Optimization of production scheduling with time-dependent and machine-dependent electricity cost for industrial energy efficiency

Article *in* The International Journal of Advanced Manufacturing Technology · September 2013

DOI: 10.1007/s00170-013-4749-8

Joon-Yung Moon
Seoul National University

Kitae Shin
Daejin University

Int J Adv Manuf Technol
DOI 10.1007/s00170-013-4749-8

ORIGINAL ARTICLE

Optimization of production scheduling with time-dependent and machine-dependent electricity cost for industrial energy efficiency

Joon-Yung Moon · Kitae Shin · Jinwoo Park

Received: 28 November 2011 / Accepted: 9 January 2013

Abstract In many industrialized countries, manufacturing industries pay stratified electricity charges depending on the time of day (i.e., peak-load, mid-load, and off-peak-load). In contrast, the emerging smart grid concept may demand that industries pay real-time hourly electricity costs so as to use energy most efficiently. This paper deals with the production and energy efficiency of the unrelated parallel machine scheduling problem. This method allows the decision maker to seek a compromise solution using the weighted sum objective of production scheduling and electricity usage. Reliability models are used to consider the energy cost aspect of the problem. This paper aims to optimize the weighted sum of two criteria: the minimization of the makespan of production and the minimization of time-dependent electricity costs. We suggest a hybrid genetic algorithm with our blank job insertion algorithm and demonstrate its performance in simulation experiments.

Keywords Production scheduling · Unrelated parallel machine · Genetic algorithm · Smart grid · Demand response · Energy efficiency

J.-Y. Moon (✉) · J. Park (✉)
Department of Industrial Engineering,
Seoul National University,
1 Gwanak-ro, Gwanak-gu, Seoul 151-744, Republic of Korea
e-mail: monjyksh@snu.ac.kr
e-mail: autofact@snu.ac.kr

K. Shin
Department of Industrial Management Engineering,
Daejin University, 1007 Hogook-ro, Pocheon City,
Kyungi-do 487-711, Republic of Korea

1 Introduction

Most countries are seriously worrying about the recent global warming, the depletion of fossil fuels, and environmental degradation. In keeping with the adoption of electric vehicles, it is very important to reduce carbon dioxide emissions and increase energy efficiency. In addition, the development of IT has introduced the concept of the smart grid, which enables consumers to participate actively in a form of the two-way communication. The smart grid delivers electricity from suppliers to consumers using two-way communication technology to control appliances at consumers' homes in an effort to save energy, reduce costs, and increase the levels of reliability and transparency. This type of real-time hourly electricity pricing also mitigates price spikes. The demand response (DR) refers to changes in electricity usage by customers from their normal consumption patterns in response to changes in the price of electricity depending on the time. DR plays an important role in reducing the peak load and in increasing the efficient use of energy. In addition, consumers can obtain benefits by lowering their power costs. The Korea Power Exchange operates a day-ahead market or an hour-ahead market by sending hourly price via messages to customers (mostly industries) and thus having them shift or reduce their electricity usage. This strategy reduces the production cost of electricity and maintains the balance of supply and demand when system emergencies are expected. Consequently, manufacturing industries set a new production schedule to save energy after considering time-dependent electricity costs.

In the manufacturing industry, many production scheduling problems are concerned with minimizing what is known as the makespan (or maximal completion time) in an effort to reduce production costs. Many studies have attempted

Published online: 15 March 2013

to solve the scheduling problem by allocating limited resources according to the configuration of the workshop, the objectives, and the constraints involved. According to Garey and Johnson [1], most production scheduling problems are known as NP-hard (non-deterministic polynomial-time hard) problems. Therefore, efforts have been directed into designing fast and efficient heuristic algorithms that show good performance levels. In research related to production scheduling, it is assumed that the production cost at each time on the same machine is always the same. However, in real manufacturing systems, the machines and times associated with a process may be subject to different electricity costs or additional costs for extended labor. In terms of cost considerations, the most important task is to establish an appropriate machine scheduling by optimizing an objective function. In many countries, including South Korea, currently the periods of a day for electricity billing are divided into three parts (peak-load, mid-load, off-peak-load). By considering time-dependent electricity costs, manufacturing industries can reduce their expense by using energy efficiently.

In practice, there are several machines which perform the same function but have different processing times or capabilities because the machines were produced from different manufacturers or the machines have the different ages of production, thus leading to the unrelated parallel machine problem. In addition, as many practical job shop and open shop scheduling problems can be reduced to parallel machine scheduling problems under certain conditions, the parallel machine scheduling problem has received a great deal of attention in academic and engineering circles, according to Balin [2]. Therefore, the present study deals with the unrelated parallel machine problem as it pertains to workshop configurations. In this present work, we extend and improve our recent work [3]. Few studies have been conducted to solve this problem in this particular area, which integrates the production scheduling problem and the problem with the time- and machine-dependent hourly electricity cost.

This paper is organized as follows: Section 2 gives a survey of scheduling problems related to our problem. Section 3 describes the integrated model of the production and electricity cost scheduling. Section 4 explains the new algorithm to solve our problem. Section 5 experiments with the meta-heuristic presented in Section 4. Finally, Section 6 concludes the paper and presents ideas for future research.

2 Literature review

For time-dependent scheduling, Cheng et al.[4] considered a class of machine scheduling problems in which the processing time of a task was dependent on its starting time in a schedule. Alidaee and Womer [5] also presented a review on scheduling problems with time-dependent processing times. This model reflects some real-life situations. Examples are found in financial management, steel production, resource allocation, maintenance scheduling, and national defense, where any delay in tackling a task may result in an increasing or decreasing effort (time, cost, etc.) to accomplish the task.

