Proceedings of the 9th Annual World Conference of the
Society for Industrial and Systems Engineering,
2020 SISE Virtual Conference
September 17-18, 2020

# An Energy-Aware Scheduling Model Under Demand Charge and Time-Based Rate

**S Karimi and S Kwon**

Department of Systems Science and Industrial Engineering,
State University of New York at Binghamton
Binghamton, NY, USA

Corresponding author's Email: skarimi1@binghamton.edu

**Abstract**: In recent years, there has been a rising interest in improving energy efficiency and saving energy cost in the production scheduling because of the environmental concerns and energy cost. In this paper, we propose a mathematical optimization model that is designed to achieve energy-aware production scheduling for the general type of manufacturing setting where multiple jobs need to be processed on multiple machines. Considering energy charge based on time-based electricity price and demand charge based on peak power demand that are common practice of utility company to charge electricity bills for commercial and industrial consumers, the proposed optimization model can be formulated to minimize electricity bill. The key idea of the proposed model is to adjust production schedule in terms of the assignment and the deployment of each job in response to time-based electricity price while reducing peak power demand. Specifically, the proposed optimization model can be formulated to determine production schedule to adjust overall electricity power consumption while being aware of the power consumption pattern of each job, which can be extracted and formalized in a stage-wise fashion based on the nature of process. In particular, the proposed model can be formulated as a mixed integer linear program that can be solved by general purpose optimization package. To validate the proposed model, numerical experiments are conducted, and the results show that production schedule can be properly adjusted to reduce energy cost.

*Keywords*: Energy-Aware Production Scheduling, Time-Based Electricity Price, Demand Charge, Mixed Integer Linear Program

## 1. Introduction and Literature Review

In the next several decades, energy consumption will continue rising in the world (EIA, 2014). The industrial activities are the responsible for spending 37% and 33% of the total energy in the world and the United States respectively (Energy Information Administration, 2012; Park et al., 2009). Climate change caused by increasing energy consumption and CO2 emission becomes growing serious environmental concerns. On the other hand, in terms of the economic perspective, cost of energy plays an important role in the final price of products and consequently affects the profit of companies. Regarding the environmental and economic concerns, there have been a significant effort to improve energy efficiency in the industrial sector, especially in manufacturing systems, for the purpose of reducing the negative environmental impacts and energy cost. Specifically, the rapid advance in network and information technologies, e.g., Internet of Things, and the expansion of modernized electric power grid infrastructure, e.g., smart grid, create an opportunity to achieve energy-efficient and energy-aware production.

The researchers have addressed the energy efficiency of the manufacturing systems in several aspects. One of the interesting directions of the researches in this subject is trying to develop an energy-aware production plan that aims to reduce energy consumption or energy cost. Since electricity is the major source of energy for the production systems, most of the researches in this area have considered this kind of energy. Based on current practices, electricity bills of industrial customers will be charged based on two primary components: *energy charges* and *demand charges*. Energy charges will be billed based on the total amount of energy used during a billing period, and the customers need to pay at a $/kWh rate. Most of the utility markets consider time-dependent electricity price and offer Demand Response (DR) programs to calculate the energy charge. DR is defined as changing the electric usage by the customers from their normal consumption pattern in response to changes the price of electricity provided by the market over the time (Albadi & El-Saadany, 2007). The other factor of electricity cost, demand charge, will be paid based on the maximum usage on a short interval (usually 15-minute or 30-minute) during a billing period, and will be billed based on a $/kW basis. Motivated by the opportunity to reduce energy cost by adjusting electricity consumption to reduce peak power under demand charge and avoid peak price while participating in demand response (DR) program, there have been studies that focus on developing optimization models tailored to energy-aware production scheduling in various settings. Schulz et al. (2019) propose a multi-objective optimization model for the hybrid flow shop scheduling model which minimizes the energy cost in a time varying electricity price environment beside other objectives. Shrouf et al. (2014) consider the single machine scheduling problem and developed an optimization model to reduce energy cost in the real time pricing mechanism. Luo et al. (2013) develop a new ant colony algorithm for hybrid flow shop scheduling to minimize electricity cost under time-of-use (ToU) pricing.

