



Batch scheduling for minimal energy consumption and tardiness under uncertainties: A heat treatment application



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ABSTRACT

A novel multiple-objective model for batch scheduling of an energy-intensive manufacturing process, e.g., heat treatment, is proposed. The model minimizes energy consumption and total weighted tardiness while considering the arrival times of each workpiece and the inherent uncertainties in gas heating values, processing times, and due dates. Fuzzy logic is adopted to characterize these uncertainties and to interpret objective dominance when finding a Pareto frontier. A non-dominated sorting genetic algorithm is employed. The approach is demonstrated using a pre-treatment (soaking) process prior to a hot rolling operation. Pareto optimal performance of the model under different parameter settings is discussed.

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1. Introduction

Heat treatment is one of the most energy intensive manufacturing processes. For example, the heating of ingots prior to a hot rolling operation accounts for up to 70% of the process energy consumption (2–2.4 GJ/ton). There exists significant potential for energy conservation in these processes [1]. One promising approach is to explore efficient production schedules. Recent years have seen several studies directed at manufacturing scheduling for improved energy efficiency while considering peak load [2], carbon footprint [3], and time-of-use (TOU) and real-time electricity pricing (RTP) [4]. Other work has aimed at optimizing energy related objectives and production efficiency simultaneously. For example, Liu [5] addressed a batch scheduling problem considering carbon emissions and total tardiness. Luo et al. [6] studied electricity cost and makespan minimization in a hybrid flow shop. Most of these studies on energy efficient scheduling have concentrated on electricity related energy consumption, and all the input parameters (e.g., processing time and due dates) and thus objectives (such as energy consumption and completion time) are assumed to be deterministic.

Significant uncertainties exist in the operation of heat treatment equipment, which have to be considered in scheduling. In a hot roll mill process, the primary energy required for heating is in the form of a mixed gas (e.g., H₂, CO, and CH₄), which is generated from coke oven (COG) and blast furnace (BFG) gases [7]. The total energy consumption is calculated using the amount of each type of gas consumed and its heating value. In practice, an empirical heating value is used, and uncertainty in the data and in the composition of the gas itself leads to uncertainty in the

calculated total energy consumption. Uncertainties also exist in many critical process parameters, with some parameters only loosely defined when creating a production schedule. For example, the heating time for a given batch may be from 25 to 35 min, with the exact value selected based on experience at the time of process execution. Due to the inherent imprecision in the parameter, the exact heating time is unknown when making a schedule.

In general, there are two approaches to describe variables with uncertainty: random numbers and fuzzy numbers. The fuzzy number approach has significant appeal, since it is sometimes difficult in practice to collect sufficient data to characterize the distribution of uncertain variables. Moreover, in a scheduling context, some stochastic scheduling models are computationally too expensive and cumbersome to apply in real-world applications. With this in mind, this paper will use a fuzzy logic approach to address uncertainty. The literature reports that relative to stochastic approaches, fuzzy logic is computationally simpler and faster and provides more flexibility. Cheng et al. [8] employed fuzzy processing time for a batch machine scheduling problem to minimize makespan. However, uncertainty in due dates and energy related objectives were not considered.

This paper presents a model to minimize the total energy consumption associated with the mixed gas input and total tardiness for a heat treatment batch scheduling problem. This will be achieved via a novel multi-objective fuzzy logic based optimization model, which will be solved using a non-dominated sorting genetic algorithm. The method considers uncertainties in gas energy consumption, processing time, and due dates.

2. Model description

This work considers the problem of batch scheduling of n workpieces in a gas-fired heat treatment operation, where

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the workpieces have different arrival times. Two types of gas, COG and BFG, are supplied to the heat-treat furnace. The gas flow rates when the furnace is idle are assumed to be much lower than during the actual operation, and are only sufficient to maintain furnace temperature. Furnace interruption and breakdown are not considered. The processing time of a batch of workpieces is determined by the workpiece in the batch that has the longest processing time.

2.1. Gas energy consumption

The heating values of COG and BFG often fluctuate owing to changes in gas composition (amounts of H_2 , CH_4 , etc.). To address this issue, the heat values may be expressed as a fuzzy number, denoted as \tilde{h}_{COG} and \tilde{h}_{BFG} (in MJ/m^3). During idling and active heating the flow rates of COG and BFG are $f_{COG}^i, f_{BFG}^i, f_{COG}^s$, and f_{BFG}^s (all in m^3/min), respectively. The processing time of a batch and the idle time between batches are nondeterministic. For a given batch schedule, π , which has m batches, the total energy consumption may be described as:

$$\begin{aligned} \tilde{E}(\pi) &= \tilde{E}(\pi)_s + \tilde{E}(\pi)_a \\ &= \sum_{j=1}^m \{(\tilde{h}_{COG} \cdot f_{COG}^s + \tilde{h}_{BFG} \cdot f_{BFG}^s) \cdot \tilde{T}_j^s + (\tilde{h}_{COG} \cdot f_{COG}^i \\ &\quad + \tilde{h}_{BFG} \cdot f_{BFG}^i) \cdot \tilde{T}_j^i\}, \end{aligned} \quad (1)$$

where \tilde{T}_j^s denotes the processing time of the j th batch, B_j , and \tilde{T}_j^i denotes the idle time between batch B_{j-1} and B_j (both \tilde{T}_j^s and \tilde{T}_j^i are fuzzy numbers). From the above assumption,

$$\tilde{T}_j^s = \max_{J_i \in B_j}(\tilde{t}_i), \quad (2)$$

where J_i refers to the i th workpiece within B_j , and \tilde{t}_i is its nominal processing time.

