A Dynamic Control Approach for Energy-Efficient Production Scheduling on a Single Machine Under Time-Varying Electricity Pricing

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Abstract

fThis paper proposes a dynamic control algorithm to enable an energy-aware single machine scheduling under the time-varying electricity pricing policy, in which price rates remain fixed day-to-day over the season. The key issue is to assign a set of jobs to available time periods where different electricity prices are assigned, while considering requested due dates of jobs so as to minimize total penalty costs for earliness and tardiness of jobs and total energy consumption costs, simultaneously. As the first contribution of this study, we develop a new mixed integer nonlinear programming (MINLP) model that aims at determining job arrival times and resulting earliness and tardiness of jobs and energy consumption costs for machine idle and normal processing. Second, an efficient heuristic approach based on continuous-time variable control models and algorithm is developed. The proposed heuristic adaptively changes job arrival times and due dates, which finally determine production sequence over the time periods of different electricity prices, machine turn-off, and machine idle with minimum energy consumption costs and just-in-time (JIT) penalty. Energy and JIT performance of the proposed approach is examined using real energy and machining parameters of a HAAS machine and compared to those of the metaheuristic approach. For relatively large size data groups, the proposed approach incurs about $4 \sim 11\%$ higher energy consumption costs

on average, which are offset by up to 99% lower JIT costs, resulting in 10 $\sim$ 94% lower total costs on average compared to the metaheuristic approach. The proposed time-scaled heuristic algorithm yields extremely short computational time, which enables production managers to flexibly select proper production strategies and to implement them for different production environments.
Keywords: Machine idle time, just-in-time production, energy consumption, single machine scheduling, machine on-off scheduling, time-varying electricity pricing.

1. Introduction

Concerns over air pollution and the associated dramatic climate change have led to increasing pressure to reduce energy consumption in manufacturing plants and to develop more advanced energy-aware production strategies. Various research trials have been performed to reduce energy consumption and cost at both the machining and facility levels taking into account time related production performance by implementing advanced machining technologies and operation methods. From a production operation point of view, in particular, energy-consumption reduction during machine processing could be achieved by several means; for example, production capacity can be adjusted considering production demand and power price variations to reduce energy consumption (Johansson et al., 2009). Machine capacity (i.e., machining speed) variation also contributes not only to keeping track of production time but also to possibly changing energy consumption levels during operation (Lee & Prabhu, 2015).

As an active energy-saving strategy and operation in production lines, turning machinery on and off to save energy rather than remaining idle for a certain time contributes to significant reduction in energy consumption, thereby cost. Such energy-aware machine state controlling with effective production scheduling has been studied and addressed by various heuristic and optimization approaches. Since Mouzon et al. (2007) proposed a machine

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scheduling problem combined with a machine power switch (i.e., turn-on and turn-off) strategy for machine idle while taking into account energy consumption cost, similar studies have been conducted considering different energy-related conditions and production performance.

The initial attempts to materialize the idea of switching machine power based on production demands and machine idle time distribution have focused on developing mathematical models and their solution approaches aiming at minimizing energy consumption costs with several performance measures such as total tardiness (Mouzon & Yildirim, 2008) and total completion time Yildirim & Mouzon (2012). Extending these research, Chen et al. (2013) discussed the trade-off between production performance and energy efficiency in different operations schedules considering Bernoulli serial lines with dynamic machine turn-on and turn-off strategies. Markovian analysis on machine state control showed marginal impacts of the machine power-switch strategy on system performance. Dai et al. (2013) applied the machine switch strategy to the flexible flow shop scheduling problem with the two objective functions of minimizing makespan and total energy consumption. They developed a genetic-simulated annealing algorithm to solve such a multi-objective scheduling problem, resulting in an effective set of Pareto optimal solutions.

Most of the studies around this time were conducted under the assumption that electricity prices were fixed over the planning horizon. This has proven to be an unrealistic conditions, and time-varying electricity prices and tariffs are commonly used today. Since Shrouf et al. (2014) proposed the single machine scheduling problem combined with a machine power switch strategy while taking into account time-varying energy prices, several studies have been recently conducted to provide the most effective production scheduling methods under the energy and production efficiency perspectives. They established a mathematical model for a single machine scheduling problem to minimize the total energy consumption costs. In the problem, the continuous changes in energy price, the energy consumption of each machine status, and the energy consumption of transitions between status are simultaneously considered. A genetic algorithm and an analytical solution are developed.

Aghelinejad et al. (2016) modified the basic models in Shrouf et al. (2014) by introducing a variable that defines job situations integrally rather than using separate variables in the basic model, resulting in alleviating the computational complexity. Unlike the basic model in which job sequences are input values and not changed, they were also optimized by removing several constraints in the basic model while guaranteeing low computational times.

Extending the models with dynamic electricity variations, Che et al. (2016) considered a single machine scheduling problem under dynamic electricity tariffs. The objective function in this study was to minimize the total electricity cost by effectively assigning a set of jobs to specific time periods in which different electricity prices are applied. The problem was formulated by a continuous-time mixed-integer linear programming (MILP) model, and a greedy insertion heuristic algorithm was implemented to guarantee a short computational time. Assuming the preemption of jobs, each job is inserted in non-increasing order of power consumption rate into any idle time slots enough to hold it, while considering electricity costs.

Fang et al. (2016) also studied a single machine scheduling problem aiming at minimizing electricity costs under time-varying tariffs. They considered two scheduling conditions such that jobs are processed at a constant speed as well as an exponential function of speed that is called uniform-speed and speed-scalable machine conditions, respectively. They analytically showed NP-hard and polynomial properties for the non-preemptive and preemptive machine conditions and suggested approximate and exact polynomial-time algorithms for each case.

While those previous studies focused on a single machine problem with only an energy-related objective, Wang et al. (2016) recently solved a bi-objective single machine batch scheduling problem with the objective function of minimizing the makespan and total energy consumption costs, which depends on the energy price variations. An exact $\epsilon-$constraint method was implemented by solving the problems of constructing job batches and sequences. Overcoming computational complexity caused by NP-hardness of the problem, two constructive heuristic methods were also proposed to determine batch size and sequence separately and showed their algorithmic benefits in terms of production, energy and computational performance.