A few researchers studied time-dependent industrial planning under the point of view of electricity cost. Nilsson and Sonderstrom [6] studied the influence of the electricity cost on industrial production planning. According to Nilsson and Sonderstrom [6], since industrial electricity subscriptions usually include a differentiated tariff with a high rate during daytime and a low rate during nighttime and weekends, it is profitable for customers to shift their electricity demand to periods with low rates. The differentiation implies an opportunity to shift the electricity demand to time periods with a lower electricity price and thereby to make economic savings. The electricity producer may also benefit when peaks in the electricity demand can be removed [7]. Castro et al. [8] studied on the modeling for continuous plants with a continuous time scheduling formulation that could effectively handle time-dependent electricity costs and availability. In this work, a further investigation was made on the influence of the differentiation of the electricity tariff on the production schedule with optimal electricity cost. Electricity spot markets have introduced hourly variation in the price of electricity. Yusta et al. [9] formulated a mathematical optimization model which simulated electricity costs and demand of a machining process to find the optimum production schedule that could maximize the industry profit considering the hourly variations of the price of electricity in the spot market. Ghobeity et al. [10] studied operation cost-saving methods in reverse osmosis via time-dependent optimization. They optimized the operation of seawater reverse osmosis with the objective to reduce the electricity charges, which constituted the largest portion of the operation costs. They suggested that their results showed significant electricity and production cost-saving potentials with establishing the optimal operation plan.

There are often number of machines with different processing times or capabilities that can process the jobs [2]. Chen and Chen [11] insisted that unrelated parallel machine scheduling has been widely applied in manufacturing environments. Even though each job has only single operation to be processed on some machines, it is a common problem in the industry. According to Chen [12], this type of environment is often encountered in injection molding departments where unrelated parallel machines are used to process different components and setup times are sequence and machine-dependent. The dicing of semiconductor wafer manufacturing is a major bottleneck operation since it takes longer processing times than other operations. Furthermore, the production efficiency of this operation significantly affects the overall production efficiency. Machines used in the dicing operation are non-identical, that is, their processing times vary according to ages and manufacturers. Thus, optimization is required for an unrelated parallel machine scheduling problem [13]. The drilling operation of the printed circuit board is very critical and usually is a bottleneck operation of the whole manufacturing processes. Therefore, the scheduling problem of the drilling operation is very challenging and difficult. The machines on the shop floor are not identical in production capacities which means an unrelated parallel machine scheduling problem [14].

For solving the parallel machine problem, Lee [15] proved that the problem of minimizing the makespan with availability constraints in a non-preemptive case was NP-hard. Schmidt [16] examined the problem on m parallel machines, where each machine could be only used during several availability periods. Liao et al. [17] considered a two-parallel machine problem in which one machine was not available during a time period.

Berrich et al. [18] proposed a bi-objective model to solve the joint production and maintenance scheduling problem in a parallel machine case. In their paper, they compared two evolutionary genetic algorithms to minimize the makespan and the system unavailability in order to determine when to carry out preventive maintenance actions. Chen [12] considered the scheduling problem on unrelated parallel machines with sequence and machine-dependent setup times and due-date constraints to minimize the total tardiness with a genetic algorithm. Likewise, Vallada and Ruiz [19] proposed a genetic algorithm for the unrelated parallel machine scheduling problem in which machine- and job-sequence-dependent setup times were considered. Their proposed algorithms include a fast local search and a local search enhanced crossover operator with several statistical analyses.

To hybridize a genetic algorithm, Pan and Huang [20] proposed a hybrid genetic algorithm to solve no-wait job shop problems. The main purpose of this hybrid operator is to improve the efficiency of the traditional genetic approach with a fast local search method. Gao et al. [21] developed a new approach hybridizing genetic algorithm with a variable neighborhood descent scheme to exploit the global search ability of the genetic algorithm and the local search ability of the variable neighborhood descent scheme to solve multi-objective flexible job shop scheduling problem. A two-vector representation scheme was proposed and an effective decoding method was used to interpret each chromosome in an active schedule.

Table 1 Five-job problem instance with job processing time for two machines (hours)

	Job 1	Job 2	Job 3	Job 4	Job 5
M/C 1	6	5	8	2	9
M/C 2	4	3	5	1	5

3 Problem definition and modeling

To save energy or reduce energy costs is important not only for manufacturing companies but for our environment. Therefore, each manufacturing company and each country should establish a method to reduce energy use or energy costs. Hence, the DR of manufacturing companies is important, and it will become more important in a smart grid environment. Our new production scheduling scheme enables companies to minimize their production costs, defined as the weighted sum of time-dependent electricity costs and completion time-related costs of production.

3.1 Problem definition

A manufacturing company has machines that perform the same function but have different capabilities or capacities (especially different power consumption rates per hour). The company has several independent jobs with the same due date. In addition, its machines have three different rates (peak-load, mid-load, and off-peak-load) depending on the time of day. Inserted idling times (or blank jobs) are necessary to avoid a high electricity cost. We assume that idling times entail no electricity cost. However, an increase in the makespan (or the total operating hours) incurs excessive overtime costs. Therefore, the objective is to minimize the sum of the makespan multiplied by the penalty cost (or the

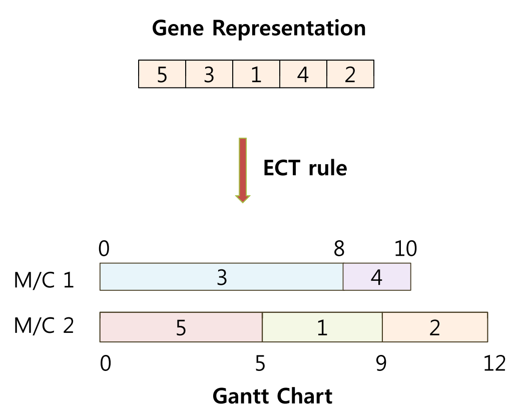


Fig. 1 Gene representation of ordinary genetic algorithm and its corresponding Gantt chart

