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Many countries are actively trying to cope with recent effects of climate change and the energy crisis. At the same time, efficient energy use and the reduction of greenhouse gas emissions are very important, not only to reduce energy costs but also to contribute to an environment-friendly, sustainable lifestyle. Currently, manufacturing industries in some countries pay stratified electricity rates that depend on the time of the day (i.e. peak load, mid-load and off-peak load). Hence, the production scheduling process, which considers time-dependent and machine-dependent electricity costs, enables these industries to minimise energy expenses. Additionally, the emerging Smart Grid is supposed to require industries to pay real-time hourly electricity costs. More energy-efficient, intelligent production scheduling is thus a major goal. This paper deals with minimising the total production cost of the flexible job-shop scheduling problem. Our method allows each decision-maker in the manufacturing industry to seek a compromise solution for total production costs, by considering electricity costs with distributed energy resources and energy storage. We use constraint programming and mixed-integer programming approaches to solve this problem, and compare our proposed models with the classical computational method.

Keywords: production scheduling; flexible job-shop scheduling; energy efficiency; Smart Grid; distributed energy resources; energy storage

1. Introduction

Most developed countries around the world are seriously concerned about recent global warming, the depletion of fossil fuels and environmental degradation. Accordingly, effective energy use and reduction of greenhouse gas (GHG) emissions are becoming increasingly important goals. For this reason, manufacturing companies are investing considerable efforts in the field of energy savings.

Electricity rates for manufacturing industries in many countries depend on the time of the day. Such differential rates are referred to as time-of-use (TOU) rates. In the Republic of Korea, there are three time zones (i.e. peak load, mid-load and off-peak load) for industry, and the peak-load price is almost three times the off-peak-load price. The daily electricity rates in Figure 1 were obtained from the Korea Electricity Power Corporation website (http://cyber.kepco.co.kr). Sooner or later, if critical peak pricing (CPP) rates are applied to industry, the peak-load price should be approximately eight times the off-peak-load price. Accordingly, efficient energy use by industry will be required to save energy and reduce energy costs. Figure 1 shows daily electricity TOU and CPP pricing.

In the Smart Grid environment, efficient energy use will be a very important issue for economic production, since the Smart Grid introduces fluctuating real-time electricity pricing. Demand-side management for efficient energy use, which can help reduce peak load and adapt elastic demand to fluctuating electricity price and generation, will be a key component of future Smart Grid (Li, Chen, and Low 2011). Manufacturing companies can minimise costs by implementing demand-side management for their production scheduling, considering time-dependent electricity costs.

In the manufacturing industry, many scheduling problems are focused on minimising makespan (or maximal completion time) in an effort to reduce production costs. Although two scheduling solutions can have the same makespan, they may have different electricity costs. Additionally, even if the makespan of one scheduling solution is slightly longer than that of other solutions, avoiding operations at peak-load time, or on a machine that consumes more power, can reduce total production costs. In the production scheduling literature, it is assumed that production costs for a specific time-period on the same machine do not differ at different times. However, electricity costs for production depend on the time of day and on the power consumed for each process by the specific machine. In other words, economic production scheduling for manufacturing companies relies not only on time-dependent electricity costs but also on machine-dependent electricity costs.

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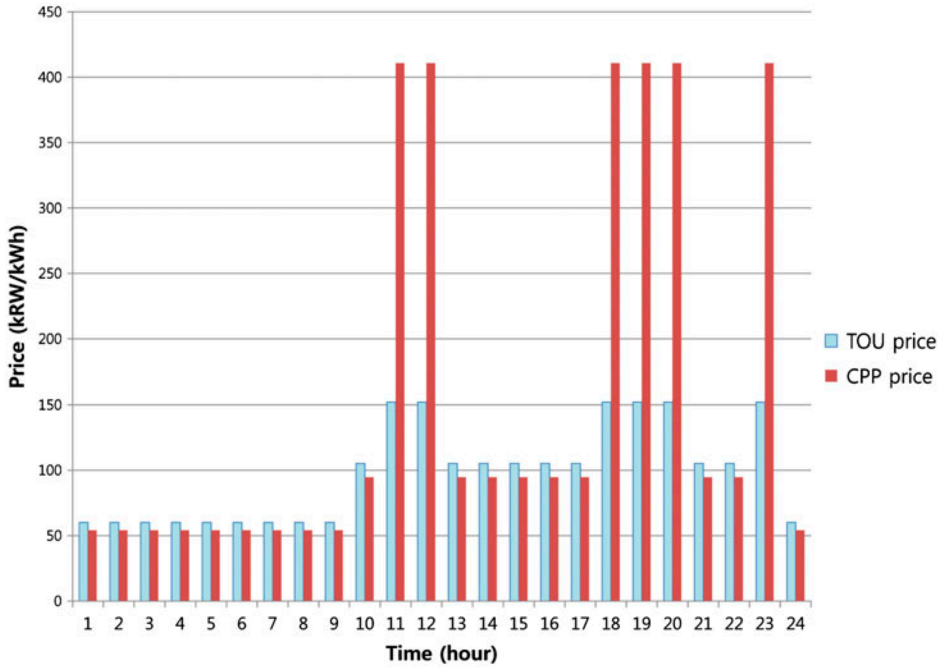

Figure 1. Daily electricity TOU and CPP pricing for winter.

Numerous studies have attempted to solve the scheduling problem by allocating limited resources according to objectives and constraints. Distributed energy resources (DERs), such as photovoltaics, wind turbines, fuel cells and energy storage systems (ESSs), are expected to play an important role in future electricity supply and in a low-carbon economy (Moghaddam et al. 2011; Sanseverino et al. 2011). For this reason, by considering time-dependent and machine-dependent electricity costs with DERs, manufacturing industries can significantly reduce their expenses, by finding an optimal solution based on economic considerations. The integration of DERs with conventional centralised grid (or Macro Grid) will make manufacturing more reliable and more efficient. Optimal operation management of production scheduling with the scheduling of DERs is an important research issue, and solving this issue will be of immense benefit to manufacturing industries.

In this paper, we define smart production scheduling as an energy-efficient, intelligent production scheduling that is integrated with optimal operation management of energy sources. It minimises not only production costs but also the costs for purchasing electricity, generating energy and charging/discharging energy storage. Smart production scheduling finds an optimal solution for production schedule and energy schedule in order to minimise total production-related costs and energy costs either in the current environment or in the Smart Grid environment.

Most production scheduling problems, including the job-shop scheduling problem (JSP), are classified as Non-deterministic Polynomial-time hard (NP-hard) problems (Garey, Johnson, and Sethi 1976; Garey and Johnson 1979). Because of the complexity of the flexible job-shop scheduling problem (FJSP), researchers usually adopt a heuristic algorithm that finds a near-optimal solution in reasonable time, instead of finding an optimal solution (Pazzella, Morganti, and Ciaschetti 2007). Therefore, efforts have been directed to designing fast and efficient heuristic algorithms that exhibit good performance levels.

In this paper, we introduce two FJSP models which consider electricity costs. The first one is an FJSP model in which time-dependent and machine-dependent electricity costs are considered. Its objective is to minimise the sum of production costs related to makespan, as well as total electricity costs. The second is an FJSP model in which electricity costs are considered, with the optimal operation management of DERs and energy storage. Its objective is to minimise the sum of production costs related to makespan, and total electricity costs (including the costs of DERs and ESS).

Few studies have been conducted to solve such problems in which production scheduling and time-dependent and machine-dependent electricity costs are integrated. Our previous research (Moon et al. 2011) dealt with the unrelated parallel machine problem, by considering time-dependent and machine-dependent hourly electricity costs. The problem was solved using a hybrid inserted genetic algorithm (HIGA). The results showed that manufacturing industries can reduce their costs by finding an optimal schedule by considering time-dependent and machine-dependent electricity costs. In this study, we extend the previous research, thus considering scheduling of distributed generations (DGs), including DERs and ESS, as well as FJSP scheduling. The mixed-integer programming (MIP) and constraint programming (CP) approaches are proposed for solving our problems.

The paper is organised as follows. Section 2 provides a review of relevant literature on this subject. In Section 3, we give the definition and formulation of our problem. Section 4 presents the test data, obtained results and their analysis. Finally, Section 5 is devoted to the conclusion and recommendation for future studies.

