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MINIMIZING TOTAL WEIGHTED TARDINESS ON A BPM WITH INCOMPATIBLE JOB-FAMILIES AND DYNAMIC JOB-ARRIVALS

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ABSTRACT

This study addresses the scheduling of a diffusion furnace, a Batch Processing Machine (BPM) with dynamic job-arrivals, and incompatible job-families with the objective of minimizing total weighted tardiness (TWT). Due to the computational intractability, a few variants, based on the EDD, CR, ST, and different versions of ATC dispatching rules, of a greedy heuristic method (GHM) are proposed. A series of computational experiments carried-out indicated that one of the variant of the ATC rule has excellent performance in comparison with an estimated optimal solution.

Keywords: Batch Processing Machine, Incompatible Job-Families, Total Weighted Tardiness, Greedy Heuristic Method, Estimated Optimal Solution.

1. INTRODUCTION

A batch processing machine is a machine that can simultaneously process several jobs in a batch. Once processing of a batch is initiated, no job (lot) can be removed or added to the batch. Various problems of scheduling on BPM in many discrete parts manufacturing industries (Ref. Table 1) have been addressed extensively in the literature. This study is mainly motivated by an industrial application, namely, scheduling of BPM in Semiconductor Manufacturing.

Table 1: Applications of BPM(s) in Discrete Parts Manufacturing

Industry / Manufacturer	**Operations / BPM**	**Sample References**
Aircraft Industry	Hardening of Synthetic parts / Oven	Zee, *et al* .(2001)
Automobile Gear Manufacturing	Hardening & Soaking / Heat-Treatment Furnace	Ravindra and Mathirajan (2011)
Electronics Manufacturing industry	Testing PCBs in Environmental Stress Screening (ESS) chambers	Damodaran and Srihari. (2004)
Furniture Manufacturing Industry	Dry Kiln	Yaghubiana *et al* .(2001)
Glass Container Industry	Annealing / Lehr or Annealing Kiln	Almada-Loba *et al*. (2008)
Hospital (Hospital Sterilization Services)	Washing of RMD (Reusable Medical Devices)	Ozturk *et al*. (2010)
Ion Plating (IP) Industry	IP machine (has been widely used in Watch and Clock Industry)	Chan *et al*.(2006)
Iron and Steel Industry	Multi-Head Hole-Punching Machine	Oulamara (2007)
Multi-Layer-Ceramic Capacitor Manufacturing	Bake-out / Box-Oven	Koh *et al*. (2004)
Semiconductor Manufacturing	Oxidation or Diffusion Furnace, Burn-in Oven	Uzsoy *et al*. (1992), Potts and Kovolyov (2000), Mathirajan & Sivakumar (2006b), Monch *et al*. (2009)
Shoe Manufacturing Factory	Carousel rotation / Carousel	Fanti *et al.* (1996)
Steal Casting Industry	Heat-Treatment Furnace	Mathirajan & Sivakumar (2006a), Mathirajan *et al*. (2010)
Steel Ingot Production	Preheating / Soaking Bit	Li *et al*, (2011)

The Semiconductor Manufacturing industry is one of the fastest growing industries in the world having annual sales of $25.8 billion worldwide at the end September 2011 (SIA, 2011). This is because of the diverse market focusing on integrated circuits for networking, storage components, telecommunications and/or wireless, consumer, computer and storage systems that have become necessary tools of today.

The Semiconductor Manufacturing is a highly competitive business. In the past, competition was primarily in the product design arena, but in the last several years the cost of manufacturing integrated circuits has become an important competitive factor. Furthermore, the time to manufacture a product is becoming increasingly important. Planning and Scheduling research addresses these needs.

The manufacturing of semiconductor products consists of four distinct stages: wafer fabrication, wafer probe, assembly, and final testing. These four stages can be divided into two categories. Wafer fabrication and wafer probe are referred to as the front-end manufacturing operations; Assembly and final testing are referred to as the backend manufacturing operations. A general explanation of the basic product flow in a Semiconductor Manufacturing chain can be seen in Uzsoy et al (1992) and Knuston et al (1999).

The Semiconductor Manufacturing industries today represent one of the most complex industrial processes. In Semiconductor Manufacturing, we have to deal with parallel machines, different types of processes like batch processes and single wafer processes, sequence dependent setup times, prescribed customer due-dates for the lots, very expensive equipment and reentrant process flows. In such a volatile scenario, maintaining a competitive advantage and remaining profitable in operational terms requires minimization of cycle time and work-in-process inventory and the maximization of throughput.

As a part of the complex production line that exists in a Semiconductor Manufacturing facility, operations involved in BPM are considered to be a bottleneck. This paper addresses one such BPM, observed in wafer fabrication process.

