Bi-objective Optimization of a Single Machine Batch Scheduling Problem with Energy Cost Consideration

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Abstract

With the increasing energy price, the rapid growth of electricity demand and severe challenges for sustainable development, energy-efficient scheduling is becoming more and more important for power-intensive manufacturing industry, especially for batch production companies. This paper investigates a bi-objective single machine batch scheduling problem with non-identical job sizes, the time-of-use (TOU) electricity prices, and different energy consumption rates of the machine. The first objective is to minimize the makespan and the second is to minimize the total energy costs, by considering both the machine utilization and the economic cost. The problem is formulated as an integer programming model. Then, an exact ϵ -constraint method is adapted to obtain the exact Pareto front. To deal with large scale problems, based on decomposition ideas, **two heuristic methods are developed to obtain approximate Pareto fronts**. Computational experiments on randomly generated instances show the effectiveness of the methods. A study case of a real-world glass manufacturing company is also conducted to show that the proposed methods are promising for practical usages.

Keywords:

Batch scheduling, Bi-objective optimization, Energy consumption cost, Makespan, Single machine

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1. Introduction

The issue of batch scheduling optimization has attracted significant research attention, since on the one hand, many practical applications are highly related to batch-processing including chemical processes (Seid and Majazi, 2014; Fabre et al., 2011; Liu et al., 2010; Méndez et al., 2006), testing process in burn-in oven in the semiconductor manufacturing (Jula and Leachman, 2010; Sung et al., 2002; Sung and Choung, 2000), heat-treating ovens (Melouk et al., 2004). On the other hand, many batch scheduling problems are NP-hard (Potts and Kovalyov, 2000), even for most single-machine environment, which makes them difficult to be solved in theoretical perspective.

However, in existing literature, few researches consider the energy cost for batch scheduling optimization even though most of batch processes are power-intensive industries and the electricity cost accounts for 10-50% of the final product costs (Cheng et al., 2015). Meanwhile, energy cost is continuously rising (Kilian, 2008; Liu et al., 2015) due to the rapid and ongoing growth of energy demand. For example, demand for electric power in China grew 41% from 2000 to 2007 (Fisher-Vanden et al., 2015). Moreover, energy consumption is one of the main reasons for the environment pollution due to the increasing amount of the green house gas emissions, in particular, the carbon dioxide (CO_2) (Ding et al., 2016). For example, about 28% greenhouse gas emissions in U.S.(Mouzon, 2008), about 18-20% CO_2 emission in Germany (Luo et al., 2013), and at least 26% of the total CO_2 emission in China (Liu et al., 2014a), are from the manufacturing energy consumption. Therefore, it is highly important to improve energy usage efficiency in manufacturing (especially for energy-intensive industries) to save energy cost and to reduce greenhouse gas emissions (Gahm et al., 2016; Giret et al., 2015; Merkert, et al., 2015; He et al., 2015; Gong et al., 2016).

In this paper, motivated by scheduling challenges of the glass decoration and ceramization in the manufacturing, we study a single machine batch scheduling problem with non-identical job sizes. The key resource of the manufacturing process is a furnace (i.e., a batch machine), which is used to accommodate and ceramize glasses. The furnace has a fixed capacity (or space) that can accommodate different types of glasses with different sizes for simultaneous processing, i.e., glasses are processed in batches. The total size of the glasses in each batch should not exceed the furnace space capacity. Two objectives of the glass firm are considered: the makespan and the total

energy cost. The reasons are as follows: (i) a minimum makespan usually implies a high utilization of the furnace since in the process the furnace is the bottleneck resource, and (ii) energy takes a large portion of the total costs in the glass firm.

The contributions of the paper can be summarized as follows:

- (i) A bi-objective single machine batch scheduling problem is derived from a real-world glass manufacturing environment and an integer programming model is formulated by considering the decision makings of batch creation, batch sequence and furnace temperature choice;
- (ii) An exact ϵ -constraint method is adapted to obtain the exact Pareto front;
- (iii) Two constructive heuristic methods are proposed based on the idea of two-stage hierarchical problem separations, to obtain good approximate Pareto fronts in a reasonable computation time;
- (iv) Performance of the methods are validated by computational experiments and a case study from the real-world glass manufacturing.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the problem and develops an integer program. Section 4 introduces the exact ϵ -constraint method. Section 5 proposes two constructive heuristic methods based on the concept of two-stage hierarchical batching and sequencing-temperature choice subproblem separations. The computational experiments and a study case are conducted to evaluate the proposed methods in Section 6. Finally, Section 7 concludes the paper and gives out the future research directions.

2. Literature review

In recent years, due to the energy shortage and the recognition of urgency in reducing energy consumption, there are more and more researches on energy-efficient scheduling in different manufacturing settings, including parallel machine (e.g., Li et al., 2016; Wang et al., 2015; Ji et al., 2013; Shabtay and Kaspi, 2006), job shop (e.g., Zhang and Chiong, 2016; Liu et al., 2015; Lei and Guo, 2015; Liu et al., 2014a), flow shop (e.g., Mansouri et al., 2016; Ding et al., 2016; Lin et al., 2015), and hybrid flow shop (e.g., Tang et al., 2015; Dai et al., 2013; Luo et al., 2013; Bruzzone et al., 2012).

Readers can refer to recent survey papers by Gahm et al.(2015), Rager et al.(2015) and Giret et al.(2016) for more information. In this section, we mainly review the researches that are most highly related to this study, i.e., single machine scheduling with energy consideration, with and without batch setting.

Mouzon and Yildirim (2008) showed that large amounts of energy is wasted if machines can not be fully utilized and they investigated a bi-objective single machine scheduling problem to minimize the total energy consumption and the total tardiness. They developed a hierarchical bi-level framework in which a greedy randomized multi-objective adaptive search meta-heuristic to obtain an approximate Pareto front. Later, Yildirim and Mouzon (2012) studied a bi-objective single machine scheduling problem to minimize the energy consumption and the total completion time, in which the machine can be switched from idle to offline. They developed a multi-objective genetic algorithm to obtain an approximate Pareto front within reasonable computation time. Liu et al. (2014b) investigated a single machine scheduling problem with deterministic job arrival time to optimize two objectives: the total completion time and the total carbon dioxide emission. The Non-dominant Sorting Genetic Algorithm (NSGA-II) is applied to obtain an approximate Pareto front. Both Yildirim and Mouzon (2012) and Liu et al.(2014b) suggest that other conflicting objectives should be extensively investigated.