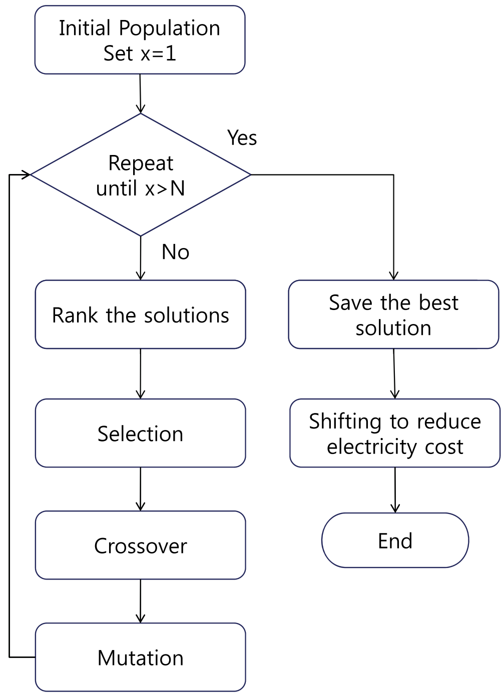


Fig. 2 Flowchart of the shifted genetic algorithm

overtime cost) and the total electricity cost. The assumptions of our problem are as follows:

Assumption

1. Unrelated parallel machine system
2. N independent, single-operation jobs
3. Idle time is allowed
4. Predefined processing time and due dates
5. No interruption once a job has started(non-preemption)
6. One-day (24-hour) production scheduling

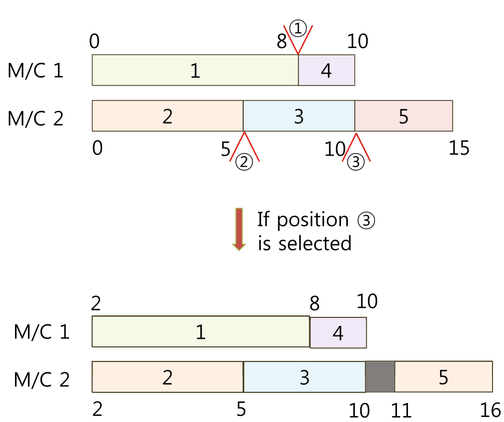


Fig. 3 Modified gene representation of the inserted genetic algorithm and its corresponding Gantt chart

Table 2 Example of the cost ranking and the probability for selection for each position

Position	Cost(in won)	Ranking	Probability for selection
①	7,625	2	1/3
②	4,670	1	1/6
③	15,250	3	1/2

3.2 Mathematical modeling

To describe an unrelated parallel machine problem with machine-dependent and time-dependent costs mathematically, we developed a new mathematical model. The parameters, decision variables, and the proposed model are as follows:

Parameters

PC: penalty cost
EC: electricity cost
st: available start time
dt: available due time
m: number of machines
n: number of jobs
p_{ij}: processing time(in hour), $i = 1, \cdots, m$, $j = 1, \cdots, n$
e_k: hourly electricity price(in won), $k = 1, \cdots, 24$
c_i: power consumption(in kilowatt hour), $i = 1, \cdots, m$

Decision variables

$$x_{ijk} = \begin{cases} 1 & \text{if job } j \text{ is processed at time } k \text{ on machine } i \\ 0 & \text{otherwise} \end{cases}$$

$$y_{ij} = \begin{cases} 1 & \text{if job } j \text{ is assigned to machine } i \\ 0 & \text{otherwise} \end{cases}$$

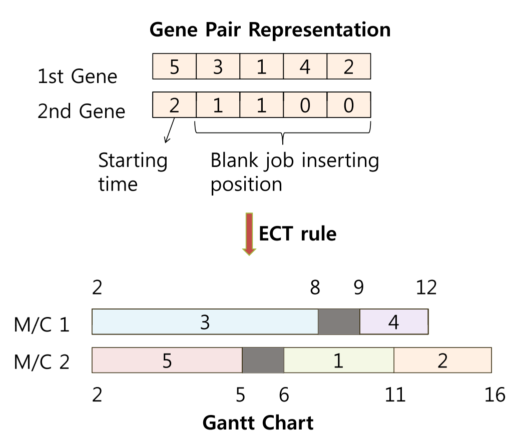


Fig. 4 Inserting blank job into the Gantt chart for selected position

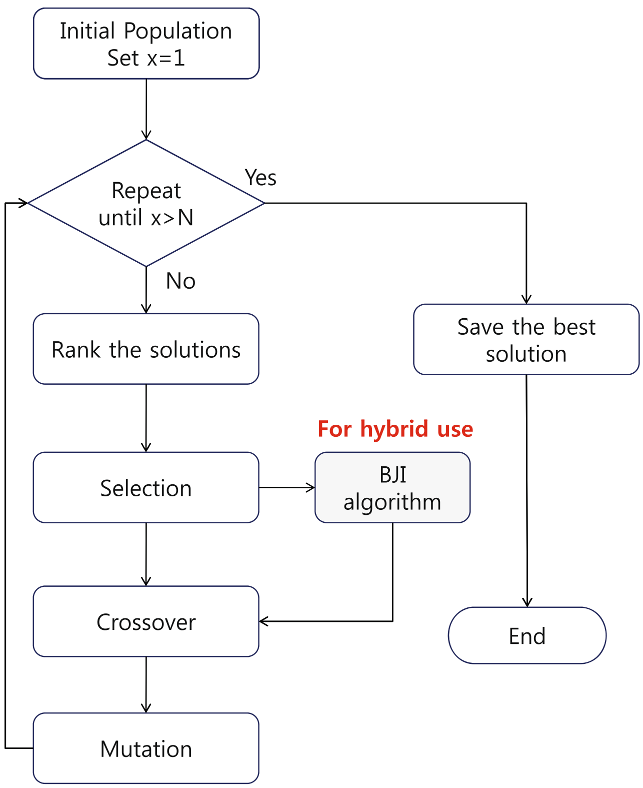


Fig. 5 Flowchart of the hybrid inserted genetic algorithm

Table 3 The daily electricity price

Time	Summer (won/kWh)	Winter (won/kWh)
1	45.0	50.1
2	45.0	50.1
3	45.0	50.1
4	45.0	50.1
5	45.0	50.1
6	45.0	50.1
7	45.0	50.1
8	45.0	50.1
9	45.0	50.1
10	90.8	88.8
11	90.8	135.5
12	158.9	135.5
13	90.8	88.8
14	158.9	88.8
15	158.9	88.8
16	158.9	88.8
17	158.9	88.8
18	90.8	135.5
19	90.8	135.5
20	90.8	135.5
21	90.8	88.8
22	90.8	88.8
23	90.8	135.5
24	45.0	50.1

