12-5-2017

Optimizing Production Schedule with Energy Consumption and Demand Charges in Parallel Machine Setting

Farnaz Ghazi Nezami
Kettering University, fghazinezami@kettering.edu

Mojtaba Heydar
University of Newcastle, mojtaba.heydar@newcastle.edu.au

Regina Berretta
University of Newcastle, regina.berretta@newcastle.edu.au

MISTA
2017

Optimizing Production Schedule with Energy Consumption and Demand Charges in Parallel Machine Setting

Farnaz Ghazi Nezami • Mojtaba Heydar • Regina Berretta

Abstract Environmental sustainability concerns, along with the growing need for electricity and associated costs, make energy-cost reduction an inevitable decision-making criterion in production scheduling. In this research, we study the problem of production scheduling on non-identical parallel machines with machine-dependent processing times and known job release dates to minimize total completion time and energy costs. The energy costs in this study include demand and consumption charges. We present a mixed-integer nonlinear model to formulate the problem. The model is then linearized and its performance is tested through numerical experiments.

1 Introduction

This paper proposes a new energy-aware parallel-machine production scheduling model in order to minimize total production completion time, energy consumption costs and peak power charges. The industrial sector uses 266 quadrillions BTU of energy, which accounts for 51% of total energy consumption in the world[1]. The breakdown of global energy consumption data reveals that 22% of the total amount of energy used in the industrial sector is electrical energy [1]. In the past 50 years, industrial electricity consumption has doubled [2]. In addition, the US Energy Information Administration (EIA) reports that the price of electricity is expected to

[1] https://www.eia.gov/tools/faqs/faq.cfm?id=447&t=1

Farnaz Ghazi Nezami
Department of Industrial and Manufacturing Engineering, Kettering University, 1700 University Ave., Flint, MI 48504, USA
E-mail: fghazinezami@kettering.edu

Mojtaba Heydar
University of Newcastle, University Drive, Callaghan, NSW 2308, Australia
E-mail: mojtaba.heydar@newcastle.edu.au

Regina Berretta
School of Electrical Engineering and Computing, University of Newcastle, University Drive, Callaghan, NSW 2308, Australia
E-mail: regina.berretta@newcastle.edu.au

increase by 18% by 2040[2]. Currently, the cost of electricity for manufacturing in the United States exceeds 100 billion dollars [2], and this number will continue to increase the in future.

The surge in energy prices, along with the scarcity of natural sources, the growth of public awareness of environmental concerns, and the establishment of sustainability-based standards magnify the necessity of incorporating energy consumption and associated costs into planning and scheduling decisions at manufacturing facilities. The increase in energy demand causes difficulty for electrical energy providers, who must keep up with demand, which is particularly difficult during peak-demand periods. Time-of-Use (TOU) tariffs implemented by utility companies aim to shift demand from the expensive peak periods to less-expensive non-peak hours in order to flatten the load curve and decrease the deficit risks in supply.

In general, electricity charges can be categorized into two types: consumption charges and demand charges. Consumption charges are calculated according to the total amount of electrical energy consumed by a company during a given period, based on kilowatt-hour, and may vary throughout the day to motivate a shift of consumption away from peak hours. Demand charges try to address the overhead expenses that utility companies bear to provide the service. This charge is based on the highest level of power demanded over a given period of time during the billing period and is usually calculated as the highest "average fifteen-minute demand" for a month. Energy demand is measured in kilowatts (kW) and often represents a significant percentage of charges on utility bills for the industrial user.

