Optimization of bi-objective permutation flow shop scheduling with electricity cost consideration

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Abstract. Increasing energy demand can create undesired problems for many governments worldwide. Several policies, such as time-of-use (TOU) tariffs, have been put in place to overcome such demand. The TOU policy's objective is to reduce electrical load during peak periods by shifting the use to off-peak periods. To that end, this paper addresses the bi-objective permutation flow-shop scheduling, minimizing total weighted tardiness and electricity costs. We propose a meta-heuristic algorithm based on SPEA2 to solve the problem. We conducted numerical experiments to evaluate the efficacy of the proposed algorithm by comparing it with NSGA-II. The results show that the proposed approach was more efficient compare with NSGA-II.

1. Introduction
Climate change and global warming are primarily due to the emissions of greenhouse gases. Emissions mainly resulted from the combustion of fossil fuels for economic and household activities. Because fossils fuels have been the primary source of energy generation, more and more greenhouse carbon dioxide will be emitted as the demand for electricity increases due to economic development and population growth.

The manufacturing sector consumes a massive amount of global energy consumption. In Japan, it consumes about 45% of the total energy [1]. Therefore, many countries have imposed several regulations to enforce the manufacturing sector to adopt energy-saving initiatives. One of the policies is time-of-use (TOU) tariffs. Energy suppliers charge different prices for different usage times. The TOU policy relocates the usage from the peak (higher prices) to off-peak (lower prices) periods [2].

Moon et al. [3] initiated the adoption of TOU policy in production scheduling. They proposed a hybrid genetic algorithm (HIGA) that outperformed standard genetic algorithm (GA). A multi-objective optimization (MOO) involving ecology, economic, and environmental of a flow-shop scheduling problem was solved by using simulated annealing [4]. Fang et al. [5] studied the effects of speed of machines a single machine scheduling. Ding et al. [6] proposed a mixed-integer programming (MIP) model for an unrelated parallel machine scheduling that minimizes the cost of electricity. They solved it using the column generation technique. Kurniawan et al. [7] investigated a bi-objective job-shop scheduling for minimizing the total weighted tardiness and electricity cost. They proposed a local search framework based on the distribution of elites to balance the exploration space towards both objectives.
This research studies bi-objective permutation flow-shop scheduling considering electricity cost that follows the TOU price scheme (FPSPTOU). The contributions from this research are as the followings. First, we presented the energy-conscious bi-objective permutation flow-shop scheduling under TOU (FPSPTOU). Second, we proposed a meta-heuristic algorithm based on the Strength Pareto Archive Evolutionary Algorithm 2 (SPEA2) to solve the bi-objective problem. Third, we compared the proposed algorithm with the Non-dominated Sorting Genetic Algorithm II (NSGA-II). Finally, this paper can inspire the manufacturing sector to embrace the TOU policy.

2. Related Works
The permutation flow-shop scheduling problem (PFSP) is a difficult combinatorial optimization problem. PFSP aims to seek the permutation of jobs such that a specific criterion is achieved. Garey has shown that PFSP is an NP-hard [8]. Several heuristic algorithms have been developed for solving FPSP, such as the CDS algorithm and NEH algorithm [9, 10].

For energy-aware FPSP, Schulz et al. [11] developed an iterated local search to minimize the makespan, energy consumption, and peak load. Chen et al. [12] have developed an innovative algorithm for distributed no-idle flow-shop scheduling. Fu et al. [13] proposed a chance-constraint approach to distributed PFSP with the total tardiness. A backtracking search algorithm was proposed to minimize the energy cost and makespan [14].

For scheduling under TOU, Moon et al. [3] proposed a hybrid GA to solve unrelated parallel machine scheduling with the sum of weighted makespan and energy cost. The problem is also solved by different approaches [15, 16]. Single machine scheduling under TOU also has been investigated extensively [2, 17-18]. Specifically, Wang et al. [19] studied a two-stage permutation flow-shop under TOU with machine states consideration. Zhang et al. [20] investigated a flow-shop scheduling problem and developed a MIP model. The objectives of their problem are to minimize the electricity cost and carbon emission for environment under TOU.

3. Formulation
The formulation of FPSPTOU is as follows. A feasible solution is represented as a permutation of \( n \) jobs, \( \pi = \{\pi_1, \pi_2, ..., \pi_n\} \). Each job \( J_j \) consists of \( m \) stages of operation, and each stage is processed on machine \( M_i \). Each job has a due date, \( d_j \). Each job is processed on a machine with processing time \( p_{ij} \). The sequence of jobs for each stage is the same. Once a machine processes a job, it cannot be interrupted until it finishes.

Time horizon of \( u \) periods is divided into several periods, \( \mathcal{U} = \{U_1, U_2, ..., U_u\} \). Each period \( U_v \in \mathcal{U} \) has an electricity price \( e_v \). All jobs are available at time zero. Electricity cost incurs when a machine process a job. Machines can be idle to decrease electricity consumption. The total weighted tardiness and electricity cost are the objective that must be minimized.