Shrouf et al. (2014) established a mathematical model for a single machine scheduling problem to minimize the total energy consumption costs. In the problem, the continuous changes in energy price, the energy consumption of each machine status, and the energy consumption of transitions between status are simultaneously considered. A genetic algorithm and an analytical solution are developed. Che et al. (2016) investigated a single machine scheduling under TOU policy to minimize the total electricity cost. They developed a new continuous-time mixed-integer linear programming (MILP) and proposed an efficient greedy insertion heuristic to solve the problem. However, in Shrouf et al.(2014) and Che et al.(2016), only energy-related objective is considered, performance indicator of production like makespan is not considered.

The main differences between these researches and this study are three-folds: (i) Different scheduling objectives with economic and environmental indicators are considered. We consider the makespan and the total energy cost simultaneously. (ii) Methods are significantly different. In these researches, only meta-heuristic methods are applied, while both exact and

heuristic methods are proposed in this study. (iii) More importantly, batch scheduling is not considered in these researches, though batch productions are widely applied in industry and energy-intensive in many practical cases. Batch scheduling incurs extra decisions including how to form a batch and when to start a batch, which makes the problem more complicated but more practical.

Recently, there are some researches in single machine batch scheduling with energy cost consideration. Oron (2011) studied a single machine batch scheduling problem in which the job processing time is controlled by the resource (like energy) allocated on it. The relationship between the amount of resource allocation and job's processing time is a non-linear and convex function. Makespan and total completion time are considered as objectives, separately. **However, only single objective is considered.** Yue and You (2013) addressed a bi-objective batch scheduling problem with economic and environmental concerns. The two objectives are to maximize the productivity and to minimize the environmental impact per functional unit. They developed a bi-objective optimization model and proposed an ϵ -constraint method to solve it. **However, no heuristic or meta-heuristic methods are developed, which limits its application for practical large-scale problems.** Cheng et al. (2015) studied a single machine batch scheduling problem to minimize two objectives: makespan and total electricity costs. A bi-objective model is proposed. An ϵ -constraint method is applied to find the Pareto front and a fuzzy logic-based approach is used to get the preferable solution. However, in their study, each job has same size.

These researches provide significant insights on single machine energy-efficient scheduling with batch. However, compared with abundant researches without batch consideration, this direction are still unexplored, whereas batch processes are power-intensive industries and the electricity cost accounts for 10-50% of the final product costs. Therefore, it is worth for further research.

3. Problem statement and modeling

3.1. Production process

The scheduling problem is originated from a special glass-ceramic manufacturing shop floor. The schematic manufacturing process of this kind of glass is shown in Figure 1. Once production orders are placed by customers, raw glass already fabricated are cut into the customers' desired sizes. Then,

the edges of each glass are smoothed and beveled. Next, small and large holes are drilled for future controlling knobs installation. After cleaning, customized logos and graphs are printed on the glass immediately followed by drying process. In the last step, each piece of glass is heated to a certain high degree, which makes the glass change at the molecular level and the glass is partially crystallizing, such that the special glass-ceramic is formed.

Figure 1: Schematic illustration of a special glass production process

In this study, we focus on the manufacturing process of the glass ceramization (highlighted by dashed line rectangular in Figure 1), in which a single furnace is used to process the glasses in batch. During the process of ceramization, pallets are used to hold different sizes of glasses. The question is how to form a batch and how to schedule each batch to minimize the makespan and the total energy cost.

3.2. Problem description and formulation

There is a set K with m different types of jobs (glass orders), each type of job has its size s_i , $i \in K = \{1, 2, \dots, m\}$. The total number of jobs is N , among which n_i is the number of jobs with type i , where $i \in K$ and $\sum_{i \in K} n_i = N$. These jobs are to be processed on a batch heat-treating furnace within a scheduling horizon of $|T|$ periods (the duration of a period is a smallest interval on the time horizon), where T denotes the set of all time periods. The number of batches $|B|$ is to be determined, where B is the set of batches. The furnace has a size restriction with maximum size S . Only a batch with the total size not larger than S can be processed by the furnace.

The temperature of the furnace can be adjusted between two levels: high and low. The energy consumption rates of the furnace are E_H and E_L for the high and low temperature, respectively. In general, $E_H > E_L$. If the furnace

is not in processing, the energy consumption is zero. Once the temperature is set, it can not be changed until a batch is completed. Moreover, under the TOU policy, the unit energy price per period is variable and set as c_t , where $t \in T$. The processing time of a job of type i for the high and low temperature is p_i^h and p_i^l , $i \in K$, respectively. In general, p_i^h and p_i^l lasts for several periods and $p_i^h < p_i^l$. For the same job type, the processing time is the same. For a temperature level, the processing time of a batch is determined by the longest processing time of the jobs in that batch since it is acceptable for a glass ceramization to be kept in the furnace for a longer time than its specified heating time but not for a shorter time. It is assumed that the processing of a batch is non-preemptive and non-resumable, i.e., a batch processing can not be interrupted until it is finished and each of jobs in the batch must be entirely processed.

The scheduling decisions are to be made: (i) to form batches such that the furnace size is not violated, (ii) to determine the starting time of each batch in the scheduling period, and (iii) to determine the temperature level at the start of each batch, in order to minimize the makespan and the total energy costs simultaneously. Using the three-field notation (Graham et al., 1979), the problem can be denoted by $1, TOU|B|\{C_{max}, TEC\}$, where ‘ TOU ’ represents the time-of-use policy of energy price, ‘ B ’ represents the batch processing, ‘ C_{max} ’ represents the makespan, and ‘ TEC ’ represents the total energy cost.

In the following the mathematical model is formulated. First, the parameters are summarized and the decision variables are defined.