Most of the existing research on energy-aware job scheduling does not differentiate between these two types of energy costs. In addition, in the majority of energy-aware job scheduling studies, the impact of various machine operating modes on decision making output is not considered. In a typical manufacturing system, the machines may be running idle for a significant amount of time waiting for the next job to arrive and be processed. One study showed that in a machining process, 85% of total energy consumption is used when the machine is idling, and only 15% is applied to the actual machining process [3]. The idle energy is used to run the auxiliary components. Therefore, it is critical to study the impact of various operating states on the production schedule, energy requirements, and cost planning. In the past few years, the number of studies investigating the energy-aware production scheduling has increased significantly. A literature survey of studies on energy efficiency in manufacturing companies is provided by [4]. This survey presents a breakdown of studies based on energy coverage (production system, internal and external conversion system), energy supply, energy demand (processing and non-processing energy demand), objective criteria (monetary, non-monetary), the system of objectives (multi/single objectives), the manufacturing model (single machine, parallel machines, flow shop, job shop/project scheduling, or hoist scheduling), the model type (linear, mixed integer linear, mixed integer quadratic constrained, mixed integer non-linear programing, queuing theory and simulation, and other analytical models such as Markov decision model), and solution approach (heuristic, exact, standard solver). To integrate energy concerns into classic scheduling problems, [5] investigated a single machine problem to minimize total energy consumption and maximum tardiness, with the possibility of machine shut-down between consecutive jobs following the break-even period. They considered only processing and idle energy consumption in their model. A bi-objective optimization problem to minimize weighted tardiness and non-process (idle and switch) energy consumption in a job-shop setting is proposed in [6]. Their model also allows for switching off a machine if the idle time is long enough, considering a breakeven time, and they solved the problem using Genetic Algorithm (GA). In another study, a job-shop scheduling problem with machine speed scaling to minimize makespan and energy consumption using GA was proposed by [7]. A job-shop problem with energy threshold and makespan minimization was investigated by [8] using a mixed integer linear model. They considered extra energy consumption at the beginning of the operation, and energy consumption was divided into "peak" and "processing" categories. An energy-aware scheduling model with tool selection and operation sequencing was introduced by [9]. Their bi-objective model minimized total energy consumption (idle, setup, and process

[2] http://www.eia.gov/forecasts/aeo/pdf/0383(2015).pdf

energy) and makespan in a flexible job-shop system. To incorporate TOU policy on energy aware scheduling, [10] minimized total electricity cost and number of machines based on TOU pricing in a uniform parallel-machine problem. In another study, [11] performed a job-machine assignment and scheduling in an unrelated parallel machine setting in order to minimize total energy costs according to TOU policy. In 2016, [12] minimized total energy consumption using TOU via job scheduling for a single machine problem.

In the existing research studies on energy-aware scheduling problem, the concurrent integration of operating mode-based energy consumption, TOU policies, and peak power demand is not well investigated in a parallel machine environment. The main contribution of this paper is to propose a new comprehensive framework to minimize total completion time, as well as time-dependent energy consumption and peak power charges simultaneously in a non-homogenous parallel-machine manufacturing system.

The remainder of this paper is organized as follows: Section 2 introduces the underlying assumptions of the model and presents the mathematical model. An illustration of the problem is presented via a case study in Section 3. Section 4 presents our numerical experiments as well as the results. Our conclusions are discussed in Section 5.

2 Problem Definition and Mathematical Modeling

This section describes the mathematical formulation proposed for a parallel machine scheduling problem where the total completion time of jobs, energy consumption, and power demand charges are minimized through determining the optimum sequence of jobs, job-machine assignment, and machine operating schedule. The proposed mixed-integer nonlinear programming (MINLP) model is built on the following underlying assumptions:

- Job processing times are known and the processing is non-preemptive.
- The machines are not identical, i.e., each machine has its own energy profile, and job processing times are machine-dependent. In other words, the processing time of a given jobs might vary on different machines.
- Machine energy consumption varies during different modes (states).
- Only one job can be processed on a given machine in each period.
- If there is no job to process on a machine in any given period, the machine will be idle and consuming idle energy. Idle mode is a very low-energy consuming mode.
- At the beginning of the scheduling horizon, the machines are off and might be turned on in an anticipation of an arriving job. The first job might arrive at the current period, or any other upcoming periods.
- The time to turn on the machines is assumed to be insignificant; therefore, it does not impact energy consumption significantly. However, the average power demand during the period at which the machine is turned on increases and is represented by *OP*. Note that *OP* is the average energy demand in the period at which the machine is turned on, accounting for power surge during the turn-on (start) process.
- When a machine switches to processing mode from idle, there will be a spike in power draw, called switch power (*SP*). The time to switch is assumed to be insignificant. As a result, when a switch to processing mode occurs in a given period, there will be an excess power demand during that period.
- The unit price of energy varies during peak/off-peak periods (TOU tariff). Demand charge is also a function of TOU and varies in different periods.
- The planning horizon is broken into *T* periods, such that the length of each period is the same as the interval used in energy demand charge calculations.