2. Literature review

There is substantial research concerning FJSP. Most studies solved the FJSP using a metaheuristic, such as genetic algorithms, particle swarm optimisation, simulated annealing, etc. Pazzella, Morganti, and Ciaschetti (2007) suggested a genetic algorithm integrated with new strategies for generating the initial population, in order to find a near-optimal solution to the FJSP in reasonable time, instead of finding an optimal solution. Gao et al. (2007) solved the multi-objective FJSP using a new approach, hybridising a genetic algorithm with a variable neighbourhood descent algorithm. Objectives of the study were focused on makespan, maximal machine workload and total workload. By hybridising particle swarm optimisation as a global search, and simulated annealing as a local search, Xia and Wu (2005) also developed a hybrid approach for the multi-objective FJSP. Moradi et al. (2011) attempted to simultaneously minimise two objectives of the makespan for the production part, and the system unavailability for the maintenance part, by using a hybrid genetic algorithm.

The coordination of generating electricity and scheduling manufacturing operations to minimise total cost is quite challenging. Research on this issue has yet to mature. Cheng, Ding, and Lin (2004) considered a class of machine scheduling problems in which the processing time of a task was dependent on its start time in a schedule. Alidaee and Womer (1999) also presented a review of scheduling problems with time-dependent processing times. The review focused on real-life situations in financial management, steel production, resource allocation, maintenance scheduling and national defense. Our research deals with fixed but different processing times for each machine. The costs of our production scheduling problem thus depend on machine and time-zone.

Achuthan and Hardjawidjaja (2001) suggested project scheduling with time-dependent cost structure for each activity. In real-life projects, the planning horizon of some projects extends over three to five years. Therefore, the underlying cost components in such projects change significantly during this long execution period. The planning horizon is divided into several regular time intervals, such as months or quarters. Subsequently, the authors define both the fixed and variable costs as functions of these intervals. The project scheduling process considered variable costs over months or quarters. However, we handle production scheduling with hourly variable electricity costs during a 1-day 24-hour period. In addition, we suggest models integrated with energy scheduling for DERs and ESS.

Yusta, Torres, and Khodr (2010) formulated a mathematical optimisation model that simulated electricity costs and demand of a machining process to determine the optimum production schedule that maximises industry profit by considering hourly variations of the price of electricity on the spot market. Nilsson and Soderstrom (1993) studied the influence of electricity cost on industrial production scheduling. According to them, it is profitable for consumers to shift their electricity demand to periods with low rates, because industrial electricity subscriptions usually include a differentiated tariff, with a high rate during daytime and a low rate during nighttime and weekends. The differentiation implies an opportunity to shift electricity demand to time periods with a lower electricity price, thereby allowing consumers to save money. The electricity producer may also benefit when peaks in the electricity demand are removed (Nilsson 1993). Castro, Harjunkoski, and Grossmann (2009) studied the modelling of continuous plants with a continuous time scheduling formulation that could effectively handle time-dependent electricity cost and availability. In their work, they considered the influence of the differentiation of the electricity tariff on the production schedule, with optimal electricity cost used to reduce overall energy expense. Ghobeity and Mitsos (2010) studied operational cost-saving methods in reverse osmosis via time-dependent optimisation. They optimised the operation of seawater reverse osmosis with the objective of reducing electricity charges, with the latter constituting the largest portion of operational costs. They suggested that their results showed significant electricity and production cost-saving potential, by establishing an optimal operational plan.

Our study deals with production scheduling with respect to time-dependent and machine-dependent electricity costs. We also integrate these with optimal operation management of DGs and ESS for efficient energy scheduling. We suggest that finding an optimal solution for the model could allow manufacturers to save energy and reduce GHG emissions. To date, no research about such an integrated model could be located.

3. Problem definition and modelling

The FJSP considering electricity costs can be formulated as follows. There is a set of n jobs and a set of m machines. Each job consists of a predetermined sequence of operations. Each operation requires a machine selected out of a set of available machines. The FJSP sets its starting and ending times on each machine. Thus, the FJSP has to solve two subproblems: determining the machine assignment for each operation and determining the operation sequence for each machine. However, the FJSP is more complex and challenging than the classical job-shop scheduling problem because it requires the proper selection of a machine from a set of available machines to process each operation of each job (Ho et al. 2007).

A manufacturing company has machines that perform the same function or different functions 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 can operate under three different electricity rates (peak load, mid-load and off-peak load) depending on the time of the day. Inserting idling times during peak-load times are necessary to avoid high electricity cost. We assume that idling times entail no electricity cost. However, an increase in the makespan (or the total number of operating hours) incurs excessive overtime costs. We suggest two models to optimise the operation management for production scheduling problem considering differential electricity pricing and DGs including ESS. One of our objectives is to minimise the sum of the makespan multiplied by the penalty cost (or the overtime cost) and the total electricity cost. In addition, the manufacturing company can save energy by discharging batteries of energy storage systems during peak time and charging batteries during off-peak time. Therefore, the other objective is to minimise the sum of the makespan multiplied by the penalty cost, the total electricity cost and the total generation cost of DGs including the operation cost of ESS.

Assumptions

The assumptions of our problem are as follows:

(1) All machines are available at a given starting time.
(2) All jobs are released at a given starting time.
(3) Each machine can process only one operation at a time.
(4) Each operation can be processed without interruption on one of a set of available machines.
(5) The order of operations for each job is predefined and cannot be modified.
(6) Electricity cost for production on each machine is zero during idling times.
(7) All jobs are scheduled during 1 day (24 h) with a 1-day-ahead electricity price.
(8) The total cost for production is the sum of the makespan-related cost and the total electricity cost.
(9) The total electricity cost is the purchase costs from the utility company, the generation costs from generators and the battery operation cost from the energy storage system.

Parameters

The following parameters are used:

n number of jobs,
m number of machines,
h_j number of operations for each job j for $j = 1, \dots, n$,
ng number of generators,
pct penalty cost,
L a large number,
$p_{i,j,h}$ processing time (hour) of operation $O_{j,h}$ if performed on machine i for $i = 1, \dots, m$, $j = 1, \dots, n$, $h = 1, \dots, h_j$,
$a_{i,j,h}$ $= \begin{cases} 1 & \text{if } O_{j,h} \text{ can be performed on machine } i, \\ 0 & \text{otherwise,} \end{cases}$ for $i = 1, \dots, m$, $j = 1, \dots, n$, $h = 1, \dots, h_j$,
e_l hourly electricity price (KRW), $l = 0, \dots, T-1$,
c_i power consumption (kWh), $i = 1, \dots, m$,
T length of the time horizon,
$BMax$ energy storage capacity,
$GMax_v$ maximum output of generator v, $v = 1, \dots, ng$,
$GMin_v$ minimum output of generator v, $v = 1, \dots, ng$,
$CBat$ operating cost per kilowatt hour of batteries,
$InitBat$ initial amount of energy storage,
DoD maximal affordable depth of charge,
$GenQ_{v,l}$ power quantity of generator v at time l, $v = 1, \dots, ng$, $l = 0, \dots, T-1$,

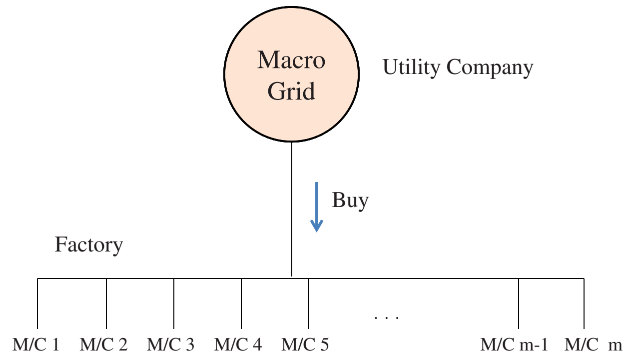

Figure 2. Structure of model I.

$PwrDmd_l$	total power consumption of all machines at time l, $l = 0, \dots, T-1$,
$PwrBat_l$	discharging amount of energy storage at time l, $l = 0, \dots, T-1$,
$GCost_{v,l}$	generation cost of generator v at time l, $v = 1, \dots, ng$, $l = 0, \dots, T-1$, and
$MkSp$	makespan (or maximal completion time) after production scheduling.