It should be noted that the goals of MOO are to obtain a set of solutions rather than a single one. Therefore, the goal of FPSTOU is to find an approximate Pareto frontier, i.e., to find a set of non-dominated permutation of jobs.

Fig. 1 shows the TOU tariffs price scheme. The periods can be categorized based on electricity price. Periods 1–8 is off-peak periods. Periods 12–17 and 21–24 are mid-peak periods. The peak periods are 9–12 and 18–20.

For total weighted tardiness minimization, the jobs should be finished as soon as possible, whereas to minimize electricity cost, jobs should be processed in periods of low electricity prices, which may delay their start times. To balance these two conflicting objectives, we propose a meta-heuristic algorithm based on SPEA2.
4. Proposed Method

The FPSTOU is an extension of FPSP. The inclusion of electricity cost objective into the FPSP makes the problem bigger and complex. Garey et al. [8] has proven FPSP is NP-hard, thus FPSPTOU is also NP-hard. Solutions from exact method such as branch and bound deteriorate as the problem bigger. Therefore, we propose a meta-heuristic based on SPEA2 [21]. In what follows, we explain the proposed method in detail.

4.1. Encoding

For FPSTOU, a job sequence is represented using an integer representation. The initial population is generated randomly. Fig. 2 shows an individual that consists of 4 jobs along with its corresponding schedule.

4.2. Genetic operators

A binary tournament is used to select parents. After that, a one-point crossover is conducted on a pair of parents. We perform job-swapping to mutate a randomly selected individual.

4.3. Overview of the proposed method

Let $N$ and $\bar{N}$ be population size and archive size. Let $T$ and $t$ be the maximum number of iterations and its index. The procedure of the propose method are as follows.

At the initialization, $t = 0$, a population $P_0$ is generated randomly. An empty archive $\bar{P}_0$ is created to store the non-dominated solutions. Then, calculate the fitness of individuals in population $P_t$ and archive $\bar{P}_t$. In the next step, non-dominated solutions in population $P_t$ and archive $\bar{P}_t$ are copied into $\bar{P}_{t+1}$. If the number of individuals in $\bar{P}_{t+1}$ exceeds $\bar{N}$, remove individuals with lower fitness. Conversely, select dominated individuals from population $P_t$ and archive $\bar{P}_t$ into $\bar{P}_{t+1}$ so that the number of individuals $\bar{N}$.

Perform tournament selection from individuals in $\bar{P}_{t+1}$ to fill the pool. Then, perform crossover and mutation on individuals in the pool. Set the population created from crossover and mutation as $P_{t+1}$. The procedure is repeated after stopping criterion is reached.
5. Numerical Experiments

To measure the efficacy of the proposed algorithm, we compare it with NSGA-II. The genetic operators of NSGA-II are the same as those of the proposed algorithm. All algorithms were implemented on a computer with a Dual core processor @ 2.4 GHz and 3 GB of RAM.

The number of non-dominated solutions, $NDS$, and the generational distance, $GD$ [22], are used as the performance metrics. $GD$ is calculated as follows

$$GD = \sqrt{\frac{\sum_{\theta=1}^{y} \Delta_\theta}{y}}$$

where $y$ denotes the number of non-dominated solutions, and $\Delta$ denotes the shortest Euclidean distance between the $\theta$-th solution and reference set. For $GD$, lower values are preferred. On the contrary, the larger $NDS$ the better.

The problem instances are taken from Taillard [23]. As for due date, it was generate by $d_j = r_j + \lceil f \times \sum_{i=1}^{m} p_{ij} \rceil$ where $f$ is constant, and $r_j$ is the release time of job. In this study, $r_j = 0$ for all jobs. The weight is categorized as follows: 20% of jobs are very important ($w_j = 4$), 60% have average importance ($w_j = 2$), and 20% of jobs are of least importance ($w_j = 1$). The number of period is calculated as $u = \lceil y \times BM \rceil$, where $y = [1.2, 1.5]$ and $BM$ is the estimated makespan. The TOU price follows the pattern shown in Fig. 1.

The population size is set to 150, the crossover rate is set to 0.7, and the mutation rate is set to 0.1. The archive size is the same as population size. Each instance is run for 10 replications. Each run is 50 s.

Table 1 shows the computational results for $f = 1.5$. The first column represent the problem size, consist of job and machine. The second column represents the number of periods. The third until sixth column show the metrics value of NSGA-II and the proposed method, respectively.

The proposed method outperformed NSGA-II in all performance metrics for all instances. In average, the proposed method also produced better results than those of NSGA-II. However, the differences were so small.

6. Conclusions

This study investigated a permutation flow-shop scheduling under TOU (PFSPTOU). The total weighted tardiness and electricity cost are the objectives that must be minimized. We proposed a meta-heuristic based on SPEA2 to solve the problem. Numerical results showed the proposed method outperformed the NSGA-II. For future research, a local search can be developed to improve the solutions quality. Moreover, genetic operators can be improved.
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