Gong et al. (2016) also studied a similar problem with the objective function of minimizing electricity costs considering three demand response programs in which different electricity pricing strategies are given. The problem was formulated by the MILP model considering the machine power switch strategy, and genetic algorithm was implemented to solve it. They showed trade-off between the electricity cost and the makespan by analyzing numerical experiment results within three Pareto frontiers.

Recent research like that described above tells us that no one addresses a scheduling problem with consideration for just-in-time (JIT) production needs, the machine power switch strategy, and energy consumption costs under the dynamic electricity pricing condition, simultaneously. Particularly with the increasing importance of time-based competition and corresponding JIT needs, production performance based on due-dates becomes more important, especially in small-volume large-variety production processes. Here, JIT needs can be materialized simply by minimizing both tardiness and earliness of jobs, which improve, for example, customer satisfaction by improving delivery reliability and minimizes the work-in-process inventory (Prabhu, 2000). Technically, however, the JIT considerations in the scheduling problem lead to much higher computational complexity compared to other conventional measures, such as makespan, completion time, and lateness (Baker & Scudder, 1990).

In this paper, we demonstrate how improvement in JIT can be incorporated with improvement in energy consumption costs in a single machine scheduling problem under time-varying electricity prices and the machine power switch strategy. To do this, first we analyze the relationship between the approximated energy consumption level and the machine idle time, which is a part of production schedules and can be effectively managed to lower the overall energy consumption level. In particular, time-varying electricity price is considered to estimate overall energy consumption costs for production, specifically based on the time-of-use (TOU) pricing policy. To overcome huge computational burdens expected by non-linearity of the objective function consisting of JIT and energy measures, a heuristic method based on a control theoretic approach is developed and its solution proximity, limitation, and effectiveness are discussed. We develop dynamic models in which dynamics of part-arrival and machine idle time are represented and controlled for energy-efficient production scheduling. Furthermore, these control models serve as a core control logic in the dynamic algorithm, called dynamic idle time and arrival time control (DIATC) algorithm, which aims for real-time production and machine vacation scheduling on a single machine in the consideration of TOU pricing, thereby simultaneously achieving better JIT production performance as well as less energy consumption cost. Finally, the performance of DIATC is compared to the metaheuristic called particle swam optimization (PSO).

The remainder of this paper is organized as follows. In section 2, the single machine scheduling and machine switch on-off problem with the consideration of energy consumption cost and JIT performance is defined, and its mixed integer nonlinear programming (MINLP) formulation is provided. In section 3, dynamic models for controlling production-job arrivals and machine idle time are proposed, and the DIATC algorithm is proposed in section 4. Lastly, in section 5, performance of the proposed approach is analyzed using sets of benchmark problems and compared to PSO.

2. Problem description and formulation

Consider a single machine scheduling problem with earliness and tardiness (ET) penalties and energy consumption cost for machine operations. A set of n independent jobs has to be scheduled on a single machine that can handle at most one job at a time during T. The machine is assumed to be continuously available from time zero onwards, and preemptions are not allowed. The fundamental problem we consider in this paper is formally defined as constructing production and machine vacation schedules to meet the requested production due dates as formulated by MINLP. The following notations are used for model parameters and decision variables.

Ω	set of n independent jobs, $\Omega = \{1, 2, \ldots, n\}$
Ω	set of inserted machine vacations among production jobs, $\Omega_{\mathrm{I}} = \{1, 2, \ldots, m\}$
T	planning horizon, $T = \{0, 1, 2, \ldots, h\}$
x_{jt}	machine status, $x_{jt} = 1$ if the machine is processing job j at t, otherwise zero
x_t^{IMV}	machine power status, $x_t^{IMV} = 1$ when the machine is shut down
x_t^{I}	machine power status, $x_t^{I} = 1$ when the machine is idle
s_{jt}	job releasing time, $s_{jt} = 1$ if the job j starts at time t, otherwise zero
s_{jt}^{IMV}	machine power status, $s_{jt}^{IMV} = 1$ if machine turn-off or idle starts at time t, otherwise zero
$y_{tt'}$	dummy job status, $y_{tt'} = 1$ when a dummy job starting at time t is processed by the machine at time t'
z_t	logical relationship among machine turn-off or idle and other machine status
p_j	processing time of job j
d_j	due date of job j
C_J	penalty cost for any positive earliness or tardiness job
(b, A)	coefficient set for machine power regression
$\bar{e}$	energy consumption (kWh) by machine idle
e_t	electricity price at time t
R_j	material removal rate for job j

The length of machine turn-off or idle is not given and is determined after an optimal solution is obtained. Therefore, in the optimization model, we treat machine turn-off or idle as a set of dummy jobs with fixed processing time that is equal to the minimum time required to turn on the machine. Moreover, to deal with the dynamic characteristic of machine turn-off or idle length, it is assumed that a machine can handle several machine turn-off or idle at a time.

Job $j, j \in \Omega$, requires p_j and should ideally be completed on its due date d_j. Also, we assume that the ET of job j identically incur C_J. The objective function for ET penalties is to find a schedule that minimizes the sum of the mean squared earliness and tardiness, which is called a JIT cost, such that

$$C_J \sum_{j \in \Omega} \left(\sum_{t \in T} t s_{jt} + p_j - d_j \right)^2 / n. \tag{1}$$

It should be noted that the given JIT cost is a form of mean squared error (MSE), which is the second moment of the error and penalizes the variance of total ET and its bias, thereby making the problem much harder than the penalty function with a simple absolute deviation form. Nevertheless, it is a much more appropriate performance measure in the production environment where the need for JIT manufacturing and delivery is crucial.