Indices:

b, q : batch index, $b, q \in B$;

i : job type index;

j : job index of type i , $j = 1, \dots, n_i$, where n_i is the number of jobs of type i ;

t : time period index.

Parameters:

K : a set representing m different types of jobs;

n_i : number of jobs of type i , $i \in K$;

- m : number of different types of jobs, $m = |K|$;
- N : total number of jobs, i.e., $N = \sum_{i=1}^m n_i$;
- B : set of batches (i.e., $B = \{1, \dots, N\}$, even though some batches may be empty), and $|B|$ denotes the number of batches;
- S : the fixed maximum size of the heat-treating furnace;
- s_i : size of job type i , $i \in K$;
- T : the set of time periods, and $|T|$ denotes the length of the planning horizon;
- E_H : amount of energy consumption during a period when the furnace is working in high temperature (i.e., the energy consumption rate of the furnace in high temperature);
- E_L : amount of energy consumption during a period when the furnace is working in low temperature;
- p_i^h : processing time of a job of type i in the high temperature;
- p_i^l : processing time of a job of type i in the low temperature. We assume that the p_i^l is prolonged from p_i^h proportionally with a ratio $g \geq 1$, i.e., $p_i^l = g \cdot p_i^h$;
- c_t : unit energy price for time period $t \in T$;
- M : a large enough positive integer.

Decision variables:

C_{max} : the makespan, i.e., the maximum completion time;

x_{ij}^b : equal to 1 if job j of type i is assigned to batch b , 0 otherwise;

y^b : equal to 1 if batch b is formed with at least one job, 0 otherwise, i.e., no job is assigned to batch b ;

ST^b : start time of batch b on the furnace;

CT^b : completion time of batch b on the furnace;

β^{bq} : equal to 1 if batch b is processed before q , 0 otherwise;

α_t^b : equal to 1 if batch b is processing at period t , 0 otherwise;

τ_h^b : equal to 1 if batch b is processed with high temperature, 0 otherwise.

τ_l^b : equal to 1 if batch b is processed with low temperature, 0 otherwise.

P^b : processing time of batch b ;

z_{ij}^{bh} : equal to 1 if job j of type i is assigned to batch b and that batch is with high temperature, 0 otherwise (That is, $z_{ij}^{bh} = 1$ if and only if $x_{ij}^b = 1$ and $\tau_h^b = 1$.);

z_{ij}^{bl} : equal to 1 if job j of type i is assigned to batch b and that batch is with low temperature, 0 otherwise (That is, $z_{ij}^{bl} = 1$ if and only if $x_{ij}^b = 1$ and $\tau_l^b = 1$.);

γ_{th}^b : equal to 1 if batch b is processed at period t with high temperature, 0 otherwise (That is, $\gamma_{th}^b = 1$ if and only if $\alpha_t^b = 1$ and $\tau_h^b = 1$);

γ_{tl}^b : equal to 1 if batch b is processed at period t with low temperature, 0 otherwise (That is, $\gamma_{tl}^b = 1$ if and only if $\alpha_t^b = 1$ and $\tau_l^b = 1$).

The mathematical formulation for the problem is as follows:

(**IP**)

$$\min \quad f_1 = \sum_{t \in T} c_t \left[\sum_{b \in B} (\gamma_{th}^b E_H + \gamma_{tl}^b E_L) \right] \quad (1)$$

$$\min \quad f_2 = C_{max} \quad (2)$$

$$\text{s.t.} \quad \sum_{b \in B} x_{ij}^b = 1, \quad \forall i \in K, j = 1, \dots, n_i \quad (3)$$

$$\sum_{i \in K} \sum_{j \in \{1, 2, \dots, n_i\}} s_i x_{ij}^b \leq y^b S, \quad \forall b \in B \quad (4)$$

$$\tau_h^b + \tau_l^b = 1, \quad \forall b \in B \quad (5)$$

$$z_{ij}^{bh} \geq 1 - (2 - x_{ij}^b - \tau_h^b)M, \quad \forall i \in K, j = 1, \dots, n_i, b \in B \quad (6)$$

$$z_{ij}^{bh} \leq \frac{x_{ij}^b + \tau_h^b}{2}, \quad \forall i \in K, j = 1, \dots, n_i, b \in B \quad (7)$$

$$z_{ij}^{bl} \geq 1 - (2 - x_{ij}^b - \tau_l^b)M, \quad \forall i \in K, j = 1, \dots, n_i, b \in B \quad (8)$$

$$z_{ij}^{bl} \leq \frac{x_{ij}^b + \tau_l^b}{2}, \quad \forall i \in K, j = 1, \dots, n_i, b \in B \quad (9)$$

$$\sum_{t \in T} \alpha_t^b = P^b, \quad \forall b \in B \quad (10)$$

$$P^b \geq z_{ij}^{bh} p_i^h + z_{ij}^{bl} p_i^l, \quad \forall i \in K, j = 1, \dots, n_i, b \in B \quad (11)$$

$$t \geq ST^b - (1 - \alpha_t^b)|T|, \quad \forall b \in B, t \in T \quad (12)$$

$$t \leq CT^b - 1 + (1 - \alpha_t^b)|T|, \quad \forall b \in B, t \in T \quad (13)$$

$$ST^b + P^b = CT^b, \quad \forall b \in B \quad (14)$$

$$CT^b \leq ST^q + (1 - \beta^{bq})|T|, \quad \forall b, q \in B, b \neq q \quad (15)$$

$$\beta^{bq} + \beta^{qb} = 1, \quad \forall b, q \in B, b \neq q \quad (16)$$

$$CT^b \leq C_{max}, \quad \forall b \in B \quad (17)$$

$$\gamma_{th}^b \geq 1 - (2 - \alpha_t^b - \tau_h^b)M, \quad \forall b \in B, t \in T \quad (18)$$

$$\gamma_{tl}^b \geq 1 - (2 - \alpha_t^b - \tau_l^b)M, \quad \forall b \in B, t \in T \quad (19)$$