The parameters considered in the MINLP are as follows:

P_{jm} Processing time of job $j \in J$ on machine $m \in M$

IP_m^t Power consumption of machine $m \in M$ in idle mode during period $t \in T$

PP_m^t	Power consumption of machine $m \in M$ in processing mode during period $t \in T$
OP_m^t	Power consumption of machine $m \in M$ during turn-on process in period $t \in T$
SP_m^t	Power consumption of machine $m \in M$ during switch process from idle to processing mode in period $t \in T$
CP	Cost of maximum power demand
CE_t	Cost of energy consumption during period $t \in T$
L	Duration of each period
F_i	Objective function i, i = 1, 2, 3

The decision variables considered in the MINLP are as follows:

P_{max}	Maximum power demand
X_{jm}^t	1 if job $j \in J$ processing started on machine $m \in M$ at period $t \in T$; zero otherwise
W_{jm}^t	1 if job $j \in J$ is being processed on machine $m \in M$ at period $t \in T$; zero otherwise
Z_m^t	1 if machine $m \in M$ is turned on from off mode at period $t \in T$; zero otherwise
Y_m^t	1 if machine $m \in M$ is idle at period $t \in T$; zero otherwise
U_m^t	1 if machine $m \in M$ is switched from idle mode to processing mode at period $t \in T$; zero otherwise

The following is the proposed mixed-integer nonlinear programming model:

$$\text{Min} \quad \sum_{j \notin J} \sum_{t \in T} \sum_{m \in M} (t + P_{jm} - 1) X_{jm}^t \tag{1}$$

$$\text{Min} \quad \sum_{t \in T} L \times CE_t \left(\sum_{m \in M} IP_m^t + \sum_{m \in M} PP_m^t \sum_{j \in J} W_{jm}^t \right) \tag{2}$$

$$\text{Min} \quad CP \times P_{\max} \tag{3}$$

Subject to

$$\sum_{m \in M} \sum_{t=1}^{T-P_{jm}+1} X_{jm}^t = 1 \quad \forall j \in J \tag{4}$$

$$\sum_{j \in J} X_{jm}^t \leq 1 \quad \forall m \in M, \forall t \in T \tag{5}$$

$$\sum_{j \in J} W_{jm}^t \leq 1 \quad \forall m \in M, \forall t \in T \tag{6}$$

$$P_{jm} X_{jm}^t \leq \sum_{\theta=t}^{t+P_{jm}-1} W_{jm}^\theta \quad \forall j \in J, \forall m \in M, \forall t \in \{1, \ldots, T - P_{jm} + 1\} \tag{7}$$

$$W_{jm}^t = \sum_{\theta=1}^{t} X_{jm}^\theta \quad \forall j \in J, \forall m \in M, \forall t \in \{1, \ldots, P_{jm} - 1\} \tag{8}$$

$$W_{jm}^t = \sum_{\theta=t-P_{jm}+1}^{t} X_{jm}^\theta \quad \forall j \in J, \forall m \in M, \forall t \in \{P_{jm}, \ldots, T\} \tag{9}$$

$$\sum_{t \in T} Z_m^t \leq 1 \quad \forall m \in M \tag{10}$$

$$\sum_{j \in J} X_{jm}^t - \sum_{\theta=1}^{t} Z_m^\theta \leq 0 \quad \forall m \in M, \forall t \in T \tag{11}$$

$$\sum_{\theta=1}^{t} Z_m^\theta + \left(1 - \sum_{j \in J} W_{jm}^t\right) \leq 1 + Y_m^t \quad \forall m \in M, \forall t \in T \tag{12}$$

$$1-\sum_{j\in J} W_{jm}^{t} \geq Y_{m}^{t} \quad \forall m \in M, \forall t \in T \tag{13}$$

$$\sum_{\theta=}^{t} Z_{m}^{\theta} \geq Y_{m}^{t} \quad \forall m \in M, \forall t \in T \tag{14}$$

$$Y_{m}^{t} - Y_{m}^{t+1} \leq U_{m}^{t+1} \quad \forall m \in M, \forall t \in \{1,\ldots,T-1\} \tag{15}$$