As an objective function for the energy consumption cost, we consider the energy consumption cost during machine idle and normal processing, which is given by

$$\sum_{t \in T} \bar{e} e_t x_t^I \tag{2}$$

and

$$\sum_{j \in \Omega} \sum_{t \in T} (bR_j + A) e_t x_{jt}, \tag{3}$$

respectively.

Finally, the single machine scheduling problem for minimizing the total costs of energy consumption and JIT penalty formulated as the following MINLP:

Production and machine vacation scheduling (PMVS):

$$\min \; C_J \sum_{j \in \Omega} \left(\sum_{t \in T} t s_{jt} + p_j - d_j \right)^2 / n \tag{4}$$

$$+ \sum_{t \in T} \bar{e} e_t x_t^I + \sum_{j \in \Omega} \sum_{t \in T} (bR_j + A) e_t x_{jt} \tag{5}$$

$$\sum_{t \in \{1, \ldots, h - p_j + 1\}} s_{jt} = 1 \quad \forall j \tag{6}$$

$$\sum_{j \in \Omega} x_{jt} + x_t^{IMV} + x_t^I = 1 \quad \forall t \tag{7}$$

$$\sum_{t' \in \{t,...,t+p_j-1\}} x_{jt'} \geq p_j s_{jt} \quad \forall j, t \tag{8}$$

$$\sum_{t' \in \{t,...,t+p^{IMV}-1\}} y_{tt'} = p^{IMV} s_{jt}^{IMV} \quad \forall t \tag{9}$$

$$y_{tt'} = 0 \quad \forall t, t' \in \{1, ..., t-1\} \cup \{t + p^{IMV}, ..., h\} \tag{10}$$

$$z_{t'} = \sum_{t \in T} y_{tt'} \quad \forall t' \tag{11}$$

$$z_t + \sum_{j \in \Omega} x_{jt} + x_t^I \geq 1 \quad \forall t \tag{12}$$

$$z_t \left(\sum_{j \in \Omega} x_{jt} + x_t^I \right) = 0 \quad \forall t \tag{13}$$

$$z_t \geq 0 \quad \forall t \tag{14}$$

$$x_{jt}, x_t^{IMV}, x_t^I, s_{jt}, s^{IMV}, y_{tt'} \in \{0, 1\} \quad \forall j, t, t' \tag{15}$$

The first term of the objective function (4) indicates the JIT cost for quadratic earliness and tardiness, and the following three cost components in (5) indicate the energy costs for machine idle and nominal processing, respectively. Here, p_j and cost components C_J, $\bar{e}$, e_t, and machine power profile, $(bR_j + A)$, are assumed to be known. Constraints (6) and (7) define the unique job releasing time and machine status, respectively. Consecutive machine status due to the given processing time is determined by constraints (8), (9) and (10). Since multiple dummy jobs can be assigned to the machine, z_t is not binary but zero or positive integer. The IMV is determined by constraints (11), (12) and (13). Lastly, the conditions of the decision variable are represented by the constraints (14) and (15).

Variation of the energy consumption would mostly depend on machining parameters and operation states (i.e., idle and normal operation) at specific time periods. In particular, there is a direct relationship between operation states and machine power, which is one of the key factors for the determination of job sequences. Figure 1 illustrates such a relationship, that is, a power consumption profile of milling processes for the HAAS VF0 machine. There are machine power fluctuations depending on machine states, such as machine idle and sub-processing. Analyzing cutting profiles and resulting machine power, Jeon et al. (2016)

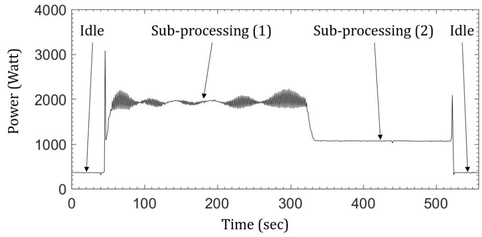


Figure 1: Power of HAAS VF0 milling machine

estimated the expected machine power of the HAAS VF0 milling machine using linear regressions, which has a form as follows:

$$E[Watt|\text{MRR}] = 2163.4 + 2.7698\text{MRR} \tag{16}$$

where MRR is in mm^3/sec with $R^2 = 98.1\%$. In the computation experiments for the proposed scheduling model, we use such specific power profiles to calculate the objective function values rather than impractical cases.

In the next section, dynamic control models and algorithm as a heuristic approach to solve PMVS is explained.

3. Dynamic control method for solving PMVS

Production and machine turn-off schedules are determined by a chronological order of production job arrivals in a production queue, and therefore the effective determination of arrival times of production jobs is essential for improving scheduling performance. In this section, we propose dynamic models for controlling arrival times of production jobs while taking account of JIT and energy performance. The following notations are used for model parameters and decision variables.

a arrival time vector in R^{n+m} where a_j is the jth element

p nominal processing time vector in R^n where p_j is the jth element

x processing time variation vector in R^n where x_j the jth element

c completion time vector in R^n where c_j is the jth element

d due-date vector in R^n where d_j the jth element

q queueing time vector in R^n where q_j the jth element

ξ_S machine startup energy

τ_j machine idle time between job j and its precedent job

τ^* time required to machine startup

For active management of the machine idle time, we consider a compulsory inserted machine vacation entity (i.e., time periods during which machine power is turned off), denoted by IMV, that replaces the machine idle time to save energy consumption during machine idle, especially when the energy consumption incurred by machine idle is greater than an energy threshold that is generally defined as the minimum energy consumption required to turn on the machine. Thus, if resulting total energy consumption is greater than the energy consumption required by machine start-up, then IMV can be implemented (i.e., turning off machine power) to save energy. The total number of IMVs, m, satisfies the following inequalities:

$$m\tau^*\xi_S \leq \sum_{j\in\Omega} \bar{e}\tau_j \leq (m+1)\,\tau^*\xi_S. \tag{17}$$

Here, $\sum_{j\in\Omega} \bar{e}\tau_j$ indicates the total energy consumption by machine idle.