$$x_{ij}^b, y^b, z_t^b, \alpha_t^b, \beta^{bq}, \tau_h^b, \tau_l^b, z_{ij}^{bh}, z_{ij}^{bl}, \gamma_{th}^b, \gamma_{tl}^b \in \{0, 1\}, \quad \forall b, q \in B, i \in K, t \in T, j = 1, \dots, n_i \quad (20)$$

$$ST^b, CT^b, C_{max} \in \mathbb{Z}_+, \quad \forall b \in B \quad (21)$$

Expression (1) is to minimize the total energy consumption costs, which depends on the temperature level of the furnace and the energy price in every period. Expression (2) is to minimize the makespan C_{max} , which is the maximum completion time of all batches. Constraint (3) ensures that a job j of type i is assigned to only one batch. Constraint (4) limits the total size of a batch not exceeding the maximum size (capacity) of the furnace. Constraint (5) ensures that a batch is processed either with the high temperature or the low one. Constraints (6) and (7) coordinate the values of z_{ij}^{bh} , x_{ij}^b and τ_h^b . Similarly, constraints (8) and (9) coordinate the values of z_{ij}^{bl} , x_{ij}^b and τ_l^b . Constraints (5)-(9) guarantee $z_{ij}^{bh} + z_{ij}^{bl} = 1$. Constraint (10) guarantees that the processing time of a batch b on the furnace is equal to its total working periods on the furnace. Constraint (11) determines the batch processing time. Constraints (12) and (13) make sure that the processing of batch b on the furnace is not interrupted. Constraints (14) guarantees that the completion time of a batch is equal to the sum of its start time and its processing time. Constraint (15) imposes the precedence constraints of two consecutive batches on the furnace. Constraint (16) expresses the convexity on β_{bq} . Constraint (17) defines the range of C_{max} . Constraints (18) and (19) are to linearize the terms $\gamma_{th}^b = \alpha_t^b \tau_h^b$ and $\gamma_{tl}^b = \alpha_t^b \tau_l^b$, respectively. Constraints (20) and (21) give the ranges of the decision variables.

3.3. Complexity of the problem

Theorem 1. *The problem 1, $TOU|B|\{C_{max}, TEC\}$ is strongly NP-hard.*

PROOF. The special case of the problem 1 $|B|\{C_{max}, TEC\}$ is the one with $c_t = 1$ for every $t \in T$. In this case, the objective TEC is equivalent to C_{max} . Then, the problem is reduced to the single-machine batch scheduling problem with different job size requirements and makespan minimization, which has been proved to be strongly NP-hard (Uzsoy, 1994). Since this special case is strongly NP-hard, the result follows. $\square$

4. An exact ϵ -constraint method

The ϵ -constraint method is one of the most popular approaches for solving multiple objective optimization problems, especially for a bi-objective optimization problem like the problem 1, $TOU|B|\{C_{max}, TEC\}$. In this section,

we introduce an exact ϵ -constraint method based on the concept of Pareto dominance.

4.1. Pareto dominance and the ϵ -constraint method

For the minimization objectives, the Pareto dominance relationship denoted by $\prec_P$ can be defined as follows: a feasible solution $\mathbf{X}$ is said to dominate another feasible solution $\mathbf{Y}$ ($\mathbf{X}, \mathbf{Y} \in \mathbf{Z}^V$, which is a V -dimensional decision variable vector) denoted by $\mathbf{f}(\mathbf{X}) \prec_P \mathbf{f}(\mathbf{Y})$, if and only if, $f_i(\mathbf{X}) \leq f_i(\mathbf{Y})$ for $i = 1, 2, \dots, p$ and $f_i(\mathbf{X}) < f_i(\mathbf{Y})$ for at least one objective function of a given set of p objective functions $\mathbf{f}(\cdot) = \{f_1, f_2, \dots, f_p\}$. For the problem defined above, $p = 2$.

With the concept of the Pareto dominance, all the non-dominated points in the objective space constitute the *Pareto front*, which provides a set of alternative solutions to decision makers for performance tradeoff.

The basic idea of the ϵ -constraint method is to construct and solve a sequence of ϵ -constraint problems by transforming one of the objectives as a constraint with a progressive reduction of ϵ value. To do this, the following points are needed (Cheng et al., 2015; Bérubé et al., 2009).

Ideal point: let $\mathbf{f}^I = (f_1^I, f_2^I)$ with $f_1^I = \min\{f_1(\mathbf{X})\}$ and $f_2^I = \min\{f_2(\mathbf{X})\}$, $\mathbf{X} \in \mathbf{Z}^V$;

Nadir point: let $\mathbf{f}^N = (f_1^N, f_2^N)$ with $f_1^N = \min\{f_1(\mathbf{X}) : f_2(\mathbf{X}) = f_2^I\}$ and $f_2^N = \min\{f_2(\mathbf{X}) : f_1(\mathbf{X}) = f_1^I\}$, $\mathbf{X} \in \mathbf{Z}^V$;

Extreme point: $\mathbf{f}^E = \{(f_1^I, f_2^N), (f_1^N, f_2^I)\}$ are the set of two extreme points on the Pareto front.

Since both objectives of TEC and C_{max} are integral for the problem under study, the following exact ϵ -constraint method can be used to find the Pareto front (Cheng et al., 2015; Bérubé et al., 2009).