Particularly, this paper addresses on the diffusion operations in the wafer fabrication process. In this operation, wafers are placed in a cylindrical reactor (generally called as a diffusion furnace, a BPM), which is then sealed, heated and filled with carrier gas to allow dopant atoms present in the gas to diffuse into the exposed layer of the wafers. Wafers are processed in standard lots of 24, dictated by material handling consideration. The diffusion furnace can usually accommodate between 6 and 12 standard lots (between $6 * 24$ wafers and $12 * 24$ wafers) that are processed simultaneously as a batch.

Due to the chemical nature of the process, it is impossible to process jobs with different recipes together in the same batch. So, all the jobs (lots) requiring same recipe can be viewed as a job-family, where all jobs of the same family require the same processing time. We shall call these job-families incompatible as jobs of different families can not be processed together. The effective scheduling of these operations is particularly important due to the fact that this operation requires longest processing time (may be more than 24 hours).

The organization of this paper is as follows: We review the previous related work on scheduling BPM, particularly the scheduling diffusion furnace with due-date based scheduling objectives in Section 2. The problem statement and assumptions in scheduling of a single diffusion furnace is presented in Section 3. We present the proposed variants of a few Greedy Heuristic Methods in Section 4. The computational experiments conducted and analyses carried out are discussed in Section 5. We conclude the paper with a summary and an indication of some possible future research directions in Section 6.

2. RELATED WORK

Many researchers have addressed scheduling of batch Processing Machine(s) problems, observed in industries (Ref. Table 1). Mathirajan and Sivakumar (2006b) reported that much research has been carried out on scheduling problems concerned with BPM, related to semiconductor manufacturing, from deterministic perspectives. The research problem of scheduling BPM related to semiconductor manufacturing can be classified into Scheduling of BPM (SBPM) in the front end (particularly the wafer fabrication phase) of the SM (Semiconductor Manufacturing) and Scheduling of BPM in the back end (particularly the testing phase) of the SM. As this study is related to SBPM related to front-end of the SM, the research issue addressed in connection with SBPM related to back-end is not discussed.

Further, the SBPM related to front-end of the SM can be classified into deterministic and stochastic. As, in practice, estimates of the required parameters for this problem can be obtained from the shop-floor information system that tracks work-in-process inventory in real time, this study assumes the deterministic situation and the related earlier research on deterministic Scheduling of BPM, particularly diffusion reactor(s), related to front-end is only reviewed. Also, the deterministic problem on scheduling of BPM can be classified into problems of minimizing (a) completion time based objectives and (b) due-date based objectives. As this study deals with the due-date based scheduling objective, the review is restricted to the scheduling of BPM with due-date based objective. In addition, the studies on deterministic scheduling of BPM can be grouped based on single objective scheduling problem and multiple objectives scheduling problem (ex. He, et al. 2007, Liu, et al. 2009). As this study is related to single objective scheduling problem, the review is carried out only to single scheduling objective.

Finally, the deterministic Scheduling of BPM can be classified into (a) considering the BPM as a single work centre, (ii) considering the BPM with upstream and/or down stream operation(s), and (iii) considering the BPM with reentrant. As this study is related scheduling diffusion furnaces as single work centre with incompatible Job-families and jobs having (i) non-agreeable release times and due-dates, (ii) identical processing time with a job-family, and (iii) specific BPM-matching constraint with BPM related to its operation, the closely related research in scheduling diffusion furnaces is reviewed and presented in Table 2.

From Table 2 it is observed that our study is different from earlier study of scheduling diffusion furnaces that is, to the best of our knowledge, no research has been reported on analyzing the efficiency of the due-date based simple and composite rules in scheduling diffusion furnace with total weighted tardiness as the scheduling objective.

3. PROBLEM STATEMENT AND ASSUMPTIONS

We are given a set of N jobs representing F different job-families. Each job, *j of a family f* (f = 1,2 …F) *) has a processing* requirement of p_f, a due-date of d_{jf}, and a release time of r_{jf} at which it becomes available for processing, the release time and due-dates are non-agreeable (that is, $r_{if} \leq r_{jf}$ not-implied $d_{if} \leq d_{jf}$) with the objective of minimizing the TWT. The tardiness of the job *j* of family f (T_{jf}) is defined as $T_{jf} = \max(0, C_{jf} - d_{jf})$, where C_{jf} and d_{jf} are completion time and due-date of job *j of family f*, respectively. The weighted tardiness of the job *j* of family f *(WT_{jf})* is defined as $WT_{jf} = w_{jf} * T_{jf}$, where w_{jf} is priority and/or cost of the job *of family f.*

To concisely describe the problem under study, 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, identical processing times within a job-family, non-agreeable release times and due-dates/TWT"* problem. We make the following assumptions:

Table 2: Summary of the Scheduling of Diffusion Furnace with Due-Date based Objective