3.1. Arrival time control for production job and IMV

Let us define the $n \times 1$ arrival time vector as

$$\mathbf{a}(t) = \begin{bmatrix} a_1(t) & \dots & a_n(t) \end{bmatrix}^{\mathrm{T}}, \tag{18}$$

and $n \times 1$ vectors of the job completion time, processing time, and due date are similarly defined as $\mathbf{c}(t)$, $\mathbf{p}(t)$, and $\mathbf{d}(t)$, respectively. It should be noted that the job arrival time can also be called the job "release" time to a machine or the "start" time of a production job because a machine operation is assumed to be immediately available and to start at the time of job arrival with zero queue.

Considering single-machine operations, time duration of machine turned-off can be treated as a virtual production job with its start time (i.e., the time at which a machine is turned off), $a_i(t)$, time duration, $p_i(t)$, and the machine turn-on time, $c_i(t)$ $i \in \Omega_{\mathrm{I}}$. Multiple m IMVs can be integrated with the vectors of $\mathbf{a}(t)$, $\mathbf{p}(t)$ and $\mathbf{d}(t)$ above, and finally the $(n+m) \times 1$ arrival time vector whose elements now represent arrival times of both production jobs and IMVs is redefined as

$$\mathbf{a}(t) = \begin{bmatrix} a_1(t) & \dots & a_m(t) & a_{m+1}(t) & \dots & a_{m+n}(t) \end{bmatrix}^{\mathrm{T}}, \tag{19}$$

and integrated completion time and processing time vectors can be similarly defined.

The dynamic model is designed to manipulate the arrival times of production jobs and IMVs, $a_j(t)$ $j \in \Omega \cup \Omega_{\mathrm{I}}$, in such a way that the discrepancy between $d_j(t)$ and $c_j(t)$ is minimized. Finally, as mentioned earlier, the order of job arrivals in a machine queue determines their operation sequences based on the first-come-first-served discipline. Hence, the arrival time dynamics for production and machine vacation schedules are explained by

$$\dot{\mathbf{a}}(t) = \mathbf{k}_a \big\{ \mathbf{d}(t) - \mathbf{c}(t) \big\} \tag{20}$$

where $\mathbf{k}_a$ is the $(n+m) \times (n+m)$ diagonal matrix with $\mathrm{diag}(\mathbf{k}_a) = \begin{bmatrix} k_1^a & k_2^a & \dots & k_{m+n}^a \end{bmatrix}^{\mathrm{T}}$ $0 < k_j^a < 1$.

Considering a positive queueing time, (20) can be rewritten as

$$\dot{\mathbf{a}}(t) = \mathbf{k}_a \Big[\mathbf{d}(t) - \big\{ \mathbf{a}(t) + \mathbf{p}(t) + \mathbf{q}(t) \big\} \Big] \tag{21}$$

where $\mathbf{q}(t)$ represents queueing times of production jobs and IMVs incurred by time conflict between the arrival time of a current job and the completion time of a previous job. It should be noted here that the actual queueing time occurs only by time conflicts of production jobs, and the IMV entities do not incur actual queueing times because for any $i \in \Omega_{\mathrm{I}}$ and $j \in \Omega$, the following inequalities are held:

$$(i) \quad a_i(t) + p_i(t) \le a_j(t) \quad \text{and} \quad (ii) \quad a_j(t) + p_j(t) \le a_i(t) \tag{22}$$

which represent the following situations: (i) starting a new production job after turning on a machine and (ii) a machine turns off after finishing a production job j.

Prabhu & Duffie (1999) showed nonlinear dynamics between arrival and completion times of production jobs with $\mathbf{q}(t) > 0.0$ in (21) and also sought to aggregate and ignore such a nonlinearity using the following integral control law:

$$a_j(t) = k_j^a \int_0^t \Big\{ d_j(s) - a_1(s) - \sum_{h=1}^{j} p_h(s) \Big\} ds + a_j(0) \tag{23}$$

where k_j^a is the control gain, and $a_j(0)$ is an arbitrary initial value. It should be noted that the arrival time controller (23) can be readily used for unified control of production jobs and IMVs due to integrated mathematical structures that are already prepared in (21) without any additional assumptions and computational increment.

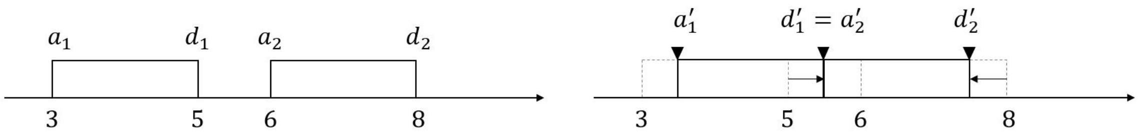
The solution of ODE in (21) is differently derived according to the feasibility of due dates; if all production jobs and IMVs have feasible due dates, then the solution is given by

$$a_j(t) = \big(d_j(t) - p_j(t)\big)e^{-k_j^a t} + a_j(0)e^{-k_j^a t}, \quad j \in \Omega \cup \Omega_{\mathrm{I}} \tag{24}$$

in which, for all $a_j(0) = 0.0$, the steady state of $a_j(t)$ is determined by $d_j(t) - p_j(t)$, and the completion time corresponds to its due date, $d_j(t)$.

Figure 2(a) illustrates the Gantt chart of two jobs with steady-state arrival times, showing that a positive idle time exists between $c_1(t) = 5.0$ and $a_2(t) = 6.0$. One possible way to reduce or remove such an idle time is that the system move backward (respectively, move forward) $a_2(t)$ to $a_2'(t)$ (respectively, $a_1(t)$ to $a_1'(t)$) simultaneously, as illustrated in Figure 2(b).

Adjusting the arrival times which already reach their steady states can be possibly performed by manipulating the reference values of the system (i.e., $\mathbf{d}(t)$) in the arrival time control system (21). Interestingly, making all feasible due dates identical leads to the conversion of the system from the feasible system to the infeasible system, resulting in continuous intersections of $\mathbf{a}(t)$ over the discontinuity region within an infinitesimal area where all arrival times are identical (i.e., $a_1(t) = \cdots = a_{n+m}(t)$). As a result, once $\mathbf{a}(t)$ enters the



(a) Positive idle time (b) Reduced idle time

Figure 2: Effect of due date adjustment

discontinuity region, the system no longer allows any time vacancy among production jobs, thereby generating zero idle time as illustrated in Figure 2(b).