4.2. An example solution with the exact ϵ -constraint method

To illustrate the problem, and also to demonstrate the conflicting relation between minimizing TEC and C_{max} , we solve a small problem with $m = 3$, $|T| = 30$, $E_H = 5$, $E_L = 2$ and $S = 10$ by using the above exact ϵ -constraint method in CPLEX 12.6. The detailed information of processing time p_i^h and p_i^l for high and low temperature, the number of jobs for each type n_i , the size

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Exact ϵ -constraint method

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1. Compute the ideal points $\mathbf{f}^I = (f_1^I, f_2^I)$ and Nadir points $\mathbf{f}^N = (f_1^N, f_2^N)$.
  2. Set $\mathbf{F}' = \{(f_1^I, f_2^N)\}$ and $\epsilon = f_2^N - \Delta$ ($\Delta = 1$ for this problem).
  3. While $\epsilon \geq f_2^I$, do:
    - (a) solve the ϵ -constraint problem with $C_{max} \leq \epsilon$ as a constraint and the TEC as the single objective function to optimality, and add the optimal solution value (f_1^*, f_2^*) to $\mathbf{F}'$.
    - (b) set $\epsilon = f_2^* - \Delta$.
  4. Obtain the Pareto front $\mathbf{F}$ by removing dominated points from $\mathbf{F}'$, if existing.
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Table 1: The detailed values for the example

Job type i	p_i^l	p_i^h	n_i	s_i
1	4	2	2	3
2	4	2	2	5
3	2	1	1	2

Table 2: The energy prices at each period c_t

t	c_t	t	c_t	t	c_t	t	c_t	t	c_t
1	5	7	1	13	3	19	5	25	1
2	6	8	4	14	2	20	3	26	2
3	3	9	2	15	6	21	1	27	5
4	5	10	5	16	3	22	3	28	1
5	3	11	5	17	4	23	4	29	5
6	2	12	4	18	1	24	5	30	3

Figure 2: The Pareto front of the example problem

of each job type s_i are given in Table 1. The energy prices at each period c_t are shown in Table 2.

The ideal point and nadir point are $\mathbf{f}^I = (30, 4)$ and $\mathbf{f}^N = (95, 26)$, respectively. Starting from one extreme point $(30, 26)$, minimizing TEC is considered as the objective and $C_{max} \leq \epsilon$ as a constraint. **Figure 2 represents the Pareto front, which includes 8 solutions. The results show that optimal TEC and C_{max} cannot be optimized at the same time.** On the other hand, it shows that if the schedule is only focused on the makespan, the energy consumption cost is much higher, even for this small scale problem.

5. Constructive heuristic methods

Due to the strongly NP-hardness of the problem, it's necessary to develop heuristics to find solutions in a reasonable computation time. Since the processing time of a batch is determined by the longest job included, it may be better to utilize the capacity of the machine fully. Therefore, an intuitive idea is: batch the jobs first and then sequence the batches. This helps to decompose the problem into two-stage hierarchical subproblems: the first one (denoted by upper subproblem) is how to batch the jobs and the second one (denoted by lower subproblem) is how to sequence the batches and determine the temperature for each batch. The whole structure of problem

decomposition and the resulting two heuristic methods are shown in Figure 3.

Figure 3: Structure of problem decomposition and two heuristic methods

5.1. Methods for upper subproblem: batch construction

We have two following batch construction methods. The first one is based on the batch first fit (FF) rule, and the second is based on optimization, i.e., solving an integer programming model by CPLEX.

5.1.1. FF rule based batch construction

For the first subproblem, the following method based on the batch first fit (FF) rule (Uzsoy, 1994) is designed. Here, let S_b be the sum of the job sizes in batch b , and G_b be the gap between the S_b and S (i.e., $G_b = S - S_b$). At the beginning, $S_b = 0$, $G_b = S$ and $b = 1$. Let U be the set of jobs that are not assigned to any batch. At the beginning, U includes all jobs.

The overall batching procedure (denoted by BF hereafter) can be summarized as follows.

Step (1). first, all jobs are sequenced with a non-increasing order of p_i^h , $i = 1, 2, \dots, m$ (or in terms of p_i^l since it is proportional to the p_i^h with a fixed ratio). The set of sequenced jobs can be denoted by $U = \{[1], \dots, [k], \dots, [N]\}$, where k is the job sequenced on k th position in U ;

- Step (2). if $U = \emptyset$ terminate, otherwise, from the first unbatched job of the sequence set U , the first longest job $[k]$ with s_i is selected. If $s_i \leq G_b$, go to Step (3); Otherwise, go to Step (4);
- Step (3). put the job $[k]$ into batch b , $S_b = S_b + s_i$, $G_b = G_b - s_i$, $U = U - [k]$. Go to Step (2);
- Step (4). if there is no job in U whose size is less than or equal to G_b , $b = b + 1$, $S_b = 0$, $G_b = S$, go to Step (2); Otherwise, select a job with the longest processing time among jobs in U whose sizes are not larger than G_b (arbitrary breaking ties). Let job $[k]$ be the selected job and go to Step (3).

Table 3: The resulting batch information for the example

Batch No.	Type i in the batch	Job j of type i in the batch	Batch size
1	1	1	3
1	1	2	6
1	3	1	8
2	2	1	5
2	2	2	10

Following the example in subsection 4.2, $S = 10$, $s_1 = 3$, $s_2 = 5$, $s_3 = 2$, $n_1 = n_2 = 2$, $n_3 = 1$, $N = 5$. Using Step (1), $U = \{1, 2, 3, 4, 5\}$ corresponds to J_{11} , J_{21} , J_{12} , J_{22} and J_{13} , respectively. Here, J_{ji} represents job j of type i . Then by following Step (2)-(4) of the BF procedure, the batches can be formed and they are shown in Table 3.

5.1.2. An optimization based batch construction

The second batch construction method is to generate batches to minimize the makespan, since makespan is one of the objectives. To achieve this, the following IP model can be formulated.

(IP for the upper subproblem (P1))

$$\min \sum_{b \in B} P^b \quad (22)$$

The constraints include:

(3)-(4)

$$P^b \geq x_{ij}^b p_i^h, \quad \forall b \in B, i \in K, j = 1, \dots, n_i \quad (23)$$

$$x_{ij}^b, y^b \in \{0, 1\}, \quad \forall b \in B, i \in K, j = 1, \dots, n_i \quad (24)$$

In expression (23), the processing time of a batch is determined by the longest processing time of job with s_i in batch b with the high temperature, where p_i^h is used to determine the batch processing time. The reason for doing this is that p_i^l is assumed to be $g \cdot p_i^h$, $g > 1$ in the problem. Therefore, in this model, the batch processing time for low temperature can be determined as $g \cdot P^b$ once P^b is obtained through this model.

5.2. An optimization based method for lower subproblem: batch sequence and temperature choice

Once $|B|$ batches are formed, a batch can be regarded as an independent job with a batch processing time. Then, the lower subproblem is transformed into a single machine scheduling problem with TOU energy price and high/low temperature choice. In this subsection, we develop an integer programming optimization based method.