Decision variables
The following decision variables are used:

C_{max}	makespan or maximal completion time,
PC	production-related cost,
EC	electricity cost for buying power from grid,
DGC	total cost of distributed generations and energy storage,
$t_{j,h}$	start time of the processing of operation $O_{j,h}$,
k_i	number of operations assigned to machine i,
$TM_{i,k}$	start working time for machine i in priority k,
$PS_{j,h}$	processing time of operation $O_{j,h}$ after selecting a machine,
SOC_l	amount of energy stored in ESS at time l, $l = 0, \dots, T-1$,
$PBat_l$	charged or discharged amount of storage at time l, $l = 0, \dots, T-1$,
$GQTY_{v,l}$	power quantity of generator v at time t, $v = 1, \dots, ng$, $l = 0, \dots, T-1$,
$z_{i,j,h}$	number of one-unit idling jobs to be inserted before operation $O_{j,h}$ on machine i,

$$x_{i,j,h,k} = \begin{cases} 1 & \text{if } O_{j,h} \text{ is on machine } i \text{ in priority } k, \\ 0 & \text{otherwise,} \end{cases}$$

$$y_{i,j,h} = \begin{cases} 1 & \text{if machine } i \text{ is selected for operation } O_{j,h}, \\ 0 & \text{otherwise,} \end{cases}$$

$$w_{i,k,l} = \begin{cases} 1 & \text{if } l \geq TM_{i,k} \text{ and } l < TM_{i,k+1}, \\ 0 & \text{otherwise.} \end{cases}$$

3.1 *Model I: FJSP considering time-dependent and machine-dependent electricity costs*

The objective of this model is to minimise the total cost, which is the sum of the production cost related to makespan and the total electricity cost for production. For industrial customers with TOU rates, the price of electricity will depend on when they use it. Therefore, it is important to optimise the production schedule to reduce the total production cost. This model finds an optimal solution for reducing the total cost for a production schedule by considering time-dependent and machine-dependent electricity costs for manufacturing companies. Figure 2 shows the structure of model I.

Our objective function for model I is the sum of the makespan-related production cost (PC) and the total electricity cost (EC) for production. As we mentioned before, it is profitable to process many job operations at times when electricity rates are lower. Moreover, manufacturers should not increase the makespan (or maximal completion time) to reduce their production-related cost. Our objective is to reduce the total cost for production ($PC + EC$).

Objective function
The objective function is

$$\min(PC + EC).$$

Constraints
We have the following constraints:

$$PC = C_{max} \times pct \tag{1}$$

$$t_{j,h_j} + PS_{j,h_j} \leq C_{max}\,, \quad j = 1,\ldots,n \tag{2}$$

$$\sum_{i=1}^{m} y_{i,j,h} \times (p_{i,j,h} + z_{i,j,h}) = PS_{j,h}\,, \quad j = 1,\ldots,n; \quad h = 1,\ldots,h_j \tag{3}$$

$$t_{j,h} + PS_{j,h} \leq t_{j,h+1}\,, \quad j = 1,\ldots,n; \quad h = 1,\ldots,h_j - 1 \tag{4}$$

$$TM_{i,k} + PS_{j,h} \times x_{i,j,h,k} \leq TM_{i,k+1}\,, \quad i = 1,\ldots,m; \quad j = 1,\ldots,n; \quad h = 1,\ldots,h_j; \quad k = 1,\ldots,k_i - 1 \tag{5}$$

$$TM_{i,k} \leq t_{j,h} + (1 - x_{i,j,h,k}) \times L\,, \quad i = 1,\ldots,m; \quad j = 1,\ldots,n; \quad h = 1,\ldots,h_j; \quad k = 1,\ldots,k_i \tag{6}$$

$$t_{j,h} \leq TM_{i,k} + (1 - x_{i,j,h,k}) \times L\,, \quad i = 1,\ldots,m; \quad j = 1,\ldots,n; \quad h = 1,\ldots,h_j; \quad k = 1,\ldots,k_i \tag{7}$$

$$y_{i,j,h} \leq a_{i,j,h}\,, \quad i = 1,\ldots,m; \quad j = 1,\ldots,n; \quad h = 1,\ldots,h_j \tag{8}$$

$$\sum_{j=1}^{n}\sum_{h=1}^{h_j} x_{i,j,h,k} = 1\,, \quad i = 1,\ldots,m; \quad k = 1,\ldots,k_i \tag{9}$$

$$\sum_{i=1}^{m} y_{i,j,h} = 1\,, \quad j = 1,\ldots,n; \quad h = 1,\ldots,h_j \tag{10}$$

$$\sum_{k=1}^{k_i} x_{i,j,h,k} = y_{i,j,h}\,, \quad i = 1,\ldots,m; \quad j = 1,\ldots,n; \quad h = 1,\ldots,h_j \tag{11}$$

$$EC = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{k_i}\sum_{h=1}^{h_j}\sum_{l=s}^{r} x_{i,j,h,k} \times e_l \times c_i\,, \quad s = TM_{i,k}; \quad r = TM_{i,k} + p_{i,j,h} - 1 \tag{12}$$

$$C_{max} \geq 0 \tag{13}$$

$$k_i \geq 0\,, \quad i = 1,\ldots,m \tag{14}$$

$$t_{j,h} \geq 0\,, \quad j = 1,\ldots,n; \quad h = 1,\ldots,h_j \tag{15}$$

$$PS_{j,h} \geq 0\,, \quad j = 1,\ldots,n; \quad h = 1,\ldots,h_j \tag{16}$$

$$TM_{i,k} \geq 0\,, \quad i = 1,\ldots,m; \quad k = 1,\ldots,k_i \tag{17}$$

$$x_{i,j,h,k} \in \{0,1\}\,, \quad i = 1,\ldots,m; \quad j = 1,\ldots,n; \quad h = 1,\ldots,h_j; \quad k = 1,\ldots,k_i \tag{18}$$

$$y_{i,j,h} \in \{0,1\}\,, \quad i = 1,\ldots,m; \quad j = 1,\ldots,n; \quad h = 1,\ldots,h_j \tag{19}$$

$$z_{i,j,h} \geq 0\,, \quad i = 1,\ldots,m; \quad j = 1,\ldots,n; \quad h = 1,\ldots,h_j \tag{20}$$

The objective is to minimise the sum of the maximal completion-time-related cost and the electricity cost. Constraint (2) ensures that the completion time of each job is less than or equal to the makespan. Constraint (3) determines the processing time of operation $O_{j,h}$ for selected machine i, which includes inserted unit time idling jobs before the operation. Constraint (4) ensures that the available start time of operation $O_{j,h+1}$ is greater than or equal to the completion time of its previous operation. Constraint (5) ensures that the available start time of the $(k+1)$th operation on machine i is greater than or equal to the completion time of the kth operation on the same machine. Constraints (6) and (7) ensure that the start time of the kth operation on machine i is equal to the start time of operation $O_{j,h}$ if $x_{i,j,h,k} = 1$. Constraint (8) determines the available machines for each operation. Constraint (9) ensures that only one operation is assigned to a given machine at a given priority.

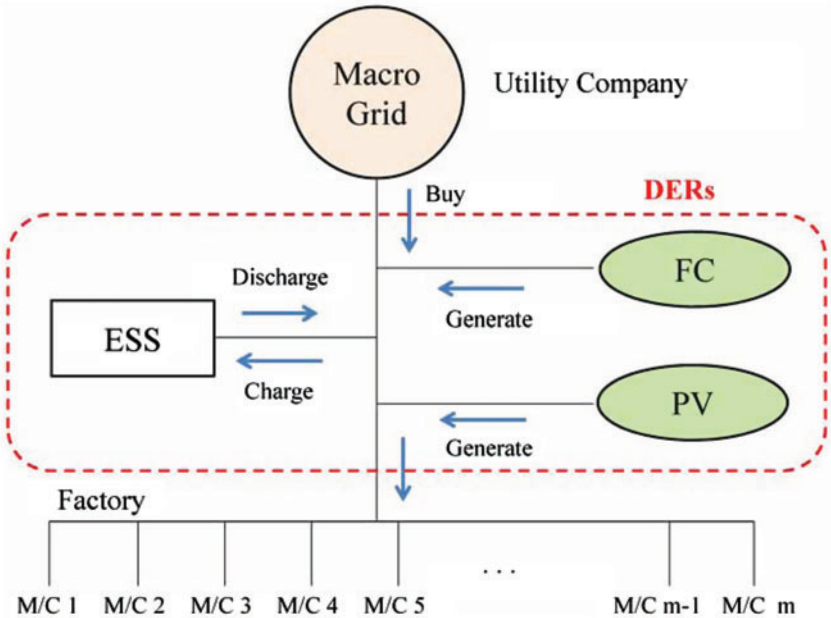

Figure 3. Structure of model II.