Artificially manipulated $\mathbf{d}(t)$ contributes to reducing the energy consumption especially incurred by machine idle, but at the same time, it should increase total due date deviation because the resulting completion times no longer meet the original due dates. To make a smarter decision on the production and IMV schedule while considering such a trade-off between two contradictory performance measures, the control mechanism on adjusting the due date vector needs to be more systematic. In the following section, we propose the idle time controller that is incorporated with the arrival time controller in order to minimize the cost of due-date deviation and energy consumption.

3.2. Idle time control

The idle time control aims to adjust $\mathbf{d}(t)$, especially when there is a positive number of IMVs, which is incorporated with the arrival time control, considering the energy consumption level of a machine and JIT performance of production jobs. As explained in the previous section, one of the simpler ways to reduce all time vacancy among production jobs is to adjust all due dates of production jobs to where all due dates are identical. The adjustment of $\mathbf{d}(t)$, however, causes the corresponding change of $\mathbf{c}(t)$ which is supposed to be equal to $\mathbf{d}(t)$ in the production schedule with all feasible due dates, thereby increasing due date deviation, that is ET. Thus, it is required to investigate a possible way to minimize the impact of due-date changes on the increment of ET. One possible way is to keep the magnitude of the vector, $\mathbf{d}(t) - \mathbf{c}(t)$, as small as possible. Hence, we design the idle time controller for the adjustment of $\mathbf{d}(t)$ of production jobs as follows:

$$\dot{\mathbf{d}}(t) = \mathbf{k}_d \left(\bar{\mathbf{d}} - \mathbf{d}(t)\right) \tag{25}$$

where $\mathbf{k}_d$ is a $n \times n$ diagonal matrix with $\text{diag}(\mathbf{k}_d) = \begin{bmatrix} k_1^d & k_2^d & \dots & k_n^d \end{bmatrix}^{\text{T}}$ $0 < k_j^d < 1$, and $\bar{\mathbf{d}}$ is the arbitrary $n \times 1$ vector located on the discontinuity region. Here, $\bar{\mathbf{d}} - \mathbf{d}(t)$ always intersects the discontinuity region at right angles.

Now let us suppose that initial $\mathbf{d}(t)$ moves toward $\bar{\mathbf{d}}$ whose elements are all identical. If we consider a two production-job case, the movement of $\mathbf{d}(t)$ can be described by the gray lines in Figure 3(a) toward three different positions (i.e., $\bar{\mathbf{d}}$, $\bar{\mathbf{d}}'$, and $\bar{\mathbf{d}}''$, respectively), which are all located in the discontinuity region, and resulting changes of completion time vectors are represented as black, blue, and red lines, respectively. When $\mathbf{d}(t)$ reaches each position, the completion time vectors are converged to $\mathbf{c}_{ss}$, $\mathbf{c}_{ss}^{'}$, and $\mathbf{c}_{ss}^{''}$, respectively. It should be emphasized that the vector $\mathbf{c}_{ss} - \bar{\mathbf{d}}$, $\mathbf{c}_{ss}^{'} - \bar{\mathbf{d}}'$, and $\mathbf{c}_{ss}^{''} - \bar{\mathbf{d}}''$ form three different hyperplanes which are perpendicular to the discontinuity region as shown in Figure 3(b). It should also be noted that conflict of the arrival time in the vicinity of the discontinuity region results in the discontinuous behavior of $\mathbf{c}(t)$, which is shown as two separate and parallel movements of the completion time vectors.

Property 1. *Let δ be the Euclidean norm such that $\delta = \|\mathbf{d}(t) - \mathbf{d}\|$ where $\mathbf{d}(t)$ is the solution of $\dot{\mathbf{d}}(t) = \mathbf{k}_d \left(\bar{\mathbf{d}} - \mathbf{d}(t)\right)$. Then, δ is the smallest norm compared to any $\|\mathbf{d}_\bullet(t) - \mathbf{d}\|$ where $\mathbf{d}_\bullet(t)$ is the solution of $\dot{\mathbf{d}}_\bullet(t) = \mathbf{k}_d^{\text{T}} \left(\bar{\mathbf{d}}_\bullet - \mathbf{d}_\bullet(t)\right)$, $\bar{\mathbf{d}} \neq \bar{\mathbf{d}}_\bullet$.*

Proof. Let $\delta_\bullet$ be $\|\mathbf{d}_\bullet(t) - \mathbf{d}\|$. Solving the ODE in (25) gives

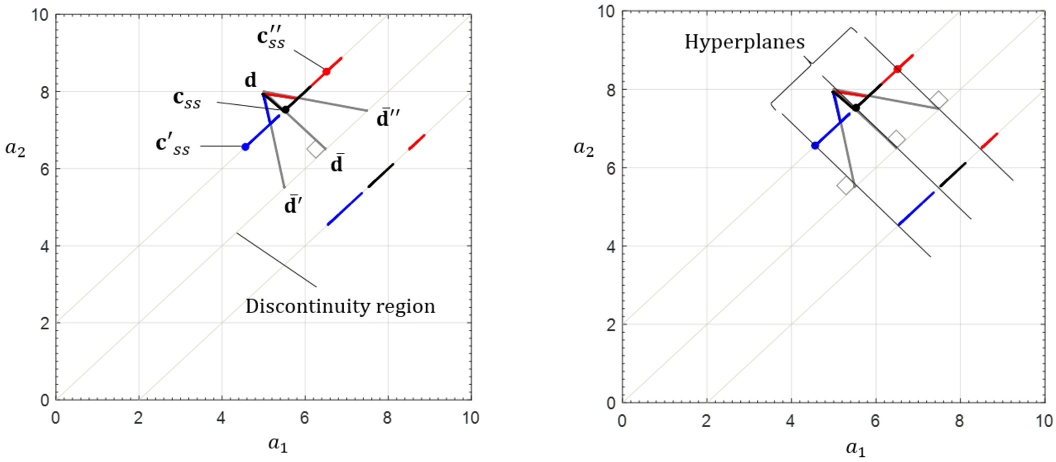
$$\mathbf{d}(t) = \left(1 - e^{-\mathbf{k}_d t}\right) \bar{\mathbf{d}} + \mathbf{d}(0) e^{-\mathbf{k}_d t} = \left(1 - e^{-\mathbf{k}_d t}\right) \bar{\mathbf{d}} + \mathbf{d} e^{-\mathbf{k}_d t}$$