The lower subproblem can be formulated as follows.

(IP for the lower subproblem (P2))

The objectives:

(1) and (2)

The constraints include:

(5), (10), (12)-(19)

$$\sum_{b \in B} \alpha_t^b \leq 1, \quad \forall t \in T \quad (25)$$

$$P^b = \tau_h^b P^H + \tau_l^b P^L, \quad \forall b \in B \quad (26)$$

$$\alpha_t^b, \beta^{bq}, \tau_h^b, \tau_l^b, \gamma_{th}^b, \gamma_{tl}^b \in \{0, 1\}, \quad \forall b, q \in B, t \in T \quad (27)$$

Inequality (25) ensures that in each period, only one batch can be processed on the machine. Since at some period, there may be no batch assigned, the sign $\leq$ is used. Constraint (26) is used to determine the processing time of a batch, in which $P^L = \max\{p_i^l\}$ and $P^H = \max\{p_i^h\}$, where i means that job type i in batch b .

Once the batch construction is done in upper subproblem, the ϵ -constraint method can be used to find non-dominated solutions.

6. Computational experiments

6.1. Data generation

The data required for an $1, TOU|B|\{C_{max}, TEC\}$ problem consists of the machine energy consumption rate for high or low temperature E_H, E_L , the number of different job types m , the number of jobs for each type n_i , the processing time of a job type i in the high temperature p_i^h , the proportional ratio rate g for job processing time between low and high temperatures, the total number of scheduling periods $|T|$, the energy price for each time period c_t , the size of a job type s_i and the total size of the machine space capacity S .

In the computational experiments, the parameters and their values are set as follows: the processing time of job type i in the high temperature p_i^h is taken from the uniform distribution between 1 and 5, which is denoted by $U[1, 5]$. The proportional ratio rate g for job processing time between low and high temperature is set as $g = 2$. c_t is taken from $U[1, 6]$ and s_i is taken from $U[1, 5]$. $S = 10$, $E_H = 6$, $E_L = 3$. The size of a problem is described by the combination of $\{m, n_i, |T|\}$. For each combination, 30 problem instances are generated. For different sizes of problems, different values of $\{m, n_i, |T|\}$ are taken. To ensure that there is a feasible solution, we take $|T| \geq \frac{m \times n_i \times \max\{p_i^h\} \times \max\{s_i\}}{S}$.

The exact ϵ -constraint method for the IP model, the two optimisation-based methods (i.e., solve the integer programming for batch sequence and temperature choice), denoted by *BF-P2*, and *P1-P2*, respectively are developed and implemented in C++ and run on a 2.3 GHz Intel Core i7 processor. The IP models are solved using CPLEX 12.6.

6.2. Performance metrics

It is necessary to use quality metrics to evaluate the performance of multi-objective algorithms. For approximate Pareto fronts, the following four metrics are used to compare the quality of two non-dominated fronts, **A** and **B**, obtained by different algorithms. The first one is diversity (DVR) (c.f., Mansouri et al., 2016), which represents the area covered by the two objective values, i.e., the product of the ranges of C_{max} and TEC .

$$DVR_{\mathbf{A}} = (\max_{i \in \mathbf{A}} C_{max}^i - \min_{i \in \mathbf{A}} C_{max}^i) \times (\max_{i \in \mathbf{A}} TEC^i - \min_{i \in \mathbf{A}} TEC^i) \quad (28)$$

$$DVR^{\mathbf{A}} = \left| 1 - \frac{DVR_{\mathbf{A}}}{DVR_{\mathbf{S}^*}} \right| \quad (29)$$

where $\mathbf{S}^*$ denotes a reference front (i.e., the Pareto-optimal front or a near Pareto-optimal front). If the Pareto front is not known, the two (or more if more than two methods used) fronts are combined and all the non-dominated solutions are selected to form the set $\mathbf{S}^*$. $\mathbf{A}$ is better than $\mathbf{B}$ if $DVR^{\mathbf{A}} < DVR^{\mathbf{B}}$.

The second one is the Chebyshev distance metric (Bérubé et al., 2009), denoted by CD , which can be used to evaluate the distribution of front $\mathbf{A}$ and the distance of $\mathbf{A}$ to a reference front $\mathbf{S}^*$. The CD measure of the front $\mathbf{A}$ is given by

$$CD_{\mathbf{A}} = \frac{1}{|\mathbf{S}^*|} \sum_{z \in \mathbf{S}^*} \min_{z' \in \mathbf{A}} \max \left(\frac{|z_{TEC} - z'_{TEC}|}{z_{TEC}}, \frac{|z_{C_{max}} - z'_{C_{max}}|}{z_{C_{max}}} \right) \quad (30)$$

$\mathbf{A}$ is regarded to be better than $\mathbf{B}$ if $CD_{\mathbf{A}} < CD_{\mathbf{B}}$

The third one is the number of solutions in front $\mathbf{A}$, denoted by CRD ,

$$CRD_{\mathbf{A}} = |\mathbf{A}| \quad (31)$$

The computation time of different algorithms are also recorded for the fourth metric.

6.3. Results for small scale problems

Table 4 shows results of the exact ϵ -constraint method for small scale problem instances with different combinations of $\{m, n_i, |T|\}$. For each combination, 30 problem instances are generated by following the data generation scheme described in subsection 6.1. The columns in the table correspond to:

- $\{m, n_i, |T|\}$: the combination of m , n_i and $|T|$;
- N : the total number of jobs;
- Nsd : the number of problem instances solved optimally by the exact ϵ -constraint method out of 30 instances within the time limit of 3600 seconds;
- $TM_{\mathbf{F}}^{max}$ ($TM_{\mathbf{F}}^{min}$): the maximum (*resp.*, minimum) total computation time (in seconds) for the problem instances solved optimally by the exact ϵ -constraint method within the time limit of 3600 seconds;

- $Avg(\overline{TM}_{\mathbf{F}})$: the average computation time (in seconds) for the problem instances solved optimally by the exact ϵ -constraint method within the time limit of 3600 seconds;
- $|\overline{\mathbf{F}}|$: the average number of solutions in the exact Pareto front for the problem instances solved optimally within the time limit of 3600 seconds.