$$Z_{m}^{t} + U_{m}^{t} \leq 1 \quad \forall m \in M, \forall t \in T \tag{16}$$

$$\begin{aligned}\sum_{m\in M} IP_{m}^{t} Y_{m}^{t} + \sum_{m\in M} PP_{m}^{t} \sum_{j\in J} W_{jm}^{t} + \sum_{m\in M}\left(OP_{m}^{t} - PP_{m}^{t}\right) Z_{m}^{t} + \sum_{m\in M}\left(SP_{m}^{t} - PP_{m}^{t}\right) U_{m}^{t} \\ + \sum_{m\in M}\left(PP_{m}^{t} - IP_{m}^{t}\right) Z_{m}^{t}\left(1-\sum_{j\in J} X_{jm}^{t}\right) \leq P_{\max} \quad \forall t \in T\end{aligned} \tag{17}$$

In the proposed multi-objective model, the objective function (1) aims to minimize the total completion time. The second and third objective functions aim to minimize the cost of time-based energy consumption and maximum power demand, respectively.

Constraint set (4) – (9) are the job scheduling-based constraints: constraints (4) and (5) show that in a given period only one job can be "started" on each machine. Based on constraint (6), each machine can "process" at most one job in a given period. In other words, based on these constraints, there is a one-to-one assignment between job and machine. Note that a job can be processed after it is started, and based on constraint (7), the total number of processing periods for a job is determined by the job processing time. Constraints (8) and (9) show that the job processing is non-preemptive once started [13].

Constraint set (10) – (17) are machine-based constraints and address machine operation and energy planning: constraint (10) indicates that each machine is turned on (from the off mode) at most once during the planning horizon. Constraint (11) indicates that if a job processing is started on a machine in a given period, the machine might have been turned on either during that period or in any other prior periods. It is worth mentioning that for energy demand reduction purposes, a machine might be turned on in a period when there is no job to be processed. This strategy is helpful to flatten the overall peak power demand in parallel machine setting. Constraints (12) and (13) show that if a machine is on, with no job to process, it is in idle mode. According to constraint (14), a machine can be idle if it has been turned on in any of the previous periods. Constraint (15) explains the switch process from idle to processing mode between periods. Constraint (16) indicates that in a given period, either a switch or turn-on process occurs. Constraint (17) is the power demand capacity constraint and accounts for the power demand during processing and idle modes, and spikes during turn-on and switch process. There is an upper bound on total amount of power consumption to prevent supply shortage and over charging. The last term on the left hand side of constraint (17) is nonlinear, which leads to a nonlinear constraint. This equation can be linearized using the following set of constraints:

$$\begin{aligned}\sum_{m\in M} IP_{m}^{t} Y_{m}^{t} + \sum_{m\in M} PP_{m}^{t} \sum_{j\in J} W_{jm}^{t} + \sum_{m\in M}\left(OP_{m}^{t} - PP_{m}^{t}\right) Z_{m}^{t} + \sum_{m\in M}\left(SP_{m}^{t} - PP_{m}^{t}\right) U_{m}^{t} \\ + \sum_{m\in M}\left(PP_{m}^{t} - IP_{m}^{t}\right) S_{m}^{t} \leq P_{\max} \quad \forall t \in T\end{aligned}$$

such that

$$\begin{aligned} & S_{m}^{t} \leq Z_{m}^{t} \\ & S_{m}^{t} \leq 1-\sum_{j\in J} X_{jm}^{t} \\ & S_{m}^{t} \geq Z_{m}^{t} - \sum_{j\in J} X_{jm}^{t} \end{aligned} \tag{18}$$

3 Model Validation: Illustrative Case Study

This section presents an eight-job three-machine scheduling example with a planning horizon of 16 periods (Table 1) to illustrate the model performance. The unit price of energy ($/kWh) fluctuates in different periods and is given as follows {0.04, 0.04, 0.2, 0.04, 0.04, 0.2, 0.04, 0.2, 0.2, 0.2, 0.2, 0.04, 0.2, 0.04, 0.2, 0.2}. The duration of each period is assumed to be L = 0.5 hour. The machines are not identical, i.e., they have different power consumption amounts, and the job processing times vary on different machines. Since the machines have different capabilities, the job processing times can be different even though the processing power consumptions are the same. Table 1 shows the machines' power specifications and machine-based job durations. The *IP*, *PP*, *OP*, *SP* are power consumption in *kW*, and job processing times are given in periods. The model is solved using a weighted approach [15], as described in the next section, where, w_i represents the weight of each objective function.