Constraints (10) and (11) guarantee that each operation can be performed only on one machine and only at one priority. Constraint (12) calculates the total electricity cost.

The scheduling problem of an FJSP consists of a routing subproblem and a scheduling subproblem. The routing subproblem assigns each operation to a machine out of a set of available machines. The scheduling subproblem sets the sequencing of assigned operations on each machine to obtain a feasible schedule optimising the objective function. As we mentioned earlier, FJSP is a strongly NP-hard and combinatorial problem. Therefore, many studies have developed heuristic approaches to this problem.

We used the CP approach to solve combinatorial problems similar to our problem. This method finds solutions by constraint propagation and search by providing declarative constraints. According to Kelbel and Hanzalek (2011), constraint propagation is the inference of the new constraints from the existing set of constraints and actually removes from the domains those values that directly violate the related constraints. After that, the search algorithm is used to systematically explore the search space pruned by the constraint propagation. ILOG OPL Studio version 6.3 was used as a CP solver for our experiments.

3.2 *Model II: FJSP considering electricity costs with DERs and ESS*

We incorporate DERs and energy storage into model I to see the effects of applying DERs and energy storage. Distributed generators such as fuel cells (FCs) and photovoltaics (PVs) are scheduled with production scheduling by using economic-based planning. In addition, the energy storage batteries are charged during less expensive times and are discharged during more expensive times to reduce energy cost. Figure 3 shows the structure of Model II. The objective function includes the term DGC for the cost of distributed generators and battery operating cost. Therefore, there are newly added constraints for distributed generators and energy storage. Our objective function for model II is the sum of the makespan-related production cost (PC), the total electricity cost (EC) for production and the cost of distributed generators and battery operating cost (DGC). We divide our problem into two subproblems: production scheduling with a given energy schedule and energy scheduling with a given production schedule.

3.2.1 *Mathematical formulation for FJSP scheduling*

The first subproblem is the problem of flexible job-shop scheduling with a given energy schedule. The energy schedule includes the battery charging or discharging schedule and the generation schedule of generators such as those supplied by solar energy, wind and fuel cells. Our objective for this formulation is to minimise $PC + EC + DGC'$, where DGC' is constant because of the given energy schedule.

Objective function
The objective function is

$$\min(PC + EC + DGC^{'}),$$

where

$$DGC^{'} = \sum_{l=0}^{T-1}\Bigg(PwrBat_l \times (-e_l) + |PwrBat_l| \times \ CBat + \sum_{v=1}^{ng}\big(GenQ_{v,l} \times (-e_l) + GenQ_{v,l} \times \ GCost_{v,l}\big)\Bigg) \tag{21}$$

Constraints
We have the following constraints: (1)–(20) and

$$\sum_{i=1}^{m}\sum_{k=1}^{k_i} w_{i,k,l} \times c_i \geq PwrBat_l + \sum_{v=1}^{ng} GenQ_{v,l}\ , \quad l = 0, \ldots, T-1 \tag{22}$$

$$w_{i,k,l} \in \{0, 1\}\ , \quad i = 1, \ldots, m; \quad k = 1, \ldots, k_i; \quad l = 0, \ldots, T-1 \tag{23}$$

Equation (21) calculates the total energy cost for DERs and ESS with a given energy schedule. Constraint (22) means that the power generation from DERs and the discharged power output from ESS are less than or equal to the total electricity demand from operating machines.

3.2.2 *Mathematical formulation for energy scheduling*

The first subproblem is the problem of energy generation scheduling and a battery charging or discharging schedule with a given flexible job-shop schedule. The given flexible job-shop schedule determines the makespan-related production cost (PC) and the electricity purchase cost (EC) from the utility company. Our objective for this formulation is to minimise $PC^{'} + EC^{'} + DGC$, where $PC^{'}$ and $EC^{'}$ are constant because of the given production schedule.

Objective function
The objective function is

$$\min(PC^{'} + EC^{'} + DGC),$$

where

$$PC^{'} = MkSp \times pct \tag{24}$$

and

$$EC^{'} = \sum_{l=0}^{T-1}(PwrDmd_l * e_l) \tag{25}$$

Constraints
We have the following constraints:

$$DGC = \sum_{l=0}^{T-1}\Bigg(PBat_l \times (-e_l) + |PBat_l| \times \ CBat + \sum_{v=1}^{ng}(GQTY_{v,l} \times (-e_l) + GQTY_{v,l} \times \ GCost_{v,l})\Bigg) \tag{26}$$

$$\sum_{i=1}^{m}\sum_{k=1}^{k_i} w_{i,k,l} \times c_i \geq PBat_l + \sum_{v=1}^{ng} GQTY_{v,l}\ , \quad l = 1, \ldots, T-1 \tag{27}$$

$$SOC_0 = SOC_T = InitBat \tag{28}$$

$$SOC_l \geq BMax \times (1 - DoD)\ , \quad l = 1, \ldots, T-1 \tag{29}$$

$$SOC_l \leq BMax\ , \quad l = 1, \ldots, T-1 \tag{30}$$

$$SOC_{l+1} = SOC_l - PBat_l\,, \quad l = 0, \ldots, T-1 \tag{31}$$

$$GQTY_{v,l} \geq GMin_v\,, \quad v = 1, \ldots, ng, \quad l = 0, \ldots, T-1 \tag{32}$$

$$GQTY_{v,l} \leq GMax_v\,, \quad v = 1, \ldots, ng, \quad l = 0, \ldots, T-1 \tag{33}$$

$$w_{i,k,l} \in \{0, 1\}\,, \quad i = 1, \ldots, m; \quad k = 1, \ldots, k_i; \quad l = 0, \ldots, T-1 \tag{34}$$

$$SOC_l \geq 0\,, \quad l = 0, \ldots, T-1 \tag{35}$$

$$PBat_l \geq 0\,, \quad l = 0, \ldots, T-1 \tag{36}$$

$$GQTY_{v,l} \geq 0\,, \quad v = 1, \ldots, ng; \quad l = 0, \ldots, T-1 \tag{37}$$

Equation (24) calculates the production-related cost with a given makespan. Equation (25) calculates the total operating cost for energy storage in the batteries. Constraint (26) calculates the total energy cost for DERs and ESS. Constraint (27) means that the power generation from DERs and the discharged power output from ESS are less than or equal to the total electricity demand from operating machines with a given production schedule. Constraint (28) sets the initial amount and the terminal amount for energy storage. Constraints (29) and (30) set the range of the amount of energy storage at time l. Constraint (31) enforces the relation between the charged or discharged amount and the state of charge for energy storage. Constraints (32) and (33) set the range of the amount of power generation from distributed generations (DGs) at time l.

3.2.3 *Hybrid production and energy scheduling (HPES) algorithm*

We introduce an algorithm to find the optimal solution of our main problem by solving the two divided subproblems repeatedly. We have to solve two subproblems by finding solutions using MIQCP (Mixed integer quadratically constrained programming) and MIP. We argue that solving the subproblems by the algorithm repeatedly make us approach the solution of our main problem. The following lemma and proposition show the basis of the previous statement. First, we prove the lemma before proving the proposition.

LEMMA 3.1 *Our objective function* $\min\{PC + EC + DGC\}$ *depends only on both a production schedule and an energy schedule. In other words, the objective function equals* $\min_{(s,e)\in S\times E} f(s, e)$*, where S is the set of FJSP schedules and E is the set of energy schedules.*

Proof PC depends only on an FJSP schedule, DGC depends only on an energy schedule and EC depends only on both an FJSP schedule and an energy schedule. Therefore, the objective function is determined only by both an FJSP schedule and an energy schedule. □

With the previous lemma, we prove the following proposition to explain the algorithm to solve for our objective.