Parallel machine is one of the most famous scheduling models in which a set of parallel machines that operate the same operation are processing a set of jobs. In this model, it is assumed that there is no precedence between jobs and splitting the jobs is not allowed. Traditional parallel machine scheduling problems aim to improve production efficiency such as makespan (Li et al., 2011) and tardiness (Yalaoui & Chu, 2002) while in recent years the researchers have considered energy efficiency objectives in this model. Abikarram et al. (2019) propose a mathematical model for the parallel machine scheduling problem in order to minimize the electricity cost under the real time pricing and demand charge. Che et al. (2017) present an energy-aware unrelated parallel machine scheduling model to reduce the electricity cost under the ToU pring. They formulate the problem as mixed-integer linear programming (MILP) model and develop two heuristic algorithms to solve the large scale problems. Zeng et al. (2018) develop a bi-objective optimization model for the uniform parallel machine to simultaneously minimize the number of machines that are used in the process and reduce the electricity cost under time varying pricing. As another studies related to the energy-aware parallel machine we can mention the paper of Wang et al. (2018) and Moon et al. (2013).

All of the aforementioned papers consider a constant power demand pattern during the process of each job. However, in some cases in real world, the process consists of stages and each stage has different power demand that has been neglected in the existing papers. To utilize this characteristic in scheduling model, in this paper, we propose an energy-aware scheduling model for the unrelated parallel machine problem to minimize the electricity cost based on the stage-wise power consumption pattern. In our proposed model, both of the energy charge (time-dependent) and demand charge are considered to compute the electricity cost. Figure 1 shows a schematic form of stage-wise power demand pattern. In this figure, the blue line shows the actual power consumption during a process. As can be seen, the process can be divided into three separate stages with different consumption rates and durations.

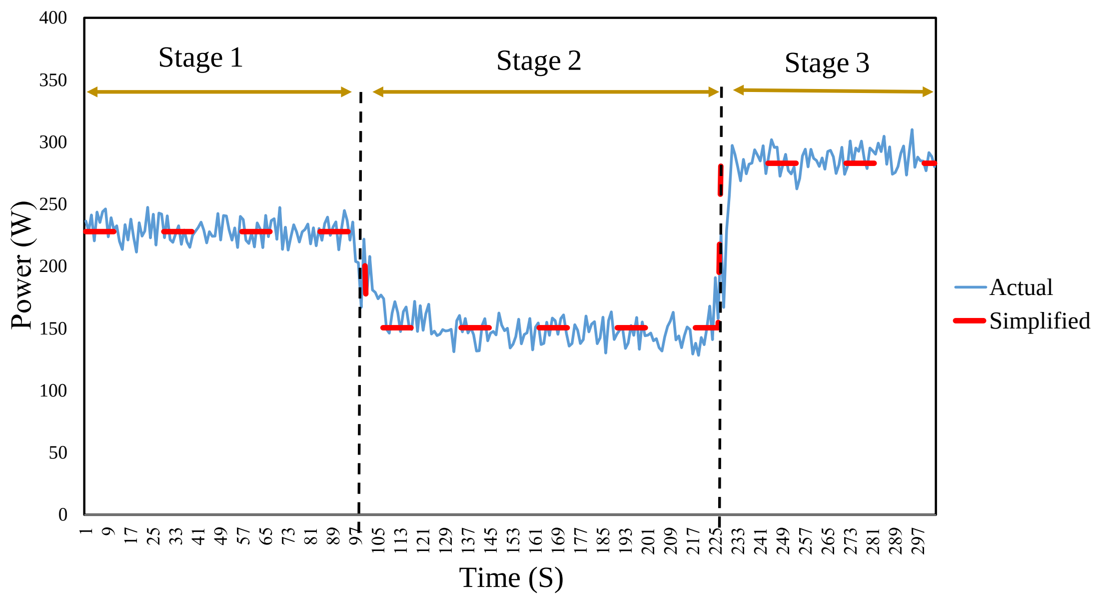



Figure 1. Actual and simplified power consumption

In order to use the consumption pattern in the mathematical model, we simplify it in such a way that the consumption rate of each stage is constant value. Therefore, the power demand pattern of each job is defined based on the duration and consumption rate of its stages. In figure 1 the red dash-line indicates the simplified version of the power demand. To get the simplified form of power demand, the average of the actual power demand of each stage is assigned to each stage. Also, for the duration of each stage, we round the actual duration. It is clear that the processing time of each job is the summation of the duration of all stages. The extracted simplified power demand pattern will be used in the mathematical modeling of the scheduling problem. The rest of this paper is organized as follows: In section 2, we define the problem, describe the assumptions and formulate the mathematical model. In section 3, a numerical experiment is conducted. Finally, the conclusion and future works are explained in the section 4.