2.2. Batch scheduling model formulation under uncertainties

Tardiness is a key performance measure to evaluate a schedule. To guarantee that the schedule satisfies the demand of customers, a decision must be made to either wait for more workpieces to arrive or start a partial batch. The former may substantially delay the workpieces that are waiting, while the latter may result in more energy consumption. Suppose each workpiece J_i has a due date \tilde{d}_i , where sometimes this due date may have flexibility. The tardiness of J_i is then defined as:

$$\tilde{T}_i = \max(0, \tilde{C}_i - \tilde{d}_i), \quad (3)$$

where \tilde{C}_i denotes the completion time of J_i . Given that the tardiness penalty weight for J_i is w_i , the total weighted tardiness may be expressed as:

$$\widetilde{TWT} = \sum_{i=1}^n (w_i \cdot \tilde{T}_i), \quad (4)$$

Given the foregoing relations, the problem can be formulated as a fuzzy multi-objective batch machine integer programming (FMBMIP) model. Optimizing this model will find the batch schedule that minimizes the total gas energy consumption and total weighted tardiness.

$$\min \tilde{E}(\pi)$$

$$\min \widetilde{TWT}$$

s.t.

$$\sum_{j=1}^m X_{ij} = 1; \quad \forall i = 1, \dots, n, \quad (5)$$

$$\sum_{i=1}^n X_{ij} \leq C; \quad \forall j = 1, \dots, m, \quad (6)$$

$$r_i \cdot X_{ij} \leq \tilde{R}_j; \quad \forall i = 1, 2, \dots, n, \quad j = 1, 2, \dots, m, \quad (7)$$

$$\tilde{t}_i \cdot X_{ij} \leq \tilde{T}_j^s; \quad \forall i = 1, 2, \dots, n, \quad j = 1, 2, \dots, m, \quad (8)$$

$$\tilde{R}_j + \tilde{T}_j^s \leq \tilde{C}_j; \quad \forall j = 1, 2, \dots, m, \quad (9)$$

$$\tilde{C}_{j-1} + \tilde{T}_j^s \leq \tilde{C}_j; \quad \forall j = 1, 2, \dots, m, \quad (10)$$

$$\frac{n}{C} \leq m \leq n; \quad m \in \text{integer}, \quad (11)$$

$$X_{ij} \in \{0, 1\}; \quad \forall i = 1, 2, \dots, n, \quad j = 1, 2, \dots, m, \quad (12)$$

$$\tilde{C}_j, \tilde{R}_j, \tilde{T}_j^s \geq 0; \quad \forall j = 1, 2, \dots, m, \quad (13)$$

where X_{ij} is equal to 1 if workpiece i is assigned to batch j , and 0 otherwise. C is the capacity of the heat treat furnace. r_i is the arrival time of workpiece i , and \tilde{R}_j is the starting time of batch j . \tilde{C}_j is the completion time of batch j .

Constraint (5) ensures that each workpiece is only assigned to one batch. Constraint (6) stipulates that the capacity of the furnace cannot be exceeded. Constraints (7) and (8) indicate the starting time and the processing time of a batch. Constraints (9) and (10) give the definition of \tilde{C}_j and establish the relation of the completion time between two consecutive batches. Constraint (11) sets up a restriction on the number of batches. Finally, Constraints (12) and (13) force nonnegativity and integer conditions.

3. Model development and optimization algorithm

3.1. Expanding the model based on fuzzy logic

The preceding section established a general model for the batch scheduling problem under uncertainty. Variables subject to uncertainty in the heat treatment problem include the heating values of COG and BFG, processing times, and due dates. A fuzzy logic approach is adopted to deal with this uncertainty. As will be evident, a triangular membership distribution is used for each fuzzy parameter in the model.

It is assumed that the heating values are represented by triplets, $\tilde{h}_{COG} = (\underline{h}_{COG}, h_{COG}^0, \bar{h}_{COG})$ and $\tilde{h}_{BFG} = (\underline{h}_{BFG}, h_{BFG}^0, \bar{h}_{BFG})$, for which h_{COG}^0 and h_{BFG}^0 are the respective defuzzifiers, and \underline{h} and \bar{h} are the left and right fuzzy bounds. As an example, for \tilde{h}_{COG} the membership function $\mu_{\tilde{h}_{COG}}(x)$ may be defined as (also see Fig. 1(a)):

$$\mu_{\tilde{h}_{COG}}(x) = \begin{cases} \frac{x - \underline{h}_{COG}}{h_{COG}^0 - \underline{h}_{COG}} & \underline{h}_{COG} \leq x \leq h_{COG}^0, \\ \frac{x - h_{COG}^0}{\bar{h}_{COG} - h_{COG}^0} & h_{COG}^0 \leq x \leq \bar{h}_{COG}, \\ 0 & \text{otherwise.} \end{cases} \quad (14)$$

Given the starting time of batch j , $\tilde{R}_j = (R_j, R_j^0, \bar{R}_j)$, and the processing time of batch j , $\tilde{T}_j^s = (T_j^s, T_j^{s0}, \bar{T}_j^s)$, the completion time of batch j may be calculated by the fuzzy summation operator:

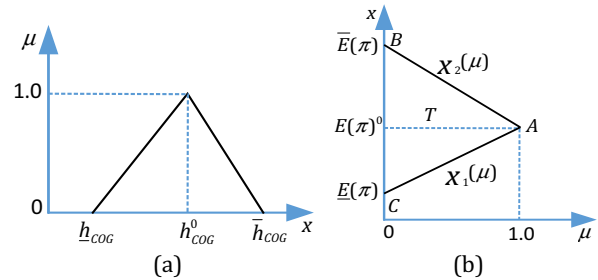


Fig. 1. Membership function and inverse membership function.

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