Table 1 Illustrative case study data

	IP	*PP*	*OP*	*SP*	J1	J2	J3	J4	J5	J6	J7	J8
M1	0.8	4	8	4.8	3	1	3	4	2	5	2	2
M2	0.8	4	8	4.8	5	5	1	4	3	3	1	2
M3	1	5	15	6	5	3	2	4	3	4	5	2

*.

Figure 1 shows the solution output for the given example when the objectives are equally weighted. As shown, only *M1* and *M2* are selected, as they are the lowest-energy consuming machines. *M1* is turned on in the first period to process *J2* and then switches to an idle mode in period 2 at which *M2* is turned on. *M1* switches to an idle mode in period 2, considering the spike resulting from *M2* during the turn-on process, assisting in reducing peak power demand and the associated charges. The equally weighted multi-objective model tries to avoid concurrent turn-on processes, as it has a significant impact on peak demand.

The model yields P_{max}=8.8 *kW*, total completion time=41 periods (half-hour), and total energy consumption charges of $5.04/kWh. It should be noted that in industrial facilities, the unit price of power demand ($/*kW*) is significantly higher than unit energy consumption charges ($/*kWh*), and minimizing peak demand leads to considerable savings for companies. High power demand can also influence future contracts with utility providers, as sometimes they use the previous year peak-power demand data as a default for the power demand during the subsequent year. In this example, a weighted sum approach was used to solve the multiple-objective model. Without loss of generality, we assume that all three objectives are equally important, meaning that all have the same weight in a weighted-sum approach.

In order to illustrate the effect of energy-related objectives (i.e. objectives two and three), we analyzed the model considering only the first objective. The result is shown in Figure 2. In this case, all machines are turned on in the first period, making the completion time as small as its minimum value (=26 periods). The peak power is at its maximum, i.e., 31 *kW*, in the first period, which increases power demand charges significantly.

Periods

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
M1	J2		J5	J5	J1	J1	J1	J4	J4	J4	J4					
M2		J7	J3	J8	J8	J6	J6	J6								
M3																
Peak load	8	8.8	8.8	8	8	8	8	8	4.5	4.8	4.8	1.6	1.6	1.6	1.6	1.6

Turn-on Idle Switch to processing

Figure 1. Solution of illustrative case when all objectives are considered (w_1=w_2=w_3)

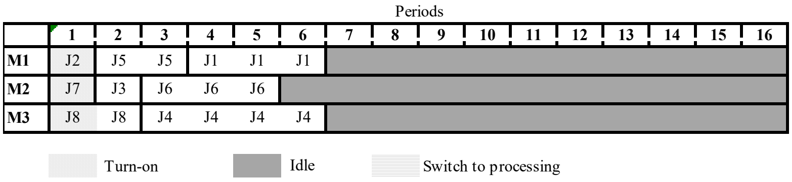

Figure 2. Solution of illustrative case when only completion time is minimized (w_1=1)

In the next scenario, we considered only the energy consumption charges objective function (second objective). The optimal value of the second objective is \$3.52. In this case, the values of the other two objectives would be deteriorated. In this schedule, as shown in Figure 3, the total completion time is 52 periods (1 period = 30 minutes) and P_{max}=16 kW, which are higher in comparison with the equally weighted scenario. In this case, only two machines are utilized.

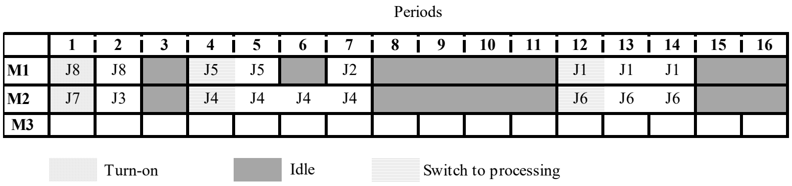

Figure 3. Solution of illustrative case when energy cost (objective 2) is minimized (w_2=1)

Finally, the model is studied considering only the third objective. In this case, the optimal value of the objective function is 88 (P_{max} = 8.8 kW), and the total completion time is 74 periods (Figure 4). Here only two machines are utilized, and the turn-on action and switches between modes occur at different periods in order to minimize power demand. It should be noted that in this schedule, *M2* is turned on in period 2 but it is kept idle until period 6.