Fig. 6 The graph of daily electricity price for summer

Fig. 7 Finding the optimal solution for scenario no. 1

$$\textit{Minimize} \;\; C_{\max} \times \mathrm{PC} + \mathrm{EC}$$

Subject to

$$\sum_{k=1}^{24} x_{ijk} = p_{ij} \times y_{ij} \,, \quad i = 1, \cdots, m, \; j = 1, \cdots, n \tag{1}$$

$$\sum_{j=1}^{n} \sum_{k=1}^{24} x_{ijk} \le C_{\max} \,, \quad i = 1, \cdots, m \tag{2}$$

$$\sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{24} x_{ijk} \times e_k \times c_i = \mathrm{EC} \tag{3}$$

$$\sum_{j=1}^{n} \sum_{k=1}^{\mathrm{st}-1} x_{ijk} = 0 \,, \quad i = 1, \cdots, m \tag{4}$$

$$\sum_{j=1}^{n} \sum_{k=\mathrm{dt}+1}^{24} x_{ijk} = 0 \,, \quad i = 1, \cdots, m \tag{5}$$

$$\sum_{i=1}^{m} y_{ij} = 1 \,, \quad j = 1, \cdots, n \tag{6}$$

The objective is to minimize the sum of the maximal completion time-related cost and the electricity cost.

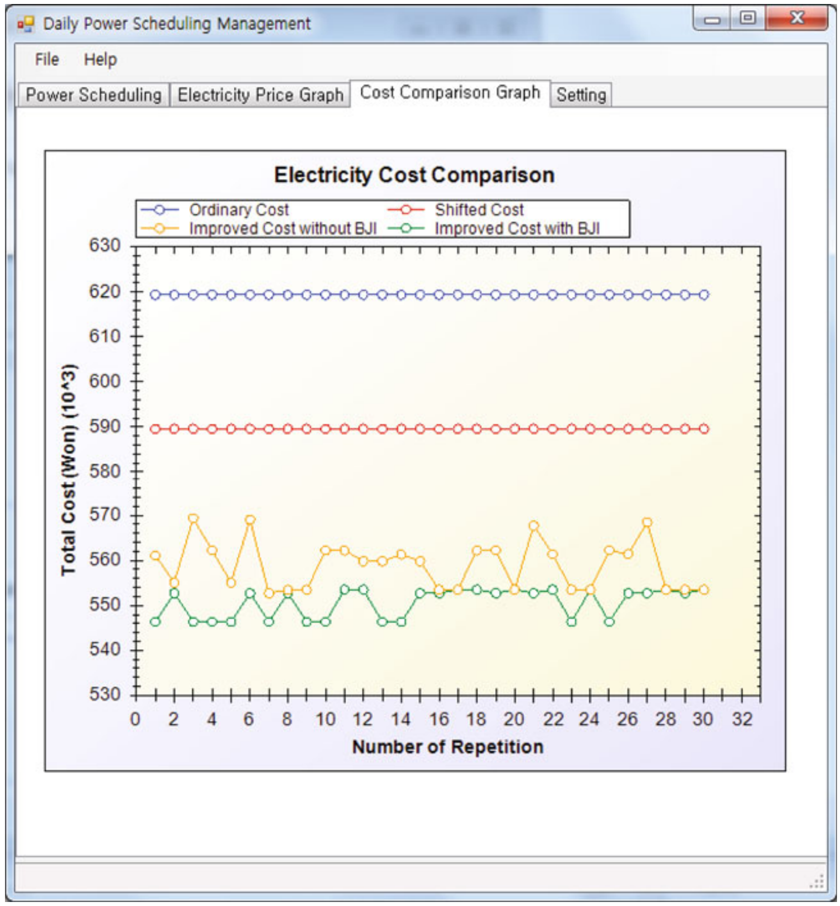
Table 4 Job processing time for scenario no. 1 (hours)

	Job 1	Job 2	Job 3	Job 4	Job 5
M/C 1	6	5	8	3	9
M/C 2	4	3	5	1	5

Table 5 Power consumption data for scenario no. 1

	M/C 1	M/C 2
Power consumption (kWh)	100	250

Fig. 8 Comparison chart of electricity costs for scenario no. 1



Equation 1 shows the relationships between the decision variables and the processing time. Inequality (2) ensures that the completion time of each machine is less than or equal to the makespan. Equation 3 calculates the total electricity cost. Equations 4 and 5 ensure that all jobs are processed during the available time. Equation 6 ensures that all jobs are assigned to a machine. This formulation can be solved in a mixed integer linear programming solver such as CPLEX. However, given that the problem is NP-hard, we cannot solve the problem efficiently in a short time. Therefore, a modified genetic algorithm is proposed in the next section.

Table 6 Job processing time for scenario no. 2 (hours)

	Job 1	Job 2	Job 3	Job 4	Job 5	Job 6
M/C 1	6	5	8	3	9	5
M/C 2	4	3	5	1	5	2
M/C 2	6	5	6	3	7	5

4 Hybrid inserted genetic algorithm

We can solve this unrelated parallel machine scheduling problem with an ordinary genetic algorithm (GA). We can also shift or change the start time to obtain better schedule with a shifted GA (SGA).