## 2. Problem Definition

In this section we propose an MILP formulation for the energy-aware identical parallel machine scheduling problem with stage-wise power demand. In this problem, it is assumed that there are $N^J$ number of jobs to be processed on $N^M$ number of machines by the end of the planning horizon (one day). There is no precedence relation among the jobs and ach job can be assigned to any machine. Each machine can process only one job at a time and the preemption is not allowed (once a machine starts processing on a job, it must complete the process without interruption). Each job consists of some stages and the processing time and power demand related to each stage on all the machines are the same. All the jobs are available at the time zero and there is enough time to complete all the jobs by the end of the planning horizon. The aim of this model is minimizing the electricity cost which includes the energy charge and demand charge. In this model, the planning horizon is divided into some equal time periods and an energy price rate is assigned to each time period to calculate the energy charge. Therefore, any demand response program that offers a time-dependent electricity price can be utilized in our proposed model. On the other hand, the demand charge is computed based on the highest peak demand in a 30-minutes interval during the day.

The notations of the mathematical model are as follows:

- Indices:
  - $m$: Index of machine, $m \in \{1,...,N^M\}$
  - $s$: Index of stages, $s \in \{1,...,N^S\}$
  - $t,k$: Indices of time units, $t,k \in \{1,...,N^T\}$
- Parameters:
  - $N^M$: Number of machines
  - $N^J$: Number of jobs
  - $N^S$: Number of stages
  - $N^T$: Number of time units in a planning horizon
  - $M$: Big number
  - $TD$: Total duration of jobs
  - $D_s$: Duration of the stage $s$ of jobs
  - $CD_s$: Cumulative duration of stage $s-1$ of jobs
  - $UP_s$: Power demand of the stage $s$ of jobs
  - $C_t$: Unit cost of energy charge at time $t$
  - $C^{max}$: Unit cost of demand charge
- Decision Variables:
  - $x_{m,t}$: Binary variable where $x_{m,t} = 1$ if a job starts at the beginning of time $t$ on machine $m$; $x_{m,t} = 0$, otherwise.
  - $y_t$: Continuous variable denotes the total power demand (by all machines) at time $t$ (W)
  - $p^{max}$: Continuous variable for peak power demand (W)

As our proposed model is discrete time period, we define index $t$ to indicate the time periods. To import the stage-wise power consumption pattern to the mathematical model, we use the parameters $D_s$ and $UP_s$ that indicate the duration and power demand of stage $s$ respectively. The MILP formulation of the proposed energy-aware scheduling model is as follows:

$$minz = \sum_{t=1}^{N^T} C_t y_t + C^{max} p^{max} \tag{1}$$

s.t.

$$M(1 - x_{m,t}) \geq \sum_{k=t+1}^{t+TD-1} x_{m,k} \qquad \forall t, m \tag{2}$$

$$x_{m,t} \leq 1 \qquad \forall t, m \tag{3}$$

$$\sum_{t=N^T-TD+2}^{N^T} x_{m,k} = 0 \qquad \forall m \tag{4}$$

ISBN: 97819384961-9-6

$$\sum_{t=1}^{N^T}\sum_{m=1}^{N^M} x_{m,k} = N^J \tag{5}$$

$$y_t = \sum_{s=1}^{N^S}\sum_{m=1}^{N^M} UP_s\left(\sum_{k=t-(D_s+CD_s)+1}^{N^T} x_{m,k}\right) = N^J \qquad \forall t \tag{6}$$

$$P_{max} \geq y_t \qquad \forall t \tag{7}$$

$$x_{m,t} \in \{0,1\} \qquad \forall t, m, p \tag{8}$$

$$P_{max}, y_t \geq 0 \qquad \forall t \tag{9}$$

In this mathematical formulation, the objective function minimizes the total electricity cost. The first term of the objective function computes the energy charge by multiplying the power demand of each time unit by the corresponding energy charge rate and the second term computes the demand charge based on the peak demand and demand charge rate. Constraint 2 ensures that there is no overlap between the jobs (e.g. each machine just operates one job at each time). Constraint 3 ensures that each time and on each machine, at most one job can be started. Constraint 4 enforces that no job can be processed after end of the planing horizon. Constraint 5 guarantees that all the jobs should be processed before end of the planing horizon. Constraint 6 calculates the amount of power consumption in each time unit. Constraint 7 computes the demand charge. Constraints 8 and 9 define the decision variables.