PROPOSITION 3.2 *For the objective function* $\min_{(s,e)\in S\times E} f(s, e)$*, suppose that* $f(s_i, e_i) = \min_{s\in S} f(s, e_i)$ *and* $f(s_i, e_{i+1}) = \min_{e\in E} f(s_i, e)$ *for* $i = 0, 1, 2, \ldots$*, where S is the set of FJSP schedules and E is the set of energy schedules. Then,* $\{f(s_i, e_i)\}$ *is a monotonically decreasing sequence,* $i = 0, 1, 2, \ldots$

Proof $f(s_i, e_{i+1}) \leq f(s_i, e)\ for\ e \in E$, E is the set of energy schedules:

$$f(s_i, e_{i+1}) \leq f(s_i, e_i), \ \ for\ i = 0, 1, 2, \ldots. \tag{38}$$

$f(s_{i+1}, e_{i+1}) \leq f(s, e_{i+1})\ for\ s \in S$, S is the set of energy schedules:

$$f(s_{i+1}, e_{i+1}) \leq f(s_i, e_{i+1}), \ \ for\ i = 0, 1, 2, \ldots. \tag{39}$$

Let $f(s^*, e^*)$ be an optimal value for our objective function. Then,

$$f(s^*, e^*) \leq f(s_k, e_l), \ \ for\ k,\ l = 0, 1, 2, \ldots. \tag{40}$$

By (38) and (39),
$f(s_{i+1}, e_{i+1}) \leq f(s_i, e_i)\ for\ i = 0, 1, 2, \ldots.$
And, by (40) if $i > j$,
$f(s^*, e^*) \leq \ldots \leq f(s_i, e_i) \leq \ldots \leq f(s_j, e_j)$, for $i,\ j = 0, 1, 2, \ldots$.
Therefore, $\{f(s_i, e_i)\}$ is a monotonically decreasing sequence, $i = 0, 1, 2, \ldots$. □

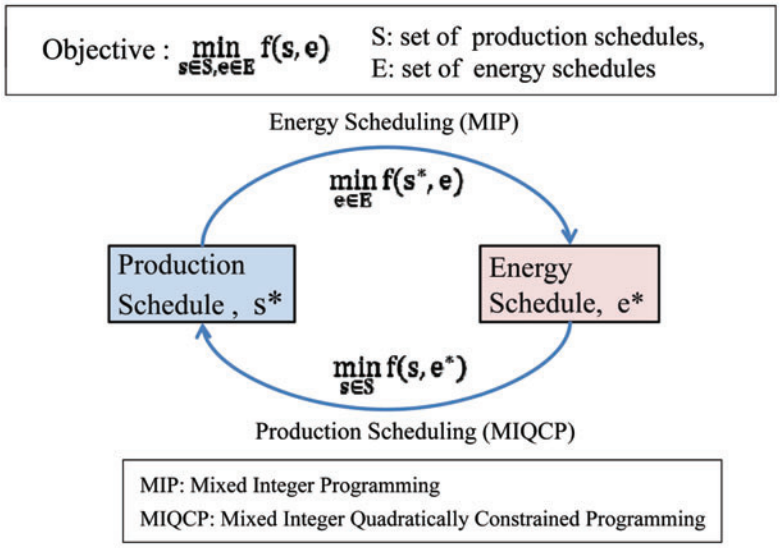

Figure 4. Hybrid production and energy scheduling algorithm.

Proposition 3.3 *To minimise* $\{PC+EC+DGC\}$*, we may find a near-optimal solution by minimising* $\{PC+EC+DGC'\}$ *and* $\{PC'+EC'+DGC\}$ *alternatively and repeatedly.*

Proof By Lemma 3.1, we may let $\min\{PC+EC+DGC\} = \min_{(s,e)\in S\times E} f(s,e)$, $\min\{PC+EC+DGC'\} = \min_{s\in S} f(s,e_i)$ for given $e_i \in E$, and $\min\{PC'+EC'+DGC\} = \min_{e\in E} f(s_i,e)$ for given $s_i \in S$ $(i = 0,1,2,\ldots)$. And, we also set $f(s_i,e_i) = \min_{s\in S} f(s,e_i)$ for given $e_i \in E$ and $f(s_i,e_{i+1}) = \min_{e\in E} f(s_i,e)$ for given $s_i \in S$. Then, $f(s_{i+1},e_{i+1}) = \min_{s\in S} f(s,e_{i+1})$ for given e_{i+1}.

By Proposition 3.2, $\{f(s_i,e_i)\}$ is monotonically decreasing, where $f(s_i,e_i)$ is a feasible solution for $i = 0,1,2,\ldots$.

Therefore, by taking turns finding optimal solutions of two objective functions for subproblems repeatedly, we may find a near-optimal solution of our main objective function. □

The following algorithm is used to solve for our objective by MIP. Figure 4 shows the brief explanation of this algorithm.

Hybrid production and energy scheduling algorithm

Step 1 Set an integer i to 0.
Step 2 Create an initial energy schedule and determine $e_i \in E$, where E is the set of energy schedules.
Step 3 For given e_i, find the optimal s_i such that $f(s_i,e_i) = \min_{s\in S} f(s,e_i)$, where S is the set of FJSP schedules, by solving using MIQCP.
Step 4 For given s_i, find the optimal e_{i+1} such that $f(s_i,e_{i+1}) = \min_{e\in E} f(s_i,e)$ by solving using MIP.
Step 5 For given e_{i+1}, find the optimal s_{i+1} such that $f(s_{i+1},e_{i+1}) = \min_{s\in S} f(s,e_{i+1})$ by solving using MIQCP.
Step 6 Set $i = i+1$.
Step 7 Go to step 4 unless $f(s_i,e_i) \geq f(s_{i-1},e_{i-1})$.
Step 8 Output the near-optimal solution for our objective.

3.2.4 *Modified HPES algorithm*

As we mentioned earlier, we use a CP solver to solve our NP-hard problem. Therefore, we replace the solving technique of the HPES algorithm, MIP, to solve the FJSP by CP. The CPLEX solver and CP optimiser of ILOG OPL Studio version 6.3

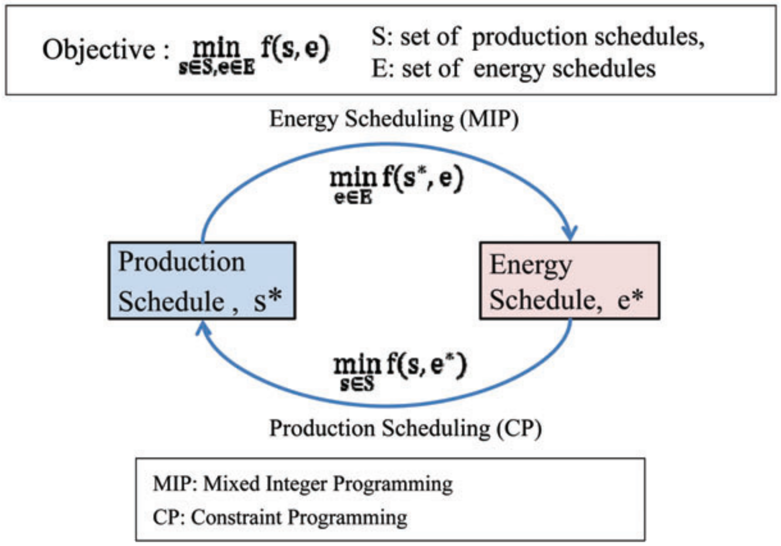

Figure 5. Modified hybrid production and energy scheduling algorithm.

are used as a MIP solver and a CP solver for finding the solution. We now introduce a modified HPES algorithm to solve for our objective by integrating the two solving techniques. Figure 5 shows the brief explanation of this algorithm.