Researcher	Problem Configuration	Algorithm	Objective
Uzsoy (1995)	• Single BPM and identical BPMs • Identical job sizes • Equal ready time / dynamic job-arrivals	Proposed exact and approximate solution procedures	2
Mehta and Uzsoy (1998)	• Single BPM • Identical job sizes • Equal ready times	Developed DP algorithms and provided heuristics	4
Balasubramanian *et al.* (2004)	• Parallel, identical BPMs • Identical job sizes • Equal ready times	Proposed two versions of genetic algorithms	5
Devpura et al. (2000)	• Single BPM • Different job sizes • Equal ready times	Decomposed problem into sub-problems & proposed heuristic	5
Jolai (2005)	• Single BPM • Different job sizes • Equal ready times	NP-hard proof was shown and a DP algorithm with polynomial time complexity proposed	1
Monch *et al.* (2005)	• Parallel, identical BPMs • Different job sizes • Unequal ready times	Decompose the problem into two sub problems and use GA	5
Perez *et al.* (2005)	• Single BPM • Identical job sizes • Equal ready times	Proposed several heuristics algorithms	5
Monch *et al.* (2006)	• Parallel, identical BPMs • Different job sizes • Unequal ready times	Used inductive decision trees and neural networks from machine learning	5
Gupta and Sivakumar (2006)	• Single BPM • Incompatible job families • Dynamic job arrivals	Propose Look ahead batching scheduling strategy	1,2& 4
Gupta and Sivakumar (2007)	• Single batch processing machine • Dynamic Job-arrival	Propose Look ahead batching strategy(LAB)	3
Malve and Uzsoy (2007)	• Parallel, identical BPMs • Different job sizes • Dynamic job-arrivals	Propose genetic algorithm	2
Li *et al.*(2008)	• Parallel batch processing machine • Incompatible job-families • Dynamic job-arrivals • Sequence dependent setup time	Propose Ant colony optimization	5
Chiang *et al.*(2008)	• Parallel BPM • Incompatible job-families • Dynamic job-arrivals	Propose local search based heuristics	2
Monch *et al.* (2009)	• Parallel batch processing machines • Incompatible job-families	Propose Ant colony systems & Max-Min Ant system(MMAS)	5
Chiang *et al.* (2010)	• Parallel batch processing machine • Incompatible job-family • Dynamic job-arrival	Propose a Memetic algorithm with a new genome encoding scheme	5

Objectives: 1 = Min. Number of tardy jobs; 2 = Min. maximum lateness; 3 = Min. TE-TL; 4 = Min. Total tardiness; 5 =Min.Total weighted tardiness

- All data related to scheduling of diffusion furnace problem considered in this study are assumed to be deterministic and known a priori. In, practice, estimates of these parameters can be obtained from engineering data and Shop Floor Information Systems that track Work-in-Process inventory and machine status in real time.
- Each job requires one operation and all jobs are independent.
- Each BPM can process up to B jobs at a time. All jobs in a batch must be of the same family.
- Splitting of jobs between different batches is not allowed.
- Once processing of a batch is initiated it cannot be interrupted and other jobs cannot be introduced into the machine until processing is completed.

Since the problem is strongly NP-hard, we follow a few variants of a simple GHM to find efficient solutions in reasonable computational time. In the following section we propose a few variants of a simple GHM for the problem under consideration.

4. SCHEDULING METHODS AND ANALYSIS

The scheduling of heterogeneous BPMs with incompatible Job-families involves three interrelated sets of decision and they are (1) batch processor selection, (2) job-family selection, and (3) batch construction. We are proposing heuristic method for scheduling on a single machine. So we are concentrating on decision (2) and (3). Due to the computational intractability, a few variants, based on the earliest due date (EDD), critical ratio (CR), slack time (ST), and different version of apparent tardiness cost (ATC) [Farhad Ghassemi- Tari & Laya Olfat. (2007)] dispatching rules, of a Greedy Heuristic Method (GHM) are proposed for scheduling the single diffusion furnace of semiconductor wafer fabrication in the presence of dynamic Job-arrivals with incompatible job-families and non-agreeable release time and due-date with the objective of minimizing TWT. The systematic procedure of these variants to schedule jobs in diffusion furnace is as follows.

Step 1: Classify the jobs based on Family.

Step 2: Calculate the ***Index*** for every job.

Step 3: Sort the jobs in each family with decreasing order of the ***Index***

Step 4: Form a temporary batches by selecting the set of jobs from the top of each family until batch capacity is utilized to the maximum extent.

Step 5: Compute and compare starting time, completion time and TWT of each temporary batches.

a) If any temporary batch has completion time ***strictly less than*** the starting time of all other temporary batches then select it.

b) Else compare ***TWT*** of all temporary batches and select the batch which has ***maximum TWT***.

Step 6: Allocate the selected batch from step 5.

Step 7: Update the family by excluding the jobs allotted to the batch processing machine.