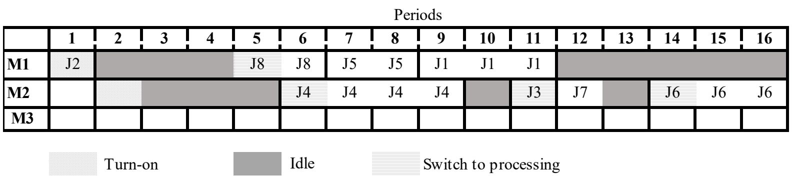

Figure 4. Solution of illustrative case when P_{max} is minimized (w_3=1)

4 Experimental Setup, Results, and Discussion

To show the effectiveness of the proposed mathematical model, we perform a numerical study in this section. For this purpose, instances were generated based on the parameters given in Table 2. To solve the generated instances, the mixed-integer linear program was implemented using C++, and the MILP solver of IBM ILOG CPLEX 12.5[3] was called to solve the instances on a desktop computer running Windows 64-bit operating system, an Intel i7-4790 CPU with eight 3.60 GHz cores, and 16 GB RAM.

[3] https://www.ibm.com/bs-en/marketplace/ibm-ilog-cplex

For the numerical study, five categories of instances were presented based on the number of machines (2 to 6 machines). Then, in each category, four random instances were generated based on the number of jobs, where the job durations and machines power consumption were generated using Table 2. The instances are solved in two ways. Firstly, each instance is solved with one objective at a time, and the optimal values of the objective functions along with the run times are reported in Table 3. The optimal values reported in Table 3 are used to find a compromise solution. From this numerical experiment, it can be seen that the run time is increasing from objective one to objective three, when the problem is solved with one objective at a time. This can be justified by the fact that the parallel machine with completion time can be solved to optimality in a polynomial time [14], while the P_{max} is a min-max objective function that increases the problem complexity.

Table 2. Parameters used to generate instances for the numerical study

Parameters	Possible Values
PP	{3, 4, 5, 6, 7, 8, 9}
IP	[0.2, 0.5]×PP
OP	[2, 3]×PP
SP	[1.2, 2] ×PP
CE	Pr (CE = 0.04) = Pr (CE = 0.2) = 0.5
L	0.5 hour
CP	10
P_{jm}	[1, 5] all integers
M	{2, 3, 4, 5, 6}
J	If M=2 or 3, then M + {1, 2, 3, 4} If M=4 or 5, then M + {7, 8, 9, 10} If M= 6, then M + {13, 14, 15,16}
T	16 = 8 hr

Table 3. Results for the first set of experiments

Instance			CPLEX Output					
#	M	J	Completion time	CPU time (sec)	2nd obj. (Energy cost)	CPU time (sec)	3rd Obj. P_{max}	CPU time (sec)
1	2	3	9	0	1.64	0	120	0
2		4	11	0	1.33	0	80	0
3		5	17	0	2.3	0	100	0
4		6	24	0	2.18	0	60	0
5	3	4	11	0	1.43	0	60	0
6		5	11	0	2.34	0	90	0
7		6	14	0	2.22	0	90	1
8		7	15	0	1.9	0	210	0
9	4	11	29	1	2.58	1	100	1
10		12	40	1	5.28	1	88	10
11		13	32	1	4.24	2	142	593
12		14	39	1	4.48	1	180	7
13	5	12	23	1	4.14	2	132	8
14		13	28	1	2.42	1	110	13
15		14	37	1	7.54	3	100	41
16		15	37	1	4.28	2	142	9,415
17	6	19	49	3	9.78	4	180	16
18		20	51	3	3.58	4	120	38
19		21	55	3	3.1	3	106	180
20		22	56	3	6.16	4	180	11
Average				1		1.5		516.7

In the second approach, the tri-objective model is solved, where the problem is converted to a single-objective using the compromised programming approach [15] to find the Pareto fronts. In this problem, the single objective is defined as follows:

$$F^{CP} = \sum_{i=1}^{3} \left(w_i \times \frac{F_i - F_i^*}{F_i^*} \right) \tag{19}$$

In Eq. (19), F^{cp} is the single objective, F^*_i, i =1, 2, 3 is the optimal value of objective i, and w_i, i = 1, 2, 3 is the weight of objective i, where $\sum_{i=1}^{3} w_i = 1$ and $0 \leq w_i \leq 1$. In this numerical study we set ($w_1 = w_2 = w_3$) and the results are given in Table 4.