For time-dependent electricity costs, it is necessary to consider the idling time or blank job insertion to avoid a high electricity cost. Therefore, we need to modify the gene structure to insert idling time when using the genetic algorithm. The modified gene structure consists of one pair of genes. The first gene represents the job sequence and the second gene represents the starting time in the first location and number of blank jobs to be inserted after each job in the other locations. We can solve our unrelated parallel machine

Table 7 Power consumption data for scenario no. 2

	M/C 1	M/C 2	M/C 3
Power consumption (kWh)	100	250	120

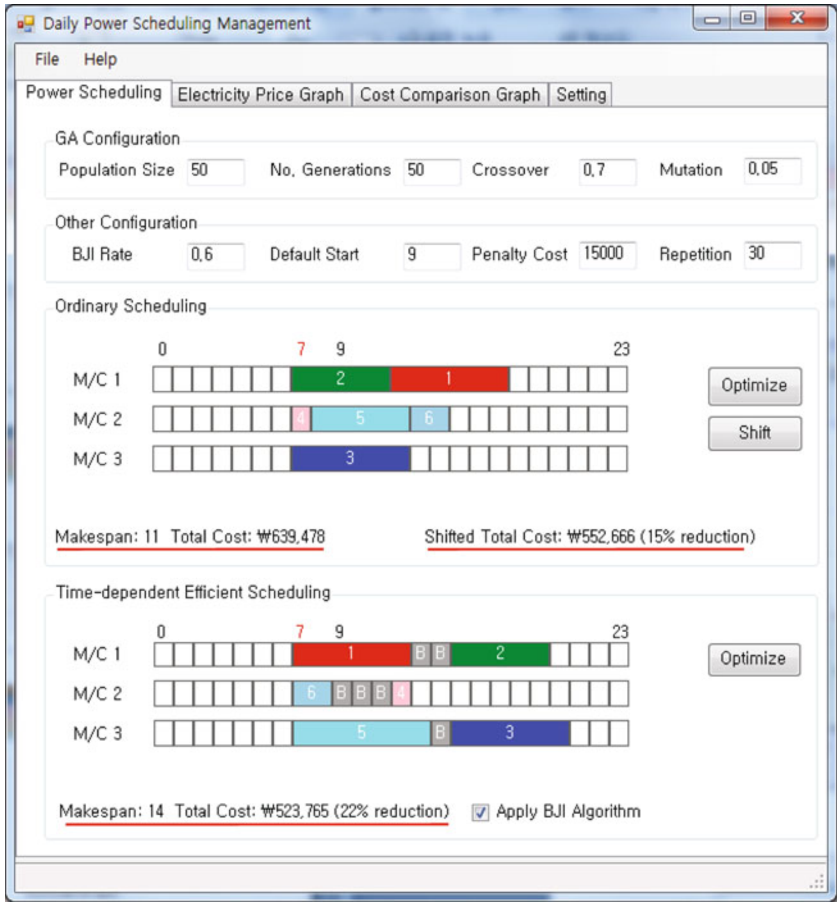


Fig. 9 Finding the optimal solution for scenario no. 2

scheduling problem by using the inserted GA (IGA) with a modified gene structure.

Our new blank job insertion (BJI) algorithm was developed to obtain an improved solution. In addition, our hybrid inserted genetic algorithm (HIGA) with the BJI algorithm was applied to the scheduling problem to improve its solution.

4.1 Genetic algorithm

The GA has been used by numerous researchers in many areas. The GA is very popular and well known. It has been used to solve many combinatorial problems, including scheduling problems. In a GA, the first population of solutions is initialized; after which, it is transferred to next generation with improved quality. A population of solutions for each generation is maintained, and its evolutions arise whenever each generation changes. The evolutions are created through crossover and mutation via some probability. In addition, the fitness values are estimated, and the best offspring is selected. With a roulette wheel selection method, this algorithm reproduces a new generation through competition. To find a more feasible solution, we repeat the same procedure until the stopping criterion is satisfied. We can use stopping criteria such as the elapsed time, the number of generations, and the difference of the best solutions between two consecutive generations.

The procedure of the proposed genetic algorithms can be outlined as shown below.

Genetic algorithm procedure

Generate an initial population
Repeat
  Select two parents from the population using tournaments
  Produce two children from the parents using crossover
  Mutate the children
  Evaluate fitness of the children
  Choose the best child
  If *entry criteria are satisfied by the chosen child*
    Choose population member to be replaced
    The child enters into population
  End if
Until *stopping criterion is satisfied*

Fig. 10 Comparison chart of electricity costs for scenario no. 2

Table 1 shows the example of job processing time for each job, and as you see in this table, two machines have different processing times for a same job, which means that they have different capabilities or performance levels for processing the same job.

Figure 1 shows gene representation (or coding) and converting to the equivalent Gantt chart by earliest completion time first (ECT) rule. If we find the best solution of gene representation, we finally get the best schedule which is represented as a Gantt chart.

4.1.1 Crossover

According to Shi [22], crossover is a significant genetic operation for information exchange between chromosomes. For ordering problems such as scheduling problems and traveling salesman problems, crossover is the most difficult operation to design for improved GA performance. From two randomly selected parents, two crossover positions are also selected randomly, and the substrings in the middle are exchanged to make the child offspring. At this time, in each child offspring, several numbers may be identical. To remove replications and supplement these, if two replicated numbers are found, two random numbers are generated to determine the order of two numbers and each missing number is filled with one of the numbers. If another replication is found, the above procedure is repeated until no replication occur.

4.1.2 Mutation

Mutation is an operation that searches the local neighborhood for a better solution. In this study, swapping between two randomly selected points for a selected gene with a certain probability is used to implement a mutation operation.

4.1.3 Fitness and reproduction

The fitness values of the offsprings in the same population are estimated. The best offspring, which has the minimum value, is stored as the best solution in the generation. Subsequently, the next generation is reproduced by a selection method. After ranking all of the genomes by fitness, we use a roulette wheel selection method. This allocates a large probability of the selection to those with the highest level of fitness.