and therefore δ and $\delta_\bullet$ are given by

$$\delta = \|\mathbf{d}(t) - \mathbf{d}\| = \| \left(1 - e^{-\mathbf{k}_d t}\right) \left(\bar{\mathbf{d}} - \mathbf{d}\right) \|,$$

$$\delta_\bullet = \|\mathbf{d}_\bullet(t) - \mathbf{d}\| = \| \left(1 - e^{-\mathbf{k}_d t}\right) \left(\bar{\mathbf{d}}_\bullet - \mathbf{d}\right) \|,$$

respectively.



(a) Completion time vector movement

(b) Hyperplanes

Figure 3: Analysis of vector space: two-job case

The vector magnitude above only depends on $\|\bar{\mathbf{d}} - \mathbf{d}\|$ and $\|\bar{\mathbf{d}}_\bullet - \mathbf{d}\|$. First,

$$\begin{aligned}\bar{\mathbf{d}} - \mathbf{d} &= \left(\frac{d_1 + \cdots + d_n}{n}, \ldots, \frac{d_1 + \cdots + d_n}{n}\right) - (d_1, \ldots, d_n)\\ &= \left(\frac{-d_1 + d_2 + \cdots + d_n}{n}, \ldots, \frac{d_1 + \cdots + d_{n-1} + d_n}{n}\right),\end{aligned}$$

Let α be $\alpha\mathbf{I}$ where $\alpha \neq 0$ is a scalar and $\mathbf{I}$ is $n \times 1$ matrix whose element is a unity. Then, $\bar{\mathbf{d}}_\bullet = \bar{\mathbf{d}} + \alpha$, and therefore

$$\begin{aligned}\bar{\mathbf{d}}_\bullet - \mathbf{d} &= \left(\frac{d_1 + \cdots + d_n + n\alpha}{n}, \ldots, \frac{d_1 + \cdots + d_n + n\alpha}{n}\right) - (d_1, \ldots, d_n)\\ &= \left(\frac{-d_1 + d_2 + \cdots + d_n + n\alpha}{n}, \ldots, \frac{d_1 + \cdots + d_{n-1} + d_n + n\alpha}{n}\right).\end{aligned}$$

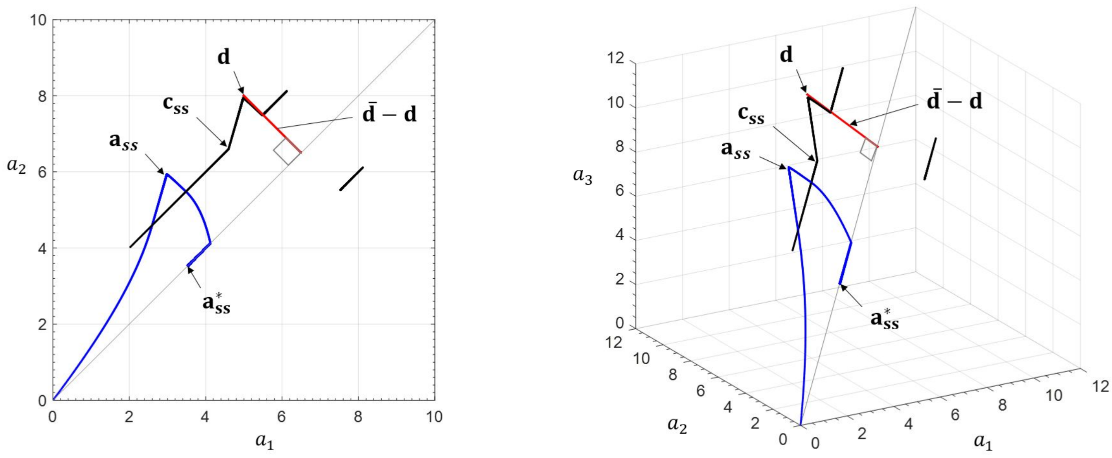
Replacing $(-d_1 + d_2 + \cdots + d_n)$, $\ldots$, $(d_1 + d_2 + \cdots - d_n)$ with x_1, $\ldots$, x_n gives

$$\delta = \|\bar{\mathbf{d}} - \mathbf{d}\| = \frac{1}{n}\sqrt{x_1^2 + \cdots + x_n^2},$$

$$\delta_\bullet = \|\bar{\mathbf{d}}_\bullet - \mathbf{d}\| = \frac{1}{n}\sqrt{(x_1 + n\alpha)^2 + \cdots + (x_n + n\alpha)^2}.$$

Then, the residual of $\delta_\bullet$ compared to δ is

$$n\alpha(x_1 + \cdots + x_n) + n^2\alpha^2 = n(n-1)\alpha(d_1 + \cdots + d_n) + n^2\alpha^2$$



(a) Two-job case

(b) Three-job case

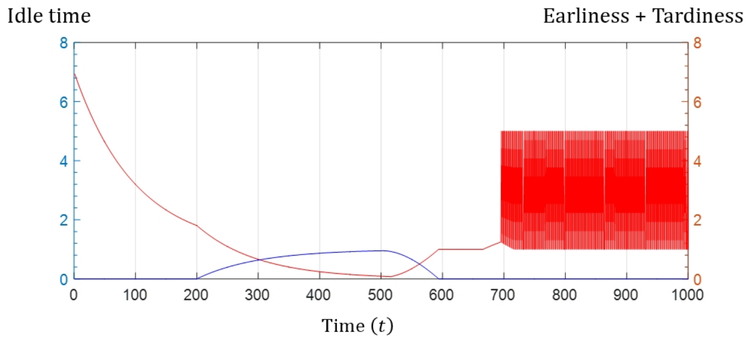
Figure 4: Analysis of vector space

which is always positive.