Table 4. Results of the compromise approach ($w_1 = w_2 = w_3$)

Instance			CPLEX Output			
#	*M*	*J*	Obj 1	Obj 2	Obj 3	CPU time (sec)
1	2	3	19	3.17	120	0
2		4	14	2.23	98	0
3		5	30	3.2	100	0
4		6	41	2.88	60	0
5	3	4	21	2.2	100	1
6		5	28	3.07	90	0
7		6	24	3.06	96	1
8		7	26	4.62	250	0
9	4	11	56	4.29	110	2
10		12	64	6.8	118	37
11		13	58	5.56	190	63
12		14	84	8.76	240	104
13	5	12	54	9.05	202	120
14		13	85	6.54	110	200
15		14	82	9.58	130	160
16		15	84	6.46	190	162
17	6	19	92	12.01	270	150
18		20	117	6.62	170	41
19		21	118	4.81	180	116
20		22	119	10.92	240	212
Average						68.45

The comparison of results in Tables 3 and 4 reveals how the trade-offs among these three objectives can be made (Figure 5) and how the required time to achieve this can be affected. Moreover, by giving different weights to each objective by a decision maker, a set of solutions can be obtained. Then, the decision-maker decides which solution is more convenient depending on the circumstances and company policies. In addition, as shown in Tables 3 and 4, the solution time for the problems of this size, which are meaningful in practice, is negligible. This shows the effectiveness and applicability of the proposed model. However, as the dimension of the problem expands (larger number of machines, periods, and jobs), a more effective approach such as metaheuristics methods like NSGA-II is required to solve the problems in a more time-efficient manner.

A more detailed trade-off between objectives one and three is studied and depicted in Figure 5. In this set of experiment, instance 14 is considered as an example to be analyzed. Then, each objective one and three is given different combination of weights from a set of weights given by (w_1, w_3) = {(0.8, 0.1), (0.7, 0.2), (0.6, 0.3), (0.5, 0.4), (0.4, 0.5), (0.3, 0.6), (0.2, 0.7), (0.1, 0.8)} while w_2 is fixed at 0.1. The results in Figure 5 reveals the conflicts between these two objectives and shows how improving one will deteriorate the other.

5 Conclusion

In this paper, a mixed-integer nonlinear programming model is presented for a non-identical parallel machine scheduling problem with three objectives: total completion time, total energy cost, and maximum power demand charges to be minimized. This is the first study that considers maximum power demand in each period as a decision variable where energy consumption is a function of operating modes, and energy costs are following TOU policy. Then, in order to find Pareto fronts, the compromise approach is used to help the decision-maker and production-scheduler to apply the best schedule. The proposed algorithm handles the practical size cases efficiently.

Different directions can be employed for future work. First, multi-objective techniques can be utilized to obtain a set of Pareto optimal solutions. Second, the model can be extended to other machine configurations. Third, the model can be modified to address some other scheduling objectives, such as makespan or tardiness minimization. Finally, a heuristic approach can be proposed to solve the large-scale problems in a more time-efficient manner.