Modified HPES algorithm

Step 1 Set an integer i to 0.
Step 2 Set an iteration number N.
Step 3 Create an initial energy schedule and determine $e_i \in E$, where E is the set of energy schedules.
Step 4 For given e_i, find the optimal s_i such that $f(s_i, e_i) = \min_{s\in S} f(s, e_i)$, where S is the set of FJSP schedules, by solving using CP.
Step 5 For given s_i, find the optimal e_{i+1} such that $f(s_i, e_{i+1}) = \min_{e\in E} f(s_i, e)$ by solving using MIP.
Step 6 For given e_{i+1}, find the optimal s_{i+1} such that $f(s_{i+1}, e_{i+1}) = \min_{s\in S} f(s, e_{i+1})$ by solving using CP.
Step 7 Set $i = i + 1$.
Step 8 Go to step 4 unless $i < N$.
Step 9 Output the best solution for our objective.

By using the modified HPES algorithm, we can solve for our objective for model II and find the near-optimal production schedule and energy schedule.

4. Computational experiments

There are three different time frames during the day (i.e. on peak, mid peak and off peak) with three different rates in many countries. However, some countries, including the Republic of Korea, adopt or are going to adopt CPP to reduce energy use for several days per month. The TOU price for on-peak electricity is about three times that for off-peak electricity if TOU pricing is applied. However, the CPP price for on-peak electricity is almost eight times the price for off-peak electricity if CPP pricing is applied. Figure 1 shows CPP and TOU pricing.

Table 1. Generation costs and power output of FC and PV.

Time	FC			PV		
	Cost (KRW)	Min (kWh)	Max (kWh)	Cost (KRW)	Min (kWh)	Max (kWh)
0	100	0	50	140	0	0
1	100	0	50	140	0	0
2	100	0	50	140	0	0
3	100	0	50	140	0	0
4	100	0	50	140	0	0
5	100	0	50	140	0	0
6	100	0	50	140	0	0
7	100	0	50	140	0	0
8	100	0	50	140	0	20
9	120	0	80	140	0	30
10	120	0	80	140	0	30
11	120	0	80	140	0	40
12	120	0	80	140	0	50
13	120	0	80	140	0	50
14	120	0	80	140	0	50
15	120	0	80	140	0	40
16	120	0	80	140	0	30
17	120	0	80	140	0	30
18	100	0	80	140	0	0
19	100	0	50	140	0	0
20	100	0	50	140	0	0
21	100	0	50	140	0	0
22	100	0	50	140	0	0
23	100	0	50	140	0	0

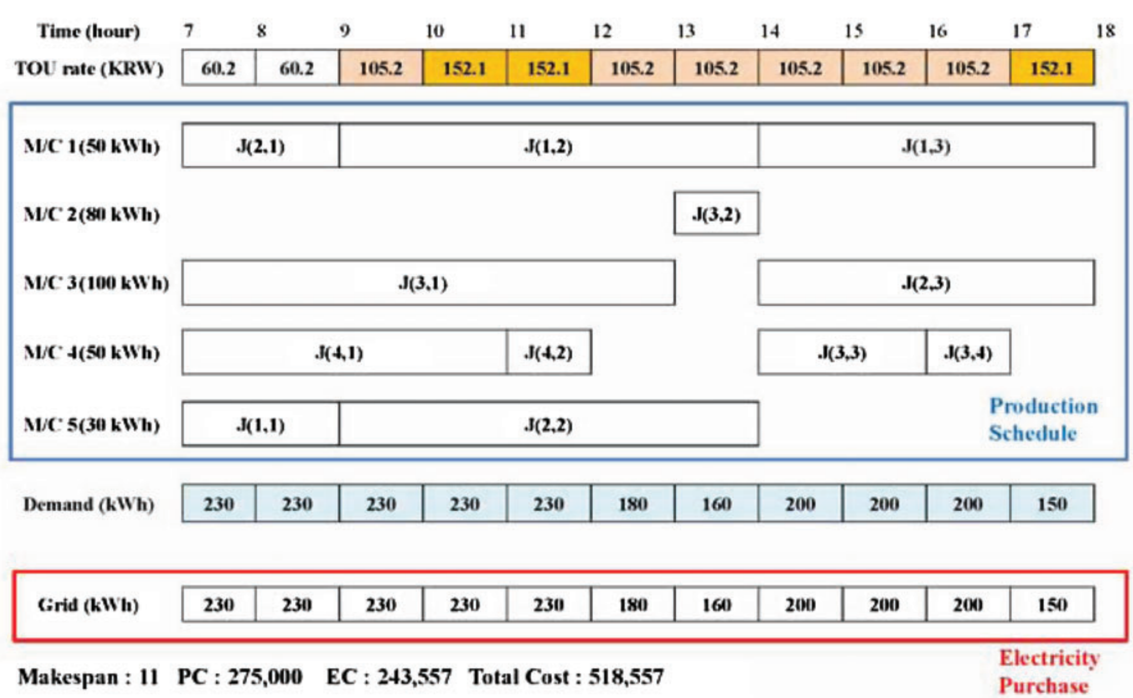

Figure 6. Gantt chart and power consumption of a near-optimal solution of the 4 × 5 case for classical FJSP with TOU rates.

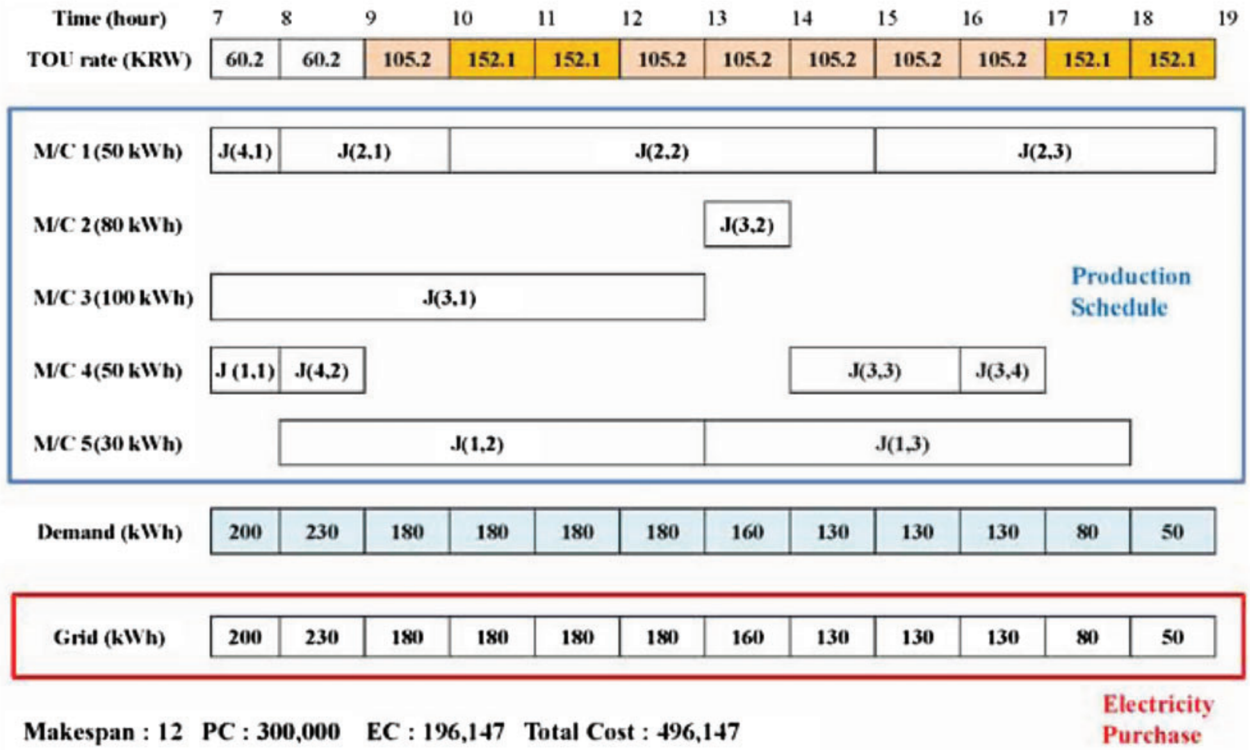

Figure 7. Gantt chart and power consumption of a near-optimal solution of the 4 × 5 case for model I with TOU rates.