Step 8: Repeat step2, until all jobs are scheduled.

The proposed 13 variants of the above GHM differ across the other variants only in step 2 of the GHM. That is, the rule used for computing the Index differs in these 13 variants of the GHM. The method of computing this index for each of these 13 variants is given in Table 3. In addition to these 13 variants of the GHM, random method is also developed for scheduling diffusion furnace. All the 13 variants of the GHM and the random method are implemented using Turbo c++.

5. EVALUATION OF THE PROPOSED VARIANTS OF THE GHM

Due to computational intractability, the proposed variants of the GHM are compared with estimated optimal solutions. We have used the procedure discussed in Rardin and Uzsoy (2001) for the statistical estimation of optimal value, which is based on weibull distribution.

Table 3: Variant wise the formulae for computing Index

S.No	The name of the Variant	The Formulae for computing the Index for the name of the variant
1	ATC1	$Index = \left(\left(1/p_f\right)\exp^{-\left(\max\left(0, d_{jf} - \left(p_f + t\right)\right)\right)}\right) \Big/ \left(\left(1/n\right) * \sum_{j=1}^{N} p_f\right)$
2	ATC1 with Penalty: (ATC1_P)	$Index = \left[\left(\left(1/p_f\right)\exp^{-\left(\max\left(0, d_{jf} - \left(p_f + t\right)\right)\right)}\right) \Big/ \left(\left(1/n\right) * \sum_{j=1}^{N} p_f\right)\right] * w_{jf}$
3	ATC2	$Index = \left(\left(1/\left(p_f * d_{jf}\right)\right)\exp^{-\left(\max\left(0, d_{jf} - \left(p_f + t\right)\right)\right)}\right) \Big/ \left(\left(1/n\right) * \sum_{j=1}^{N} p_f\right)$
4	ATC2_P	$Index = \left[\left(\left(1/\left(p_f * d_{jf}\right)\right)\exp^{-\left(\max\left(0, d_{jf} - \left(p_f + t\right)\right)\right)}\right) \Big/ \left(\left(1/n\right) * \sum_{j=1}^{N} p_f\right)\right] * w_{jf}$
5	ATC3	$Index = \left(\left(1/p_f\right)\exp^{-\left(\max\left(0, d_{jf} - \left(p_f + \max\left(p_f + t\right)\right)\right)\right)}\right) \Big/ \left(\left(1/n\right) * \sum_{j=1}^{N} p_f\right)$
6	ATC3_P	$Index = \left[\left(\left(1/p_f\right)\exp^{-\left(\max\left(0, d_{jf} - \left(p_f + \max\left(p_f + t\right)\right)\right)\right)}\right) \Big/ \left(\left(1/n\right) * \sum_{j=1}^{N} p_f\right)\right] * w_{jf}$
7	ATC4	$Index = \left(\left(1/\left(p_f * d_{jf}\right)\right)\exp^{-\left(\max\left(0, d_{jf} - \left(p_f + \max\left(p_f + t\right)\right)\right)\right)}\right) \Big/ \left(\left(1/n\right) * \sum_{j=1}^{N} p_f\right)$
8	ATC4_P	$Index = \left[\left(\left(1/\left(p_f * d_{jf}\right)\right)\exp^{-\left(\max\left(0, d_{jf} - \left(p_f + \max\left(p_f + t\right)\right)\right)\right)}\right) \Big/ \left(\left(1/n\right) * \sum_{j=1}^{N} p_f\right)\right] * w_{jf}$
9	CR	$Index = \left(d_{jf} - today\_date\right) / p_f$
10	CR_P	$Index = \left(\left(d_{jf} - today\_date\right) / p_f\right) * w_{jf}$
11	ST	$Index = d_{jf} - today\_date$
12	ST_P	$Index = \left(d_{jf} - today\_date\right) * w_{jf}$
13	EDD	Index is Earliest Due-date (EDD)

The computational experiments and the analysis carried out for evaluating the proposed variants of the GHM are discussed in the subsequent sections.

5.1 Computational experiments

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.

5.1.1 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.

Based on the observation made in the literature, we identified six important problem parameters which could affect the performance of the proposed variants of the GHM: number of jobs (N), arrival time of jobs (r_{jf}), processing time of jobs (p_f), due-date of jobs (d_{jf}), family (f) and penalty of jobs (w_{jf}).

In the proposed experimental design, it is assumed that the value for the parameters except number of jobs and processing time is drawn from uniform distributions. The uniform distribution was chosen because it is a relatively high variance distribution which would allow the heuristics to be tested under conditions relatively unfavorable to them. Further, to control the tightness of due-dates, the following relationship is also used during the generation of problem instances for obtaining value for each jobs due-date: $\left(due\_date\left(d_{jf}\right) \geq release\_time\left(r_{jf}\right) + processing\_time\left(p_f\right)\right)$.Finally the processing time of family 1, 2, 3 is 3, 6, 9 respectively and batch capacity is assumed to be 6 for all test data. Based on this, a summary of experimental design is given in Table 4.