4.2 Shifted genetic algorithm

Figure 2 shows a flowchart of the SGA procedure. The SGA is the algorithm to adjust the available starting time of the production to obtain a better solution than that of the GA.

4.3 Inserted genetic algorithm

The modified gene structure consists of one pair of genes. The first gene represents the job sequence. According to the job sequence and the ECT rule, a corresponding Gantt chart is made. In addition, the second gene represents the starting time in the first position and the number of unit blank jobs to be inserted after each job in the other positions. The IGA is executed under the same conditions used with the GA or the SGA apart from the gene structure. Due to the complex gene structure shown in Fig. 3, crossover and mutation operations of the IGA are more complicated than those of the GA or SGA.

4.4 Blank job insertion algorithm

With the BJI algorithm, the idling times are inserted into the Gantt chart with some probability of the inserted positions based on the ranking of the electricity cost. This algorithm continues to search for a solution with a better fitness value until the due date.

BJI algorithm

```
Set starting_time to 0
Set makespan to old_makespan
Set objective value to old_objective_value
Set due date to due_date
While( starting_time < due_date - old_makespan)
    new_makespan=old_makespan
    new_objective_value=old_objective_value
    While(new_makespan < due_date) do
      Calculate probability for the position
         for inserting
      Select the position randomly
         by using the probability
      Insert an unit blank job into the position
      Calculate new makespan and set it
         to new_makespan
      Calculate new objective value and set it
      Save the solution with the best_objective_value
    End While
    starting_time = starting_time + 1
End While
```

In Table 2, example data of the cost ranking and the probability for the BJI algorithm are given. First, the probabilities of each available position are calculated. If some position is selected with its probability, a blank job (or 1 time unit idling time) is inserted into the position. Figure 4 shows the procedure involving the Gantt chart.

4.5 Hybrid inserted genetic algorithm

The proposed HIGA combines the IGA and the BJI algorithm. Figure 5 shows a flow chart of the HIGA. The advantage of the proposed algorithm is that it avoids the local minima and strengthens the global search ability. Of course, the disadvantage would be the computational time.

5 Simulation results

Our problem sets consisted of five jobs and two machines, and six jobs and three machines for two scenarios. The jobs had different processing times for each machine with different power consumption levels (Fig. 6). The current hourly electricity price for the peak-load, the mid-load, and the off-peak-load were used as the input data. The data of industrial electricity price in Table 3 were from the Korea Electric Power Corporation in South Korea. We developed a UI application to test our algorithms and show our simulation result in C#. This was executed on a Pentium 2.4 GHz PC. The problems were solved using a simple GA, the SGA, the IGA, and the HIGA. According to our result, the total cost after applying the SGA was lower than that after applying simple GA only. Moreover, we noted from the result that the total cost after applying the HIGA was reduced by more than 10 % compared to that of the simple GA

- Population size, 50; number of generations, 50; crossover rate, 0.7; mutation rate, 0.05.
- BJI rate, 0.6; default start time, 9; available start time, 7; due time, 23; number of repetition, 30.

Also, we assume that penalty cost (or labor charge for each extended hour) was 15,000 won/h.

Scenario no. 1 Figure 7 shows the data input for scenario no. 1.

- We had 5-job and 2-machine problem to solve (Table 4).
- The power consumptions for each machine were 100 and 250 kWh, respectively (Table 5).

Result of scenario no. 1 Figure 7 shows the screen of configuration data input and resulting Gantt charts for scenario no. 1. It also shows the makespan and the total cost for each method. In Fig. 8, the screen displays the graph for comparing four methods.

- SGA reduced the total cost by 5 % compared to that of the simple GA.
- HIGA reduced the total cost by 13 % compared to that of the simple GA.

Scenario no. 2 Tables 6 and 7 show the data input for scenario no. 2.

- We had 6-job and 3-machine problem to solve.
- The power consumptions for each machine are 100, 250, and 120 kWh, respectively.

Result of scenario no. 2 Figure 9 shows the screen of configuration data input and resulting Gantt charts for scenario no. 2. It also shows the makespan and total cost for each method. In Fig. 10, the screen displays the graph for comparing 4 methods.

- SGA reduced the total cost by 15 % compared to that of the simple GA.
- HIGA reduced the total cost by 22 % compared to that of the simple GA.

In addition, we solved 24 instances by using four algorithms for summer and winter, respectively. Table 8 shows the simulation result for the electricity price of summer season, and Table 9 shows the result for the electricity of winter season. We compared four genetic algorithms in the tables.

Analysis

- According to our simulation, the simple GA and the SGA model are limited in terms of their ability to improve their solutions because they do not allow for any inserted blank job (or idling time) at times of high electricity costs.
- However, we noted that IGA and HIGA model improve their solutions by allowing the appropriate insertion of blank jobs (or idling times).
- Moreover, by adding the BJI algorithm, the simulation shows that HIGA improves the solution in a superior manner compared to the IGA.