## 3. Numerical Experiment

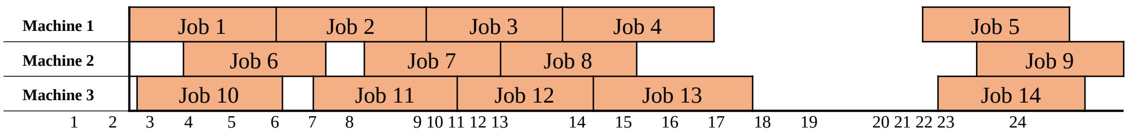
In this section a numerical experiment is conducted to illustrate the solution based on our proposed approach and investigate the impact of demand charge on the solutions. Our proposed model can be applied in all kind of time-dependent electricity price (ToU, Day-ahead, etc.). In this numerical experiment, the real data of the ToU pricing for the Texas state (May-Oct) (Wang & Li, 2015) that is also includes the demand charge is used. This ToU pricing has two blocks, on-peak and off-peak hours. On-peak hours are from 13 to 21 with 4.5 cent per kW/h and off-peak hour are from 21 to 13 and the rate is 1.7 cent for each kW/h. Also, the demand charge rate is equal to $7.9 for the highest peak demand in an interval during billing period. Since our planning horizon is one day and the demand charge is assigned to the entire billing period (one month), the demand charge rate is divided into 30 (the number of days in a month). A problem is generated to be solved by our proposed model to minimize the electricity cost under the ToU and demand charge pricing. This problem consists of 3 machines and 14 jobs. The jobs and machines are identical and each job has three stages. Table 1 shows the value of processing time and power demand of each stage of the jobs. As the jobs and machines are identical, the processing time and power demand of all the jobs on all the machines are the same.

Table 1. Processing times and power consumption rate of each stage of the job

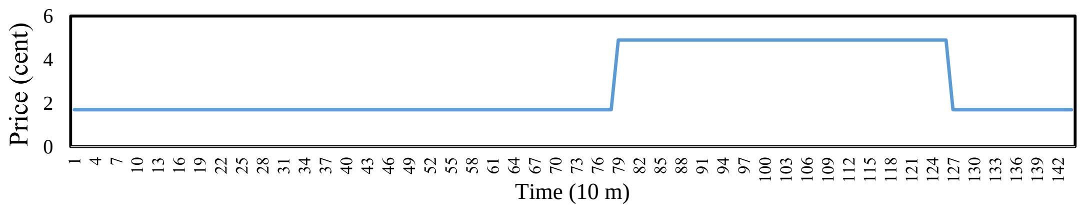
| | Stage 1 | Stage 2 | Stage 3 |
|---|---|---|---|
| Processing time (10 m) | 5 | 10 | 7 |
| Power (W) | 400 | 230 | 350 |

The mathematical model is coded in IBM ILOG CPLEX 12.8.0 and run on a system with Intel I7 3.4GHZ processor with 16GB RAM and the problem is solved to find the optimum solution. The total electricity cost is 73.63 cents (41.94 cent energy charge and 31.69 cents demand charge). The Guantt charte of the solution, the ToU pricing and the overall power demand related to the solution are shown in the Figure 2. As can be seen, the model avoids the peak-hours and sets the processing time of the jobs in the off-peak hours with lower electricity cost to reduce the energy cost.

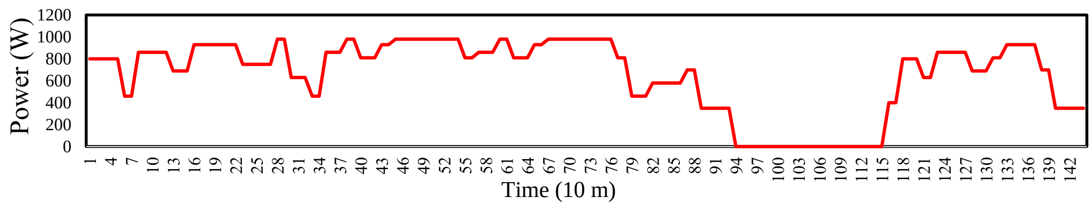
ISBN: 97819384961-9-6




(a) Resulted production scheduling




(b) Sampled ToU pricing




(c) Overall power consumption pattern

Figure 2. Sampled power demand patterns and production scheduling for the instance with 4 machines and 13 jobs under ToU pricing

As another analysis, we solve the problem without the demand charge to investigate the impact of the demand charge on the solution. All the other information is the same as the previous problem, just the demand charge rate is removed. In figure 3, the comparison between power consumption of two solutions (with and without the demand charge) is shown. As can be seen, the peak demand of the solution without the demand charge is higher than other solution. The peak demand in previous solution was 980 W while in second solution is 1200 W that shows 22% increase in the demand charge. The reason of this difference is that when we consider the demand charge, the model tries to reduce the maximum power demand (by avoiding the overlap of the jobs) in order to decrease the demand charge.