Table 4: A Summary of the Proposed Experimental Design

S.No	**Parameters**	**Levels**	**Number of levels**
1	Number of jobs(N)	25,50,100	3
2	Release time of jobs(r_{jf})	[1,8], [1,16], [1,24]	3
3	Due-date of jobs(d_{jf})	[1,40], [1,60], [1,80]	3
4	Family(f)	[1,3]	1
5	Penalty(w_{jf})	[1,10]	1
6	Processing time of jobs(p_f)	[3,6,9]for family 1,2,3 respectively	1
Number of problem configurations		3*3*3*1*1*1	27
Number of instances per configuration			10
Total test instances		27*10	270

5.1.2 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.

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

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

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

5.2 Analysis

It is to be noted that in the random method, we are getting feasible solution by executing the random method 100 times for each problem instance and then taking a minimum value for the problem instance. For each of the problem instance, 14 feasible solutions, using each of the 13 variants of the proposed GHM and random method, on minimizing TWT is obtained. For each of the 270 problem instances, 14 feasible solutions obtained are given as an input to the estimates an optimal solution. And then for each of the 270 problem instances the RPD of 13 variants of the GHM and Random method 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 and random method are computed and given in Table 5. When we were computing the ARPD for each problem configuration some of the variants of the proposed GHM may provide negative value of ARPD on some of the problem configurations. In that case we identified the problem instance(s) which causes the negative value and replaced by new instances until the ARPD value becomes positive.

Similarly to the ARPD, the maximum of RPD (MRPD) are computed for each problem configuration and presented in Table 6. Irrespective of the problem configurations, the ARPD and MRPD over 270 instances for each of the 13 variants of the proposed GHM and random method are computed and shown in Figures 1 and 2 respectively.

From Tables 5 & 6 and Figures 1 & 2, we observed that penalty factor highly influence the scheduling objective on minimizing the TWT. Therefore the variants of the proposed GHM with penalty provide better solution than the other variants proposed without penalty. Particularly, the variant of the proposed GHM: ATC3_P (ATC3 with Penalty) yield consistently better solution.

This may be due to the fact that we are using only due date while computing index in ATC3_P instead of the time duration $(due\_date - arrival\_time)$ for each of the job. If the due date value is large number then the index value becomes low when we use the term "$(due\_date - arrival\_time)$ ". So there is a chance for hot jobs becoming late and in turn the entire batch becomes late, which leads to a high TWT of the batch. Probably the variant of the proposed GHM: ATC3_P is attempting to avid this to happen and in turn yield minimum TWT in comparison with other variants of the GH with penalty.

Table 5: Performance of proposed heuristic methods in comparison with average relative percentage deviation (ARPD)