Table 8 Comparison of total costs after 20 trials for the electricity price of summer season, where the numbers in parentheses denote the reduction rate compared with GA

M/C	Jobs	Minimal total cost (won)				Average total cost (won)	
		GA	SGA	IGA	HIGA	IGA	HIGA
3	6	655,547	562,101 (14 %)	529,694 (19 %)	522,866 (20 %)	551,590 (15 %)	528,509 (19 %)
3	8	809,943	749,866 (7 %)	657,336 (18 %)	648,142 (19 %)	683,004 (15 %)	679,330 (16 %)
3	10	953,797	922,195 (3 %)	745,892 (21 %)	738,416 (22 %)	761,802 (20 %)	762,823 (20 %)
3	12	1,039,823	996,771 (4 %)	940,102 (9 %)	925,574 (10 %)	970,747 (6 %)	971,277 (6 %)
5	12	518,385	418,105 (19 %)	414,700 (20 %)	404,485 (21 %)	437,540 (15 %)	408,571 (21 %)
5	15	663,020	569,550 (14 %)	542,555 (18 %)	537,770 (18 %)	563,832 (14 %)	549,950 (17 %)
5	18	728,850	649,000 (10 %)	603,770 (17 %)	590,960 (18 %)	624,107 (14 %)	621,863 (14 %)
5	20	840,570	794,770 (5 %)	676,245 (19 %)	676,950 (19 %)	715,186 (14 %)	708,347 (15 %)
8	20	844,405	681,420 (19 %)	703,260 (16 %)	662,555 (21 %)	733,160 (13 %)	664,568 (21 %)
8	25	1,001,310	855,350 (14 %)	821,460 (17 %)	827,545 (17 %)	860,475 (14 %)	843,970 (15 %)
8	30	1,272,145	1,163,640 (8 %)	1,025,175 (19 %)	1,000,375 (21 %)	1,074,684 (15 %)	1,076,384 (15 %)
10	20	704,095	523,965 (25 %)	547,645 (22 %)	500,130 (28 %)	607,959 (13 %)	508,546 (27 %)
10	25	901,155	693,785 (23 %)	723,845 (19 %)	683,570 (24 %)	769,658 (14 %)	691,252 (23 %)
10	30	1,140,485	946,735 (16 %)	929,910 (18 %)	904,740 (20 %)	974,093 (14 %)	936,721 (17 %)
15	30	1,163,675	924,125 (20 %)	952,640 (18 %)	886,670 (23 %)	992,885 (14 %)	906,566 (22 %)
15	35	1,417,915	1,154,530 (18 %)	1,126,305 (20 %)	1,105,865 (22 %)	1,193,349 (15 %)	1,136,916 (19 %)
15	40	1,618,870	1,355,485 (16 %)	1,330,655 (17 %)	1,293,060 (20 %)	1,391,586 (14 %)	1,335,225 (17 %)
15	45	1,861,790	1,598,405 (14 %)	1,506,690 (19 %)	1,492,850 (19 %)	1,573,470 (15 %)	1,550,855 (16 %)
15	50	1,982,100	1,728,930 (12 %)	1,630,305 (17 %)	1,593,805 (19 %)	1,711,778 (13 %)	1,712,865 (13 %)
20	45	1,772,065	1,418,615 (19 %)	1,466,465 (17 %)	1,392,480 (21 %)	1,538,514 (13 %)	1,445,007 (18 %)
20	50	2,024,035	1,697,825 (16 %)	1,655,940 (18 %)	1,625,185 (19 %)	1,725,274 (14 %)	1,678,548 (17 %)
20	55	2,297,600	1,954,365 (14 %)	1,856,975 (19 %)	1,838,595 (19 %)	1,944,556 (15 %)	1,899,613 (17 %)
20	60	2,436,100	2,075,840 (14 %)	1,830,940 (24 %)	1,813,555 (25 %)	2,015,037 (17 %)	2,007,455 (17 %)
20	65	2,656,320	2,330,110 (12 %)	2,121,400 (20 %)	2,112,330 (20 %)	2,244,360 (15 %)	2,253,884 (15 %)

Table 9 Comparison of total costs after 20 trials for the electricity price of winter season, where the numbers in parentheses denote the reduction rate compared with GA

M/C	Jobs	Minimal total cost (won)				Average total cost (won)	
		GA	SGA	IGA	HIGA	IGA	HIGA
3	6	562,124	516,406 (8 %)	493,056 (12 %)	493,056 (12 %)	501,880 (10 %)	493,056 (12 %)
3	8	726,283	673,560 (7 %)	661,885 (8 %)	661,885 (8 %)	667,022 (8 %)	661,885 (8 %)
3	10	904,177	855,525 (5 %)	777,588 (14 %)	755,398 (16 %)	799,901 (11 %)	798,626 (11 %)
3	12	977,313	940,935 (3 %)	937,816 (4 %)	937,816 (4 %)	942,759 (3 %)	939,912 (3 %)
5	12	446,420	407,720 (8 %)	389,040 (12 %)	389,040 (12 %)	401,250 (10 %)	390,395 (12 %)
5	15	559,560	511,520 (8 %)	489,850 (12 %)	480,970 (14 %)	503,101 (10 %)	488,036 (12 %)
5	18	619,650	557,600 (10 %)	556,255 (10 %)	534,250 (13 %)	570,804 (7 %)	541,465 (12 %)
5	20	753,150	688,765 (8 %)	680,875 (9 %)	676,665 (10 %)	691,161 (8 %)	681,341 (9 %)
8	18	627,870	552,740 (11 %)	536,930 (14 %)	522,385 (16 %)	550,952 (12 %)	529,544 (15 %)
8	20	725,550	659,760 (9 %)	612,640 (15 %)	615,435 (15 %)	644,581 (11 %)	630,854 (13 %)
8	25	852,935	770,800 (9 %)	752,485 (11 %)	718,150 (15 %)	776,233 (8 %)	740,327 (13 %)
8	30	1,112,145	1,020,670 (8 %)	988,995 (11 %)	968,400 (12 %)	1,006,784 (9 %)	983,415 (11 %)
10	20	650,760	545,340 (16 %)	513,195 (21 %)	495,990 (23 %)	545,645 (16 %)	519,717 (20 %)
10	25	781,760	699,690 (10 %)	648,360 (17 %)	640,215 (18 %)	686,481 (12 %)	658,769 (15 %)
10	30	962,060	875,320 (9 %)	851,320 (11 %)	814,250 (15 %)	869,796 (9 %)	838,061 (12 %)
10	35	1,112,335	997,575 (10 %)	985,805 (11 %)	955,640 (14 %)	1,021,269 (8 %)	978,926 (11 %)
15	35	1,245,145	1,117,370 (10 %)	1,049,040 (15 %)	1,014,595 (18 %)	1,083,609 (12 %)	1,047,248 (15 %)
15	40	1,391,430	1,261,320 (9 %)	1,222,275 (12 %)	1,195,605 (14 %)	1,258,116 (9 %)	1,228,092 (11 %)
15	45	1,590,720	1,446,600 (9 %)	1,392,010 (12 %)	1,374,435 (13 %)	1,444,352 (9 %)	1,407,602 (11 %)
15	50	1,808,475	1,659,685 (8 %)	1,528,370 (15 %)	1,525,610 (15 %)	1,605,122 (11 %)	1,600,037 (11 %)
20	45	1,574,820	1,373,320 (12 %)	1,307,265 (16 %)	1,294,740 (17 %)	1,360,114 (13 %)	1,334,057 (15 %)
20	50	1,732,815	1,575,680 (9 %)	1,495,315 (13 %)	1,479,455 (14 %)	1,548,861 (10 %)	1,513,133 (12 %)
20	55	1,930,225	1,742,735 (9 %)	1,692,965 (12 %)	1,636,515 (15 %)	1,729,219 (10 %)	1,692,961 (12 %)
20	60	2,113,880	1,910,045 (9 %)	1,852,855 (12 %)	1,827,825 (13 %)	1,915,277 (9 %)	1,874,393 (11 %)