The reported results show that the exact ϵ -constraint method can not address some problem instances within the given time limit even for those with small m and n_i . Moreover, for the problem instances that can be solved within the time limit, the computation time of the exact ϵ -constraint method varies largely even for the same m and n_i , which can be shown by the $TM_{\mathbf{F}}^{max}$ and $TM_{\mathbf{F}}^{min}$ in the table. The results also show that generally with the total number of jobs N and the length of the planning horizon $|T|$ increase, the number of the problem instances that can be solved to optimality within the time limits decreases, which can be demonstrated by the Nsd in the table.

Table 4: Statistics on the small scale problems for the exact ϵ -constraint method

$\{m, n_i, T \}$	N	Nsd	$TM_{\mathbf{F}}^{max}$	$TM_{\mathbf{F}}^{min}$	$Avg(\overline{TM}_{\mathbf{F}})$	$ \overline{\mathbf{F}} $
$\{2, 1, 10\}$	2	30	2275.39	0.089	203.65	2.67
$\{2, 1, 30\}$	2	21	2835.35	0.46	959.85	4.05
$\{3, 1, 15\}$	3	11	2911.57	0.76	976.35	2.30
$\{3, 1, 30\}$	3	9	3438.74	238.23	2225.3	2.89
$\{2, 2, 15\}$	4	8	3150.51	36.81	1242.05	3.50
$\{2, 2, 30\}$	4	4	1376.11	0.76	633.97	4.25
$\{2, 2, 50\}$	4	5	2751.80	39.32	2470.92	3.00
$\{3, 2, 30\}$	6	2	2662.97	232.71	1655.22	3.50
$\{3, 2, 50\}$	6	2	1092.71	941.97	1023.92	8.0

On the other hand, the two heuristic methods: BF-P2 and P1-P2, spend much less computation effort for the problem instances (see Table 5), and all methods get the same Pareto front as the exact ϵ -constraint method does for the problem instances that are solved optimally within the time limit. In the table, $\overline{TM}_{BF-P2}$ and $\overline{TM}_{P1-P2}$ represent the average of the total computation time (in seconds) with the BF-P2 and the P1-P2 method, respectively.

Table 5: Average total computation time for small scale problems with two heuristic methods

$\{m, n_i, T \}$	N	$\overline{TM}_{BF-P2}$	$\overline{TM}_{P1-P2}$
$\{2, 1, 10\}$	2	0.03	0.04
$\{2, 1, 30\}$	2	0.12	0.13
$\{3, 1, 15\}$	3	0.06	0.07
$\{3, 1, 30\}$	3	0.18	0.20
$\{2, 2, 15\}$	4	0.10	0.18
$\{2, 2, 30\}$	4	0.22	0.25
$\{2, 2, 50\}$	4	0.22	0.25
$\{3, 2, 30\}$	6	0.14	0.16
$\{3, 2, 50\}$	6	0.41	0.43

6.4. Results for large scale problems

The computational results of large scale problem instances are shown in Table 6-7. Table 6 summarizes the mean and standard deviation of the computation time of the two heuristic methods for the same problem instances. The ϵ -constraint method can not get any solution with time limits of 3600 CPU seconds. The computation time of BF-P2 and P1-P2 are much less than those of the ϵ -constraint method. Moreover, it can be observed that the computation time is affected by both number of total jobs, N , and the number of total planning horizon $|T|$. For the combination $\{m, n_i, |T|\} = \{5, 3, 80\}$, $\{m, n_i, |T|\} = \{5, 3, 100\}$ and $\{m, n_i, |T|\} = \{6, 3, 100\}$, BF-P2 and P1-P2 can only solve 26, 21 and 17 optimally out of 30 problem instances within the time limit of 3600 CPU seconds. It should be noted that, in Table 6-7, the mean and standard deviation results are based on the problem instances that are solved optimally within the time limit.

Table 7 reports the mean and standard deviation of the DVR, CD and CRD of the two heuristic methods for the same problem instances. In terms of DVR, BF-P2 and P1-P2 are quite close. The P1-P2 method is relatively better than the BF-P2 method, since the BF-P2 has a larger diversity. For the CD value, we observe that P1-P2 is better. This may be because that P1 and P2 obtain the optimal solutions at both stages. In terms of CRD, the results suggest that CRD increases as the parameters of N and $|T|$ increase. This can be explained by that more different batch sequences and time slots could be tested in the search space. BF-P2 and P1-P2 can obtain very close number of solutions. The BF-P2 is slightly better than the P1-P2 in terms

of CRD.

Table 6: Mean (standard deviation) computation time on the large scale problems for the two heuristic methods

$\{m, n_i, T \}$	N	BF-P2	P1-P2
$\{5, 2, 60\}$	10	30.57(93.48)	29.32(84.53)
$\{5, 2, 80\}$	10	25.91(44.29)	23.22(34.37)
$\{5, 3, 80\}$	15	423.15(676.21)	279.01(489.32)
$\{5, 3, 100\}$	15	364.7(560.83)	520.78(829.65)
$\{6, 3, 100\}$	18	880.26(730.2)	971.38(853.84)

Table 7: Mean (standard deviation) of DVR, CD and CRD on the large scale problems for the two heuristic methods

$\{m, n_i, T \}$	N	DVR^{BF-P2}	DVR^{P1-P2}	CD_{BF-P2}	CD_{P1-P2}	CRD_{BF-P2}	CRD_{P1-P2}
$\{5, 2, 60\}$	10	0.004(0.02)	0 (0)	0.016(0.067)	0 (0)	9.37(3.92)	9.37(3.94)
$\{5, 2, 80\}$	10	0.074(0.29)	0.002 (0.008)	0.021(0.06)	0.002 (0.012)	10.5(2.33)	10.37(2.57)
$\{5, 3, 80\}$	15	0.035(0.115)	0.009 (0.046)	0.020(0.05)	0 (0)	12.96(4.03)	12.5(3.71)
$\{5, 3, 100\}$	15	0.001 (0.004)	0.003(0.016)	0.003(0.015)	0.001 (0.007)	13.62(3.11)	13.43(3.29)
$\{6, 3, 100\}$	18	0.008(0.031)	0 (0)	0.010(0.028)	0 (0)	13.88(3.92)	13.77(4.02)

6.5. A case study of glass production company

The following case is originated from a real-world scheduling problem in a glass ceramization company located in Shanghai, China. Its data shares the common characteristics of the glass ceramization company. However, we have preprocessed the data for some commercial confidentiality reasons.