S.No	Problem Configuration	ATC1	ATC1_P	ATC2	ATC2_P	ATC3	ATC3_P	ATC4	ATC4_P	CR	CR_P	ST	ST_P	EDD	RANDOM
1	J1.R1,D1	25.34	45.81	25.34	40.24	25.34	45.81	25.34	40.24	25.34	87.81	25.34	87.81	25.34	73.87
2	J1.R1,D2	2.79	0.47	2.79	2.79	2.79	0.47	2.79	2.79	2.79	46.67	2.79	46.67	2.79	73.39
3	J1,R1,D3	4.33	8.27	4.33	8.27	4.33	8.27	4.33	8.27	4.33	25.15	4.33	25.15	4.33	6.91
4	J1,R2,D1	58.23	39.20	58.23	48.65	58.23	39.20	58.23	48.65	58.23	35.78	58.23	35.78	58.23	9.99
5	J1,R2,D2	33.28	0.42	33.28	0.42	33.28	0.42	33.28	0.42	33.28	67.08	33.28	67.08	33.28	106.33
6	J1,R2,D3	5.37	4.93	5.37	4.93	5.37	4.93	5.37	4.93	5.37	81.60	5.37	81.60	5.37	55.00
7	J1,R3,D1	76.47	44.63	76.47	48.72	76.47	44.63	76.47	48.72	76.47	51.15	76.47	51.15	76.47	29.82
8	J1,R3,D2	12.75	22.05	12.75	23.03	12.75	22.05	12.75	23.03	12.75	60.53	12.75	60.53	12.75	67.18
9	J1,R3,D3	8.16	11.55	8.16	11.55	8.16	11.55	8.16	11.55	8.16	55.48	8.16	55.48	8.16	32.30
10	J2.R1,D1	43.96	1.81	43.96	3.65	48.69	1.81	43.96	3.65	43.96	29.76	43.96	29.76	43.96	44.49
11	J2.R1,D2	16.24	4.79	16.24	6.58	16.24	1.08	16.24	6.58	16.24	19.64	16.24	19.64	16.24	160.49
12	J2,R1,D3	26.57	10.13	26.57	0.00	26.57	10.13	26.57	0.00	26.57	33.02	26.57	33.02	26.57	403.53
13	J2,R2,D1	52.57	7.26	52.57	7.83	52.57	6.89	52.57	7.30	52.57	60.14	52.57	60.14	52.57	29.66
14	J2,R2,D2	65.93	10.73	65.93	18.25	65.93	10.73	65.93	18.25	65.93	43.07	65.93	43.07	65.93	94.96
15	J2,R2,D3	63.23	7.76	63.23	9.69	63.23	7.76	63.23	9.69	63.23	46.84	63.23	46.84	63.23	256.61
16	J2,R3,D1	43.01	12.37	43.01	2.92	43.01	12.37	43.01	2.92	43.01	46.32	43.01	46.32	43.01	49.36
17	J2,R3,D2	36.35	22.27	36.35	18.96	36.35	22.27	36.35	18.96	36.35	54.92	36.35	54.92	36.35	63.17
18	J2,R3,D3	16.50	12.22	16.50	14.52	16.50	12.22	16.50	14.52	16.50	36.44	16.50	36.44	16.50	138.06
19	J3,R1,D1	55.08	0.93	55.08	6.72	57.83	1.95	55.08	6.22	55.08	63.97	55.08	63.97	55.08	37.39
20	J3,R1,D2	63.81	2.55	63.81	9.36	63.83	1.23	63.81	8.41	63.81	68.06	63.81	68.06	63.81	53.52
21	J3,R1,D3	69.82	4.18	69.82	8.53	69.82	2.20	69.82	8.53	69.82	74.91	69.82	74.91	69.82	85.07
22	J3,R2,D1	43.29	1.43	43.29	3.53	43.27	1.10	43.29	3.53	43.29	79.25	43.29	79.25	43.29	36.86
23	J3,R2,D2	60.44	1.44	60.44	4.00	60.44	1.44	60.44	4.00	60.44	76.99	60.44	76.99	60.44	50.14
24	J3,R2,D3	75.15	5.80	75.15	9.83	75.15	3.93	75.15	12.82	75.15	80.71	75.15	80.71	75.15	70.60
25	J3,R3,D1	48.48	2.52	48.48	3.05	48.48	2.52	48.48	3.05	48.48	71.23	48.48	71.23	48.48	45.85
26	J3,R3,D2	48.49	0.12	48.49	4.22	48.49	0.12	48.49	4.22	48.49	61.63	48.49	61.63	48.49	41.90
27	J3,R3,D3	63.12	3.96	63.12	9.50	63.12	3.96	63.12	9.50	63.12	85.02	63.12	85.02	63.12	76.11
Average(ARPD)		41.44	10.73	41.44	12.21	41.71	10.41	41.44	12.25	41.44	57.15	41.44	57.15	41.44	81.21

Table 6: Performance of proposed heuristic methods in comparison with maximum relative percentage deviation (MRPD)

