10 jobs and on large size problems up to 100 jobs. The performance of the heuristic algorithm measured as the percentage deviation between heuristic solution values and optimal solution values for small size problems was very satisfactory yielding solutions within few percentage points of the optimal solution values. For a large scale problem, the performance of the heuristic algorithm measured as the percentage deviation between heuristic solution values and estimated optimal solution values. The computational results shows that the integrated consideration of batch formation and sequencing results in high quality schedules that the proposed algorithm results reveal that the heuristic algorithm can efficiently solve the considered problem as well as practical problems and the reduction of makespan. The obtained results indicate that the proposed algorithm has ability to reduce the makespan.

However, in this paper, some simplifications are assumed. Namely, setup times are included in the process time. Considering these constraints in the scheduling problem could be the objective of our future research. One possible extension to the problem studied in this paper is to consider the problem with respect to other objective functions such as job waiting time variance or an objective function taking into account early and tardy penalties. Another possible extension to the problem addressed in this paper is to consider a hybrid flow shop where at each state there might be more than a single machine available. The considered Heat treatment problem can further be extended to include issues related to material handling time, buffer size constraints, etc.

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