6 Conclusion

Manufacturing industries, especially in South Korea, need to consider their scheduling setups while taking into account time-dependent and machine-dependent electricity costs. Solving the scheduling problem can reduce costs, save energy, and reduce greenhouse gas emissions. In this paper, we proposed a hybrid genetic algorithm to solve the unrelated parallel machine problem with the same due date and inserted idling times. A lot of instances of unrelated parallel machine scheduling problems were tested. It was found that the Hybrid Inserted GA reduces total electricity costs.

In our next study, we plan to work on a flexible job shop scheduling problem. With many operations, these problems have much larger applicability than parallel machine problems and are therefore more realistic and complex. We also intend to adopt finer time slots for the processing time. In addition, we are thinking of expanding our area of study to smart grid environments, in which electricity usage and costs have many diverse options, including distributed energy resources and renewables such as solar and wind power.

Acknowledgments We would like to thank the anonymous reviewers for helping us clarify this paper through their useful comments. We would like to acknowledge the support of the Automation and Systems Research Institute in Seoul National University in the form of resources and administrative support.

References

1. Garey MR, Johnson DS (1979) Computers and intractability: a guide to the theory of NP-completeness. WH Freeman and Company, San Francisco
2. Balin S (2011) Non-identical parallel machine scheduling using genetic algorithm. Expert Syst Appl 38:6814–6821
3. Moon JY, Na H, Choi BK, Park J (2011) Modeling and optimization of unrelated parall machine scheduling problem with time-dependent and machine-dependent electricity cost. In: APMS 2011 international conference, Stavanger (Norway), pp 26–28

4. Cheng TCE, Ding Q, Lin BMT (2004) A concise survey of scheduling with time-dependent processing times. Eur J Oper Res 152:1–13
5. Alidaee B, Womer NK (1999) Scheduling with time dependent processing times: review and extensions. J Oper Res Soc 50:711–720
6. Nilsson K, Soderstrom M (1993) Industrial applications of production planning with optimal electricity demand. Appl Energy 46(2):181–192
7. Nilsson K (1993) Industrial production planning with optimal electricity cost. Energy Convers Manage 34(3):153–158
8. Castro PM, Harjunkoski I, Grossmann IE (2009) New continuous-time scheduling formulation for continuous plants under variable electricity cost. Ind Eng Chem Res 48:6701–6714
9. Yusta JM, Torres F, Khodr HM (2010) Optimal methodology for a machining process scheduling in spot electricity markets. Energy Convers Manage 51:2647–2654
10. Ghobeity A, Mitsos A (2010) Optimal time-dependent operation of seawater reverse osmosis. Desalination 263:76–88
11. Chen CL, Chen CL (2009) Hybrid metaheuristics for unrelated parallel machine scheduling with sequence-dependent setup times. Int J Adv Manuf Technol 43:161–169
12. Chen J (2009) Scheduling on unrelated parallel machines with sequence- and machine-dependent setup times and due-date constraints. Int J Adv Manuf Technols 44:1204–1212
13. Kim DW, Kim KH, Jang W, Chen FF (2002) Unrelated parallel machine scheduling with setup times using simulated annealing. Rob Comput Integr Manuf 18:223–231
14. Hsieh JC, Chang PC, Hsu LC (2003) Scheduling of drilling operations in printed circuit board factory. Comput Ind Eng 44:461–473
15. Lee CY (1991) Parallel machine scheduling with non simultaneous machine available time. Discrete Appl Math 30:53–61
16. Schmidt G (2000) Scheduling with limited machine availability. Eur J Oper Res 121:1–15
17. Liao CJ, Shyur DL, Lin CH (2005) Makespan minimization for two parallel machines with an availability constraint. Eur J Oper Res 160:445–456
18. Berrichi A, Amodeo L, Yalaoui F et al (2009) Bi-objective optimization algorithms for joint production and maintenance scheduling: application to the parallel machine problem. J Intell Manuf 20:389–400
19. Vallada E, Ruiz R (2011) A genetic algorithm for the unrelated parallel machine scheduling problem with sequence dependent setup times. Eur J Oper Res 211:612–622
20. Pan JC, Huang H (2008) A hybrid genetic algorithm for no-wait job shop scheduling problems. Expert Syst Appl 36:5800–5806
21. Gao J, Sun L, Gen M (2008) A hybrid genetic and variable neighborhood descent algorithm for flexible job shop scheduling problems. Comput Oper Res 35:2892–2907
22. Shi G (1997) A genetic algorithm applied to a classic job-shop scheduling problem. Int J Syst Sci 28:25–32