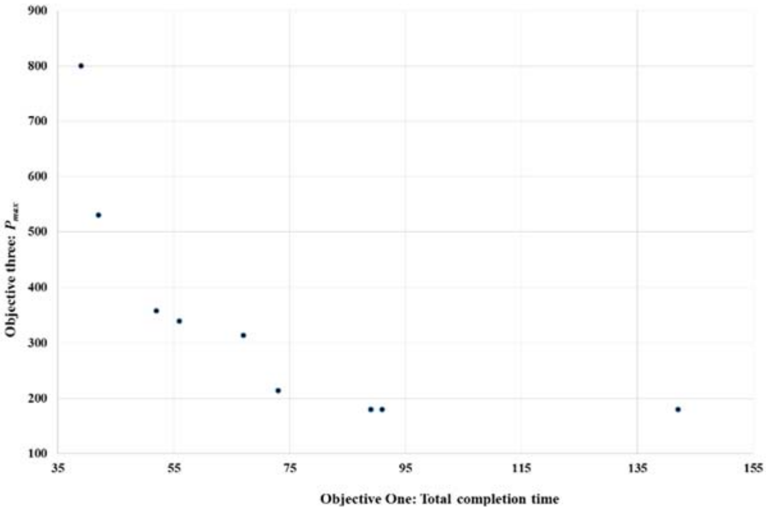

Figure 5. Values of objective one (total completion time) and objective three (P_{max}) of instance 14 where $w_2 = 0.1$, $(w_1, w_3) = \{(0.8, 0.1), (0.7, 0.2), (0.6, 0.3), (0.5, 0.4), (0.4, 0.5), (0.3, 0.6), (0.2, 0.7), (0.1, 0.8)\}$, and $w_1 + w_3 = 0.9$

References

1. Zhou, P., Ang, B., & Wang, H., Energy and CO_2 emission performance in electricity generation: A non-radial directional distance function approach. European Journal of Operational Research, 221(3), 625-635 (2012).
2. Nagasawa, K., Y. Ikeda & Irohara, T., Robust flow shop scheduling with random processing times for reduction of peak power consumption, Simulation Modelling Practice and Theory, 59, 102-113 (2015).
3. Gutowski, T., Murphy, C., Allen, D., Bauer, D., Bras, B., Piwonka, T., Sheng, P., Sutherland, J., Thurston, D., & Wolff, E., Environmentally benign manufacturing: observations from Japan, Europe and the United States, Journal of Cleaner Production, 13(1), 1-17 (2005).
4. Gahm, C., Denz, F., Dirr, M., & Tuma, A., Energy-efficient scheduling in manufacturing companies: A review and research framework, European Journal of Operational Research, 248(3), 744-757 (2016).
5. Che, A., Wu, X., Peng, J., & Yan, P., Energy-efficient bi-objective single-machine scheduling with power-down mechanism, Computers & Operations Research, 85, 172-183 (2017).
6. Liu, Y., Dong, H., Lohse, N., & Petrovic, S., A multi-objective genetic algorithm for optimisation of energy consumption and shop floor production performance, International Journal of Production Economics, 179, 259-272 (2016).

7. Salido, M. A., Escamilla, J., Giret, A., & Barber, F., A genetic algorithm for energy-efficiency in job-shop scheduling, The International Journal of Advanced Manufacturing Technology, 85(5-8), 1303-1314 (2016).
8. Kemmoe, S., Lamy, D., & Tchernev, N., A job-shop with an energy threshold issue considering operations with consumption peaks, IFAC-PapersOnLine, 48(3), 788-793 (2015).
9. He, Y., Li, Y., Wu, T., & Sutherland, J. W., An energy-responsive optimization method for machine tool selection and operation sequence in flexible machining job shops, Journal of Cleaner Production, 87, 245-254 (2015).
10. Zeng, Y., Che, A., & Wu, X., Bi-objective scheduling on uniform parallel machines considering electricity cost, Engineering Optimization, 1-18 (2017).
11. Che, A., Zhang, S., & Wu, X., Energy-conscious unrelated parallel machine scheduling under time-of-use electricity tariffs, Journal of Cleaner Production, 156, 688-697 (2017).
12. Shrouf, F., Ordieres-Meré, J., García-Sánchez, A., & Ortega-Mier, M., Optimizing the production scheduling of a single machine to minimize total energy consumption costs, Journal of Cleaner Production, 67, 197-207 (2014).
13. Zhang, H., Zhao, F., Fang, K., Sutherland, J. W., Energy-conscious flow shop scheduling under time-of-use electricity tariffs, CIRP Annals – Manufacturing Technology, 63, 34-40 (2014).
14. Pinedo, M., Scheduling: Theory, Algorithms, and Systems, 3rd Ed., Springer (2008).
15. Yousefi-Babadi, A., Tavakkoli-Moghaddam, R., Bozorgi-Amiri, A., & Seifi, S., Designing a reliable multi-objective queuing model of a petrochemical supply chain network under uncertainty: a case study, Computers & Chemical Engineering, 100, 177-197 (2017).