In the coming $|T| = 60$ time periods (one time unit corresponds to 10 minutes), there are four types of glasses which should be processed on the glass tempering furnace. All these four kinds of glasses have same height 8mm. The detailed job information are described in Table 8, in which, type 1 and type 2 jobs are circle glasses, and type 3 and type 4 jobs are rectangular ones. In practice, the different glasses will be put on the specific pallet which will be rolled into the furnace for heating (see Figure 4). The furnace can process two pallets at a same time with each pallet comprising the same combination of different glasses. The schematic diagram of these job types on one pallet is shown in Figure 5. The power of the glass tempering furnace is 900kW when it is running at 600°C, and 660kW when it is running at

450°C. The capacity of the furnace is simplified as $S = 24$. The main energy considered here is electricity and the electricity price for industry during summer periods is illustrated as follows (unit: RMB Yuan/kWh), due to the peak, normal and valley times.

$$c_t = \begin{cases} 0.3, & 0 \leq t < 10 \\ 0.7, & 10 \leq t < 22 \\ 1.2, & 22 \leq t < 32 \\ 0.3, & 32 \leq t < 44 \\ 0.7, & 44 \leq t < 60 \end{cases} \quad (32)$$

Table 8: The detailed data for the studied case

Job type i	p_i^l	p_i^h	n_i	s_i
1	2	1	15	3
2	4	2	13	6
3	10	5	6	18
4	8	4	6	12

The computational results are shown in Figure 6. For the exact ϵ -constraint method, no one solution can be obtained after 31823.64 CPU seconds. The approximate Pareto fronts of the BF-P2 and P1-P2 are the same, which includes 11 non-dominated solutions. It takes the BF-P2 and the P1-P2 methods 5648.05 and 6359.25 CPU seconds, respectively. The solutions along the front range from energy costs 4470 (RMB Yuan) to 3720 (RMB Yuan), and makespan 48 to 58. From the Pareto solutions (4470,48) to (3720,58), there is 16.8% energy cost reduction at the cost of 20.8% increase of the makespan. We also observe that, along the Pareto front, the marginal energy cost saving is 75 RMB Yuan (i.e., the cost is reduced by 75 RMB Yuan with the increase of one unit time of 10 minutes), which can provide production managers for trade-off analysis between the total energy costs and the makespan. The reason for the linear changes of the approximate Pareto fronts may be because that the electricity price is stepwise changed, not continuously changed. There is no non-dominated solution with a makespan larger than 58, which means that no energy cost savings can be further achieved

Figure 4: Two batches of glasses before rolling into the furnace

Figure 5: The examples of batch combinations of these four job types

Figure 6: The approximate Pareto fronts obtained by the two heuristic methods for the studied case

with the consumption of makespan. In addition, there is no solution with makespan less than 48. This is because that the optimal solution for batch formulation P1 is 48.

The detailed batch formulation for the solution with the objective function values (4470,48) is shown in Table 9, where P^b represents the batch processing time. It shows that there are 13 batches. In the schedule, the high temperature is selected for each batch. As for the start time, the first batch starts from time zero, and then it follows batch 2, and so on until batch 13, which leads to the solution with the objective values (4470,48). For the solution with the objective function values (3720,58), the batch formulation is the same as in Table 9, and also the high temperature is chosen for all batches. However, the start time ST^b and completion time CT^b of each batch are different, and they are shown in Table.10.

Table 9: The detailed batch information with minimum makespan 48

Batch No.	Job type in the batch	Batch size	P^b
1	{2,3}	24	5
2	{2,3}	24	5
3	{2,3}	24	5
4	{2,3}	24	5
5	{2,3}	24	5
6	{2,3}	24	5
7	{4,4}	24	4
8	{4,4}	24	4
9	{4,4}	24	4
10	{2,2,2,2}	24	2
11	{2,2,2,1,1}	24	2
12	{1,1,1,1,1,1,1,1}	24	1
13	{1,1,1,1,1}	15	1

7. Conclusions

This paper investigates a single machine batch scheduling problem to minimize two objectives simultaneously: the makespan and the total energy cost. The time-of-use energy price and temperature choice for batches are considered. A comprehensive mathematical formulation is presented. An ϵ -constraint method is applied to get the exact Pareto front, and two

Table 10: The detailed start time and completion time of each batch for the solution with objective values (3720, 58)

Batch No.	ST^b	CT^b	Batch No.	ST^b	CT^b
1	5	10	8	47	51
2	51	56	9	39	43
3	10	15	10	15	17
4	17	22	11	56	58
5	0	5	12	38	39
6	32	37	13	37	38
7	43	47			

decomposition-based heuristic methods are used to get approximate Pareto fronts.

Computational experiments are conducted on problem instances randomly generated and a case study to evaluate the efficiency and effectiveness of the methods. The results show that for small scale problems, the heuristics can obtain exact Pareto front in much shorter time compared with the ϵ -constraint method. For large scale problems and the practical size case, the P1-P2 and BF-P2 can get better solutions in terms of performance metrics with relatively short computation time. Therefore, as for managerial implications, we suggest the P1-P2 or BF-P2 method for production managers to solve middle and large scale problems, which help to find the trade-off between the furnace utilization (related to production efficiency) and the total energy cost (related to economic return).

For the future work, various multi-objective algorithms could be developed for this problem. The extension to multiple-machine environments like parallel machine is also interesting and practical, since for some glass manufacturing companies, there are more than one glass tempering furnace with similar heating functions.

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