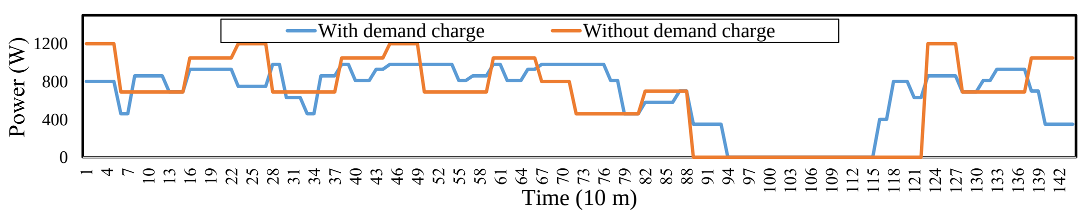



Figure 3. Comparison of the solution with and without demand charge

ISBN: 97819384961-9-6

## 4. Conclusion and Future Works

This study investigated the energy-aware scheduling problem by considering the stage-wise power demand pattern. The objective of the proposed model is to reduce the electricity cost under demand charge and time-dependent rates. In this problem, a set of identical Jobs should be completed of a set of parallel identical machines and the goal is finding the best assignment of jobs to the machines and deploy time of jobs regarding the objective function. We proposed a stage-wise power demand pattern in which the process of the job is divided into some stages (based on the nature of the process) and consider different power demand and duration for each stage. We showed that how to turn the actual power demand pattern of jobs into the stage-wise pattern and use it in the mathematical model. The model was formulated as an MILP model. A numerical experiment was conducted that indicated the ability of the model to avoid the peak hours (to reduce the energy charge) and maximum power demand (to reduce the demand charge). For the future works, we can utilize this approach in other scheduling models (e.g. flow shop, job shop, etc.)

## 5. References

Abikarram, J. B., McConky, K., & Proano, R. (2019). Energy cost minimization for unrelated parallel machine scheduling under real time and demand charge pricing. *Journal of Cleaner Production*, *208*, 232-242.

EIA, U. (2014). Energy Information Administration. 2013. *International Energy Outlook. US Department of Energy*.

Albadi, M. H., & El-Saadany, E. F. (2007, June). Demand response in electricity markets: An overview. In *2007 IEEE power engineering society general meeting* (pp. 1-5). IEEE.

Che, A., Zhang, S., & Wu, X. (2017). Energy-conscious unrelated parallel machine scheduling under time-of-use electricity tariffs. *Journal of Cleaner Production*, *156*, 688-697.

Energy Information Administration (US). (2012). *Annual energy review 2011*. Government Printing Office.

Li, K., Shi, Y., Yang, S. L., & Cheng, B. Y. (2011). Parallel machine scheduling problem to minimize the makespan with resource dependent processing times. *Applied Soft Computing*, *11*(8), 5551-5557.

Luo, H., Du, B., Huang, G. Q., Chen, H., & Li, X. (2013). Hybrid flow shop scheduling considering machine electricity consumption cost. *International Journal of Production Economics*, *146*(2), 423-439.

Moon, J. Y., Shin, K., & Park, J. (2013). Optimization of production scheduling with time-dependent and machine-dependent electricity cost for industrial energy efficiency. *The International Journal of Advanced Manufacturing Technology*, *68*(1-4), 523-535.

Park, C. W., Kwon, K. S., Kim, W. B., Min, B. K., Park, S. J., Sung, I. H., ... & Seok, J. (2009). Energy consumption reduction technology in manufacturing—A selective review of policies, standards, and research. *International journal of precision engineering and manufacturing*, *10*(5), 151-173.

Schulz, S., Neufeld, J. S., & Buscher, U. (2019). A multi-objective iterated local search algorithm for comprehensive energy-aware hybrid flow shop scheduling. *Journal of Cleaner Production*, *224*, 421-434.

Shrouf, F., Ordieres-Meré, J., García-Sánchez, A., & Ortega-Mier, M. (2014). Optimizing the production scheduling of a single machine to minimize total energy consumption costs. *Journal of Cleaner Production*, *67*, 197-207.

Wang, S., Wang, X., Yu, J., Ma, S., & Liu, M. (2018). Bi-objective identical parallel machine scheduling to minimize total energy consumption and makespan. *Journal of Cleaner Production*, *193*, 424-440.

Wang, Y., & Li, L. (2015). Time-of-use electricity pricing for industrial customers: A survey of US utilities. *Applied Energy*, *149*, 89-103.

Yalaoui, F., & Chu, C. (2002). Parallel machine scheduling to minimize total tardiness. *International Journal of Production Economics*, *76*(3), 265-279.

Zeng, Y., Che, A., & Wu, X. (2018). Bi-objective scheduling on uniform parallel machines considering electricity cost. *Engineering Optimization*, *50*(1), 19-36.