Our 4 × 5 (4 machines and 5 jobs), 8 × 8 (8 machines and 8 jobs) and 10 × 10 (10 machines and 10 jobs) flexible job-shop problems are all taken from Zhang et al. (2009). In Figure 1, the daily electricity rates come from Korea Electricity Power Corporation (KEPCO). The energy storage capacity for the three cases is 100 kWh, 100 kWh and 200 kWh, respectively. We assume generation costs per time and power output for each generator. Table 1 shows generation costs and power output for fuel cell (FC) and photovoltaic (PV). We set the depth of discharge (DOD) to 0.8. By considering the DOD rate, we may set battery operating cost for ESS to 30 KRW/kWh. The iteration number for modified HPES algorithm was set to 10. We created initial energy schedule with setting the quantities of generations to 0 kWh.

Figure 6 shows the Gantt chart and power consumption for production. This solution minimises the makespan for production without considering time-dependent and machine-dependent electricity costs. In Figure 7, the solution of model I optimises the sum of the makespan-related cost and total electricity cost by considering time-dependent and machine-dependent electricity costs. In Figure 8, the solution of model II minimises the sum of the makespan-related cost and total electricity cost by considering DERs and ESS. Figure 8 shows the resulting Gantt chart and energy schedule including the generation schedule and battery charging or discharging schedule. Figures 6–8 shows costs for each model with TOU rates. In Table 2, we see that model I can reduce the total cost by 4.3%. Moreover, model II can reduce the total cost by 7.0% with TOU rates. If CPP rates are applied to the 4 × 5 case, Table 2 shows that models I and II can reduce the total cost by 9.8% and 31.6%, respectively. In Table 3, 8 × 8 case shows that model I can reduce the total cost by 5.6%. Moreover, model II can reduce the total cost by 8.5% with TOU rates. If CPP rates are applied to the 8 × 8 case, Table 3 shows that models I and II can reduce the total cost by 14.1% and 25.1%, respectively. And, Table 4 for the 10 × 10 case also show that model I can reduce the total cost by 13.3%. Moreover, model II can reduce the total cost by 14.7% with TOU rates. If CPP rates are applied to the 10 × 10 case, Table 4 shows that models I and II can reduce the total cost by 26.8% and 36.9%, respectively. In Figures 12 and 13, we can see the results that model II reduces the cost more than model I at times of higher power rates. In addition, when we consider total cost with CPP rates, the gap between model I and model II grows even wider. Table 5 shows the comparison for computational efforts in terms of CPU time.

These are findings.

- For TOU and CPP rates, the results of all cases show that the total cost for model II is less than the total cost for model I. Model II requires more computational effort than model I since model II considers DGs. Therefore, we

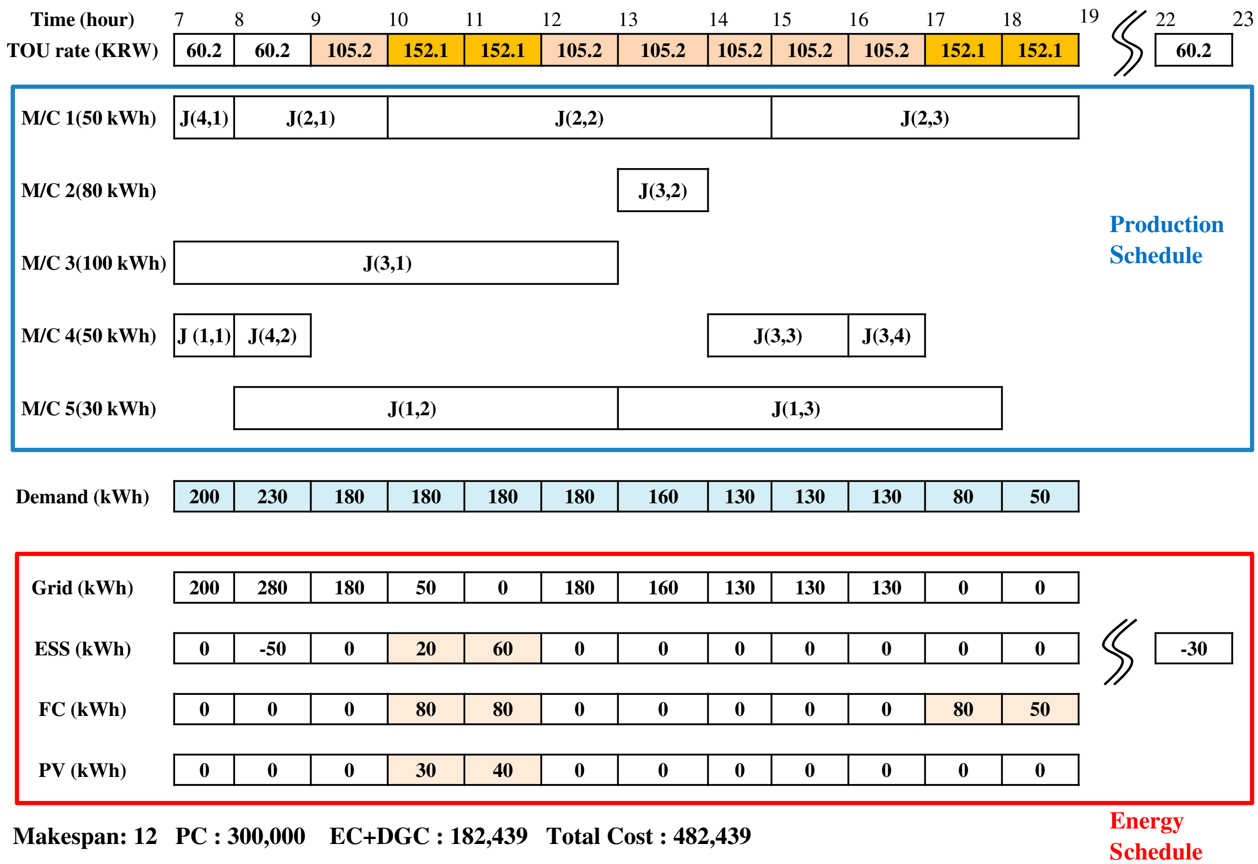

Figure 8. Gantt chart and energy schedule of a near-optimal solution of the 4 × 5 case for model II with TOU rates.

Table 2. Comparison of total costs for the 4 × 5 FJSP case.

Item	TOU rates			CPP rates		
	Classic FJSP	Model I	Model II	Classic FJSP	Model I	Model II
Makespan	11	12	12	11	12	12
PC	275,000	300,000 (9.1%)	300,000 (9.1%)	275,000	300,000 (9.1%)	300,000 (9.1%)
EC(+DGC)	243,557	196,147 (−19.4%)	182,439 (−25.1%)	386,258	296,595 (−23.2%)	152,045 (−60.6%)
Total Cost	518,557	496,147 (−4.3%)	482,439 (−7.0%)	661,258	596,595 (−9.8%)	452,045 (−31.6%)

Table 3. Comparison of total costs for the 8 × 8 FJSP case.

Item	TOU rates			CPP rates		
	Classic FJSP	Model I	Model II	Classic FJSP	Model I	Model II
Makespan	14	16	16	14	17	17
PC	560,000	640,000 (14.3%)	640,000 (14.3%)	560,000	680,000 (21.4%)	680,000 (21.4%)
EC(+DGC)	781,590	626,260 (−19.9%)	588,279 (−24.7%)	1,407,994	1,010,921 (−28.2%)	793,447 (−43.6%)
Total Cost	1,341,590	1,266,260 (−5.6%)	1,228,279 (−8.5%)	1,967,994	1,690,921 (−14.1%)	1,473,447 (−25.1%)

Table 4. Comparison of total costs for the 10 × 10 FJSP case.

Item	TOU rates			CPP rates		
	Classic FJSP	Model I	Model II	Classic FJSP	Model I	Model II
Makespan	7	8	8	7	8	8
PC	350,000	400,000 (14.3%)	400,000 (14.3%)	350,000	400,000 (14.3%)	400,000 (14.3%)
EC(+DGC)	458,785	301,413 (−34.3%)	290,327 (−36.7%)	777,133	424,740(−45.4%)	311,839 (−59.9%)
Total Cost	808,785	701,413 (−13.3%)	690,327(−14.7%)	1,127,133	824,740 (−26.8%)	711,839 (−36.9%)

Table 5. Comparison of CPU time for each case (seconds).