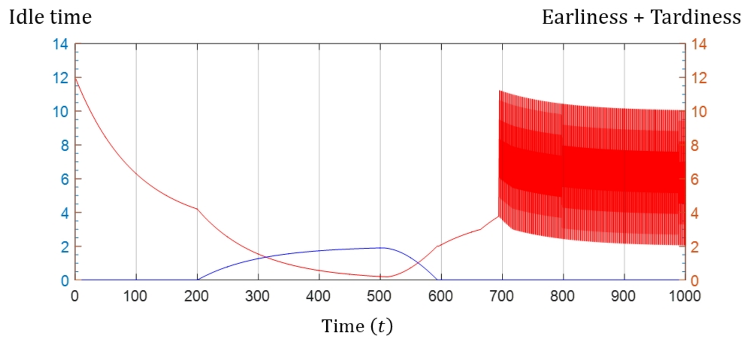
Hence, δ is always greater than $\delta_\bullet$, and we conclude that δ is the smallest norm. □

To maintain the smallest discrepancy between the controlled $\mathbf{d}(t)$ and $\mathbf{c}(t)$, $\mathbf{d}(t)$ needs to move on the plane containing $\bar{\mathbf{d}} - \mathbf{d}(t)$, which is perpendicular to the discontinuity region by Property 1. Figure 4 illustrates two examples of two- and three-job cases in which movements of arrival time and completion time vectors and $\bar{\mathbf{d}} - \mathbf{d}(t)$ are represented by blue, black, and red lines, respectively. Prior to the adjustment of $\mathbf{d}(t)$, as $t \to t'$ where t' is a certain amount of time enough to make the system stable, the arrival time controller (21) continuously adjusts $\mathbf{a}(t)$ and $\mathbf{c}(t)$, which are finally converged to $\mathbf{a}_{ss}$ and $\mathbf{c}_{ss}$, respectively, while taking into account the original $\mathbf{d}(t)$. After reaching the steady state, once $\mathbf{d}(t)$ starts to move on $\bar{\mathbf{d}} - \mathbf{d}(t)$, $\mathbf{a}(t)$ is also adjusted again and finally reaches $\mathbf{a}^*_{ss}$ where $\mathbf{a}(t)$ continues to oscillate in the vicinity of the steady-state point, resulting in continuous changes of production job sequences. It should be emphasized that once $\mathbf{a}(t)$ enters the discontinuity region, $\mathbf{c}(t)$ becomes the discontinuous function of $\mathbf{a}(t)$, thereby distinctly separated traces of the completion time vector movement are observed as shown in Figure 4.

Incorporating the arrival time control (21) with the idle time control (25), we test two simple examples used in the previous analysis and observe how the idle time and ET vary.



(a) Two-job case



(b) Three-job case

Figure 5: Energy consumption and ET variations

To show dynamics of two different measures clearly, the electricity price is assumed to be identical during the planning horizon. Figure 5 illustrates variations of the idle time (blue line) and ET (red line) for each case; in these examples, the idle time controller is implemented at time $t = 500$, and therefore, $\mathbf{d}(t)$ starts moving after $t = 500$ at which $\mathbf{c}(t)$ is equal to the original $\mathbf{d}(t)$, resulting in zero ET. As $t \to 1000$, $\mathbf{d}(t)$ moves toward $\bar{\mathbf{d}}$, and ET increases correspondingly. Oscillation of ET after around $t = 690$ is caused by $\mathbf{c}(t)$ which becomes the discontinuous function of $\mathbf{a}(t)$. In the case of idle time, it starts decreasing after $t = 500$ and finally hits zero once $\mathbf{d}(t) = \bar{\mathbf{d}}$. Overall, the idle time and ET vary concavely and convexly, respectively, and therefore the objective of the proposed dynamic control algorithm is to find the system state that minimizes the total cost which is approximately expected to vary convexly.

4. Dynamic idle time and arrival time control algorithm

The relationship between the machine idle time and ET variations is readily used to determine the production and machine turn-off schedules in such a way that the total cost of ET penalty and energy consumption cost is minimized by adjusting arrival times of production jobs and properly locating machine vacations (i.e., IMVs) among jobs.

For multiple IMVs obtained by the condition (17), grouping production jobs between IMVs and incorporating them into the solution procedures are essential for determining good production schedules and improving energy performance. Such a grouping problem can be also formulated by MINLP, but it is not suitable for large size problem due to high computational complexity. Instead of MINLP, therefore, we simply determine job groups by dividing the given production jobs into certain number of groups, which is $m - 1$, and insert IMVs into empty time slots between adjacent job groups.

Finally, we develop a discrete-event timing control algorithm for PMVS in which production jobs and IMV schedules are simultaneously determined with the objective function of minimizing total JIT and energy consumption costs. We call this algorithm Dynamic Idle and Arrival Time Control algorithm (DIATC), and its overall steps are summarized in the Algorithm table. Technically, arrival and idle time controllers in (21) and (25), respectively, can be rewritten in the discrete time domain so that they can be executed under the digitalized computing environment. Such discrete controllers are expressed in lines 5 and 10 where Δ is the discrete time step for integration.