S.No	Problem Configuration	ATC1	ATC1_P	ATC2	ATC2_P	ATC3	ATC3_P	ATC4	ATC4_P	CR	CR_P	ST	ST_P	EDD	RANDOM
1	J1.R1,D1	168.89	222.56	168.89	226.32	168.89	222.56	168.89	226.32	168.89	266.67	168.89	266.67	168.89	197.98
2	J1.R1,D2	27.94	4.65	27.94	27.94	27.94	4.65	27.94	27.94	27.94	276.00	27.94	276.00	27.94	376.00
3	J1,R1,D3	24.32	62.96	24.32	62.96	24.32	62.96	24.32	62.96	24.32	155.56	24.32	155.56	24.32	94.59
4	J1,R2,D1	195.02	160.73	195.02	168.59	195.02	160.73	195.02	168.59	195.02	195.19	195.02	195.19	195.02	103.45
5	J1,R2,D2	328.57	4.22	328.57	4.22	328.57	4.22	328.57	4.22	328.57	285.71	328.57	285.71	328.57	346.55
6	J1,R2,D3	34.21	34.21	34.21	34.21	34.21	34.21	34.21	34.21	34.21	666.67	34.21	666.67	34.21	338.64
7	J1,R3,D1	553.36	460.27	553.36	460.27	553.36	460.27	553.36	460.27	553.36	494.20	553.36	494.20	553.36	382.84
8	J1,R3,D2	44.69	178.55	44.69	178.55	44.69	178.55	44.69	178.55	44.69	342.31	44.69	342.31	44.69	396.15
9	J1,R3,D3	75.00	75.00	75.00	75.00	75.00	75.00	75.00	75.00	75.00	235.47	75.00	235.47	75.00	148.39
10	J2.R1,D1	75.39	17.16	75.39	11.91	82.64	17.16	75.39	11.91	75.39	74.34	75.39	74.34	75.39	93.34
11	J2.R1,D2	43.92	42.14	43.92	42.14	43.92	42.14	43.92	42.14	43.92	100.94	43.92	100.94	43.92	390.23
12	J2,R1,D3	121.28	32.85	121.28	0.00	121.28	32.85	121.28	0.00	121.28	114.80	121.28	114.80	121.28	1174.47
13	J2,R2,D1	98.59	54.28	98.59	34.78	98.59	54.28	98.59	34.78	98.59	98.78	98.59	98.78	98.59	62.00
14	J2,R2,D2	165.48	100.00	165.48	110.41	165.48	100.00	165.48	110.41	165.48	173.76	165.48	173.76	165.48	170.79
15	J2,R2,D3	205.41	72.50	205.41	73.33	205.41	72.50	205.41	73.33	205.41	133.48	205.41	133.48	205.41	383.19
16	J2,R3,D1	73.89	69.69	73.89	12.05	73.89	69.69	73.89	12.05	73.89	80.22	73.89	80.22	73.89	121.52
17	J2,R3,D2	113.70	140.68	113.70	61.85	113.70	140.68	113.70	61.85	113.70	234.69	113.70	234.69	113.70	261.35
18	J2,R3,D3	46.69	54.13	46.69	47.25	46.69	54.13	46.69	47.25	46.69	132.76	46.69	132.76	46.69	264.29
19	J3,R1,D1	74.57	2.97	74.57	14.24	81.64	6.95	74.57	14.24	74.57	97.41	74.57	97.41	74.57	54.28
20	J3,R1,D2	81.12	16.06	81.12	22.84	81.12	4.92	81.12	22.84	81.12	112.71	81.12	112.71	81.12	81.49
21	J3,R1,D3	107.59	26.58	107.59	30.88	107.59	12.52	107.59	30.88	107.59	108.87	107.59	108.87	107.59	140.05
22	J3,R2,D1	68.50	5.68	68.50	11.44	68.50	5.68	68.50	11.44	68.50	122.23	68.50	122.23	68.50	51.28
23	J3,R2,D2	97.16	6.38	97.16	11.21	97.16	6.38	97.16	11.21	97.16	104.84	97.16	104.84	97.16	71.26
24	J3,R2,D3	102.98	28.14	102.98	34.67	102.98	23.03	102.98	34.67	102.98	132.47	102.98	132.47	102.98	108.95
25	J3,R3,D1	66.21	25.18	66.21	6.98	66.21	25.18	66.21	6.98	66.21	117.51	66.21	117.51	66.21	81.00
26	J3,R3,D2	82.79	1.17	82.79	9.52	82.79	1.17	82.79	9.52	82.79	152.98	82.79	152.98	82.79	72.15
27	J3,R3,D3	113.28	33.15	113.28	43.50	113.28	33.15	113.28	43.50	113.28	144.82	113.28	144.82	113.28	117.01
Maximum(MRPD)		553.36	460.27	553.36	460.27	553.36	460.27	553.36	460.27	553.36	666.67	553.36	666.67	553.36	1174.47