Case	TOU rates			CPP rates		
	Classic FJSP	Model I	Model II	Classic FJSP	Model I	Model II
4 × 5	0.12	8.86	71.83	0.14	7.47	84.35
8 × 8	0.18	10.67	165.54	0.2	10.9	165.14
10 × 10	0.23	21.66	253.5	0.25	20.12	244.83
Average	0.18	13.73	163.62	0.20	12.83	164.77

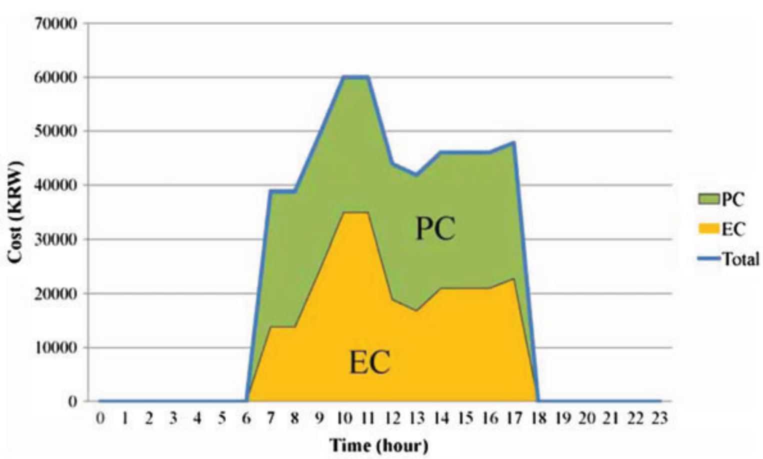

Figure 9. Costs for classic FJSP with TOU rates.

may compare the total costs of the models within an acceptable CPU time, e.g. the maximum allowable time of one hour. Then, we may say that applying model II to industry may reduce total cost than applying model I in a general sense.

- As indicated in the charts in Figures 9–11, the total cost for model II renders the graph for total cost flat, by reducing power consumption during peak-load times. This means that model II may reduce costs during peak-load times.
- If CPP rates are applied to manufacturing companies, the results show that these may save more costs. Since in CPP pricing, peak-load price is about eight times off-peak-load price, this has a strong influence on cost reduction.

Our computational results indicate that optimisation of production scheduling problem considering time-dependent electricity purchase costs and scheduling of DGs can save more energy and reduce costs. The results also show that scheduling with CPP rates can reduce costs more than that with TOU rates.

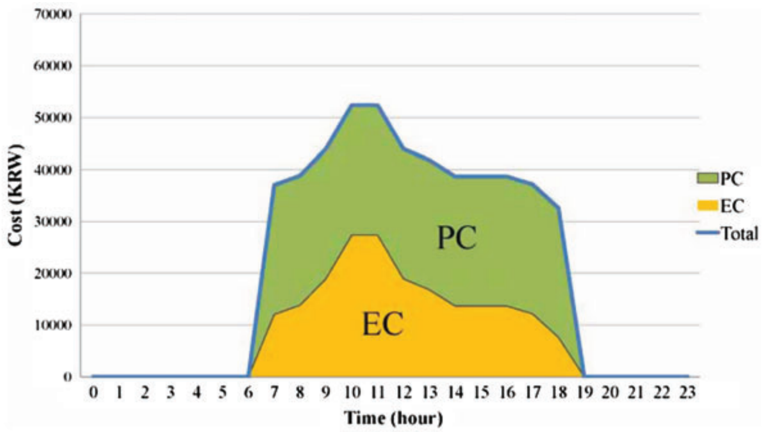

Figure 10. Costs for model I with TOU rates.

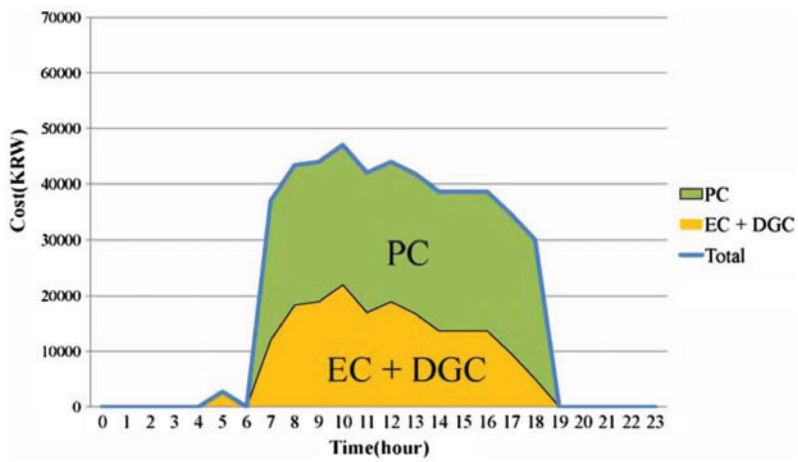

Figure 11. Costs for model II with TOU rates.

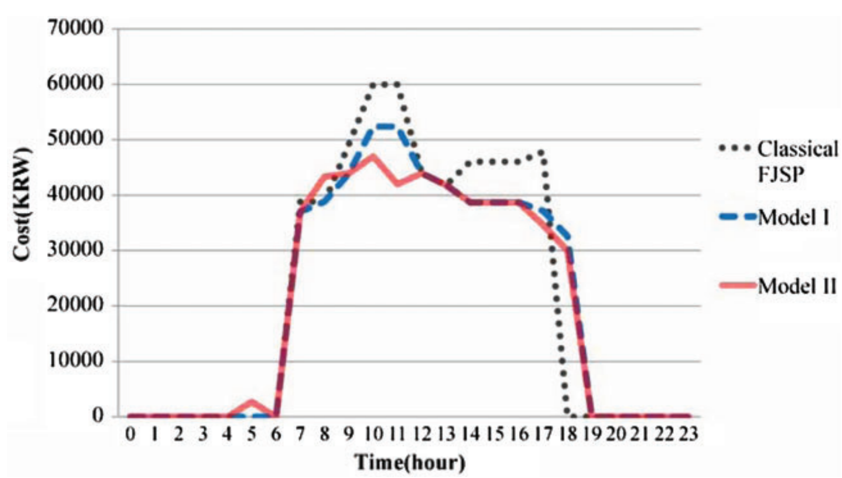

Figure 12. Comparison of total costs with TOU rates.

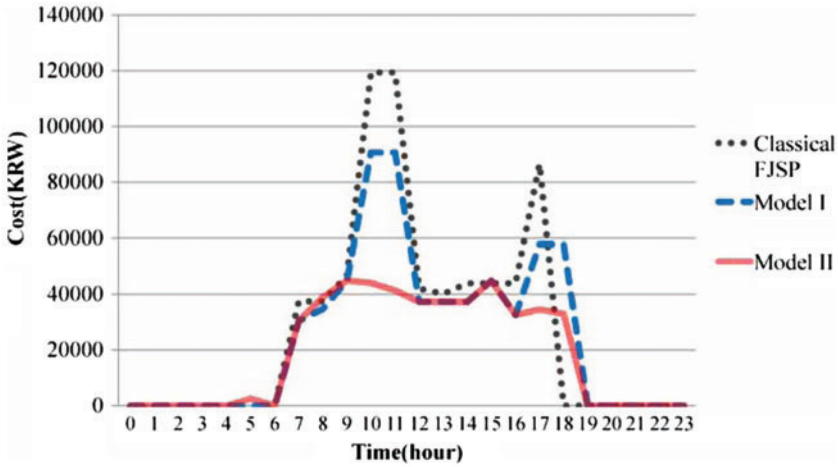

Figure 13. Comparison of total costs with CPP rates.

5. Conclusion

Manufacturing industries need to consider their scheduling set-ups while taking into account time-dependent electricity cost. Solving the scheduling problem can reduce costs, save energy and reduce greenhouse gas emissions. In this paper, we proposed models of the flexible job-shop problem by considering time-dependent and machine-dependent electricity costs with distributed energy resources that include energy storage and renewable energy resources such as solar energy and wind. Several cases of our scheduling problem were tested. It was found that our models can reduce the total electricity cost with smart production scheduling by considering time-dependent and machine-dependent costs. In addition, DERs including renewables and energy storage systems can reduce GHG emissions and save energy. Our future study will take into account scheduling problems with due dates and other objectives and consider more practical situations.

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