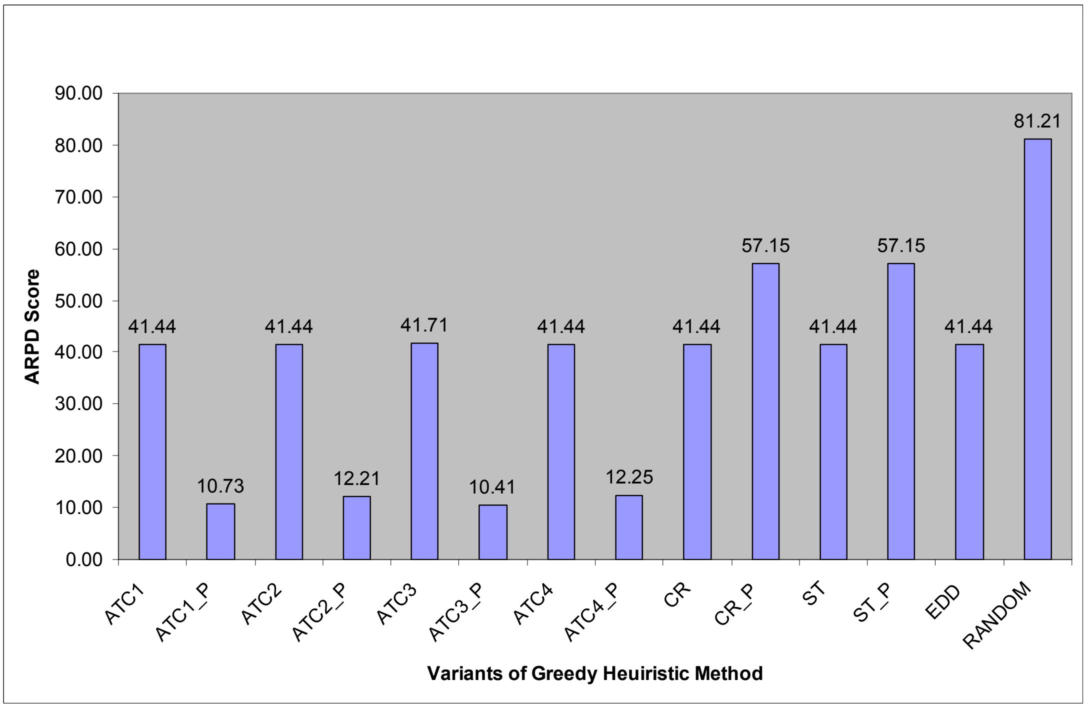

Figure1: Performance of proposed heuristic methods w.r.t. to ARPD over 270 problem instances

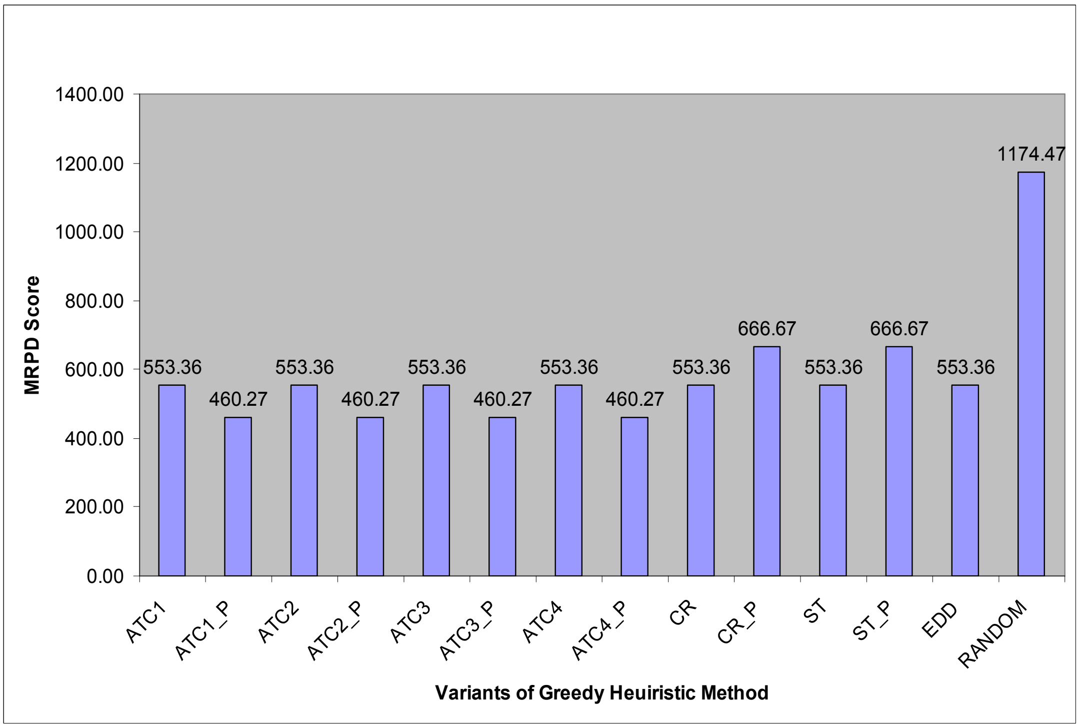

Figure 2: Performance of proposed heuristic methods w.r.t. MRPD over 270 problem instances

6. CONCLUSION

Our literature review revealed that although a large variety of scheduling diffusion furnaces have been studied, the problem of scheduling diffusion furnace with incompatible Job-families, and non-agreeable release times and due-dates with the scheduling objective of minimizing TWT using simple and composite due-date based rules has not been studied so far. Due to the computational intractability, a few variants, based on the EDD, CR, ST, and different versions of the ATC dispatching rules, of a GHM are proposed. The solution quality of the variants of the GHM is evaluated in comparison with estimated optimal solution. Based on the computational time required to obtain the solution as well as from the point of the quality of the solution, it is observed that one can run all the variants of the proposed GHMs on a given problem instance and select the best one.

The results obtained from the variants of the proposed GHM in comparison with estimated optimal solution are very encouraging. Further extension to the research problem considered in this study are scheduling of multiple machines considering due-date based scheduling objectives, incorporating (a) the current-cycle (reentrant to the diffusion operation) information appropriately as this information divides the existing lots in front of the diffusion furnaces into more incompatible Job-families, and (b) machine eligibility constraints. Another extension could be developing a few meta heuristic methods as these have not been extensively addressed so far in scheduling BPM(s).

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