DIATC has two main functions: (i) job and IMV arrival control (line 5) and (ii) idle time control for each IMV (line 10). The specific DIATC algorithm can be outlined as follows. First, the arrival times of production jobs and IMVs are initialized (line 1), and the total production cost is also initialized to an arbitrary large number (line 2). The production and IMV completion times are updated based on processing time and queueing time (line 4), and finally, the arrival times of jobs and IMVs are adjusted by the arrival time controllers (line 5). After applying these procedures for all production jobs and IMVs, they are sorted based on a FCFS discipline with respect to arrival times (line 6), and the resulting total production

Algorithm:	The overall DIATC framework
Input:	Set of production orders (jobs) with nominal processing times and requested due dates; set of job groups.
Output:	Production schedule of jobs, machine turn-off schedule, and total production cost.
1:	$a_j(0) \leftarrow$ arbitrary positive number, $\forall j \in \Omega \cup \Omega_I$
2:	$J^* \leftarrow$ arbitrary large number for initial production cost
3:	**repeat**
4:	$c_j(\mathrm{T}) \leftarrow a_j(\mathrm{T}) + p_j(\mathrm{T}) + q_j(\mathrm{T})$
5:	$a_j(\mathrm{T}) \leftarrow k_j^a \Delta \left(d_j(\mathrm{T}) - c_j(\mathrm{T})\right) + a_{j-1}(\mathrm{T}-1)\ \forall j \in \Omega \cup \Omega_I$
6:	Sort jobs based on FCFS rule with respect to $a_j(\mathrm{T})$
7:	Calculate total cost, $J(\mathrm{T})$
8:	**if** $J(\mathrm{T}) < J^*$ **then**
9:	$J^* \leftarrow J(\mathrm{T})$
10:	$d_j(\mathrm{T}) \leftarrow k_j^d \Delta \left(\bar{\mathrm{d}}_i - d_j(\mathrm{T})\right) + d_{j-1}(\mathrm{T}-1)\ \forall j \in \Omega_I$
11:	T $\leftarrow$ T+1
12:	**until** T reaches to NUM_OF_ITERATIONS

cost (JIT cost + energy consumption cost) is calculated (line 7). If the updated production and IMV schedule yields better production performance compared to the previously saved total cost, then the best sequence for each job and IMV and corresponding objective function values are updated (line 9). As the last step, the due date of IMVs is updated by the idle time controller (line 10). All these procedures are repeated for the given number of iterations (NUM_OF_ITERATIONS).

It should be noted that it is difficult to decide the exact number of feedback trials (i.e., NUM_OF_ITERATIONS) that leads to more improved routing sequences, especially when the departure time vector remains in the discontinuity region. However, this class of algorithms is known to exponentially converge in the controlled variable (i.e., departure times) and moreover is globally stable for small values of the gain (Prabhu & Duffie, 1999). It depends on the problem size, but our experience indicates 100 to 1,000 iterations with 0.01 to 0.2 gains are adequate for most problems encountered.

5. Computational analysis

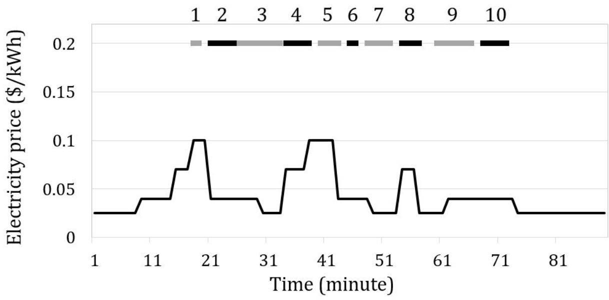
Validating performance of the proposed DIATC algorithm and comparing the results with those of PMVS, we consider datasets in which due date intervals of jobs are randomly distributed in 1.0 $\sim$ 10.0 minutes. The processing time is also randomly set to 50 $\sim$ 100% of the due-date interval considering current and previous production jobs, so that all production jobs have feasible due dates. As parameters for discrete timing control, NUM_OF_ITERATIONS $= 3,000$, and the idle time control is designed to start at T $= 1500$.

It should be emphasized that, by assigning an extremely small (respectively, large) value to C_J, the control logic can be forced to take into account more energy (respectively, JIT) performance. Considering the experimental data, therefore, we set $C_J = 0.01$ to investigate energy-JIT balanced performance, called "balanced production strategy" and denoted by S_B, and $C_J = 0.001$ for energy-focused schedules, called "energy-focused production strategy" and denoted by S_E. Lastly, for experiments reflecting real production environments, we refer to the power profile of the HAAS VF0 machine described in section 2. The material used by this experiment is a low carbon steel block, and its volume is assumed to be set to $9,000$ mm^3. DIATC is coded and tested by the Microsoft C++ compiler on the same machine. All experiments were conducted on a server with 2.93 GHz speed and 48Gb RAM.

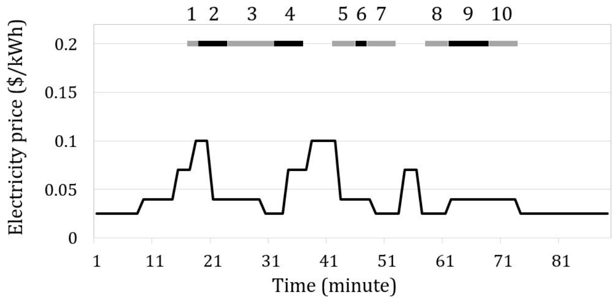
5.1. Impact of production strategy and idle time control

We first show how DIATC reflects the trade-off that is expected by time-varying electricity prices, the need for JIT, and production strategies, on job schedules. Three experimental scenarios are considered; (i) DIATC without idle time control considering S_B, (ii) DIATC with idle time control considering S_B, and (iii) DIATC with idle time control considering S_E. As a simple example, 10 production jobs with $\mathbf{d} = (20, 26, 34, 39, 44, 47, 53, 58, 67, 73)$ and $\mathbf{p} = (2, 5, 8, 5, 4, 2, 5, 4, 7, 5)$ are used to see how DIATC works properly for each scenario. For time-varying electricity prices, four different price rates are considered: off-peak, semi-peak, peak, and high-peak prices (dollar per kWh) are assumed to be used and are set to 0.025, 0.04, 0.07, and 0.1, respectively. Control gains for the arrival and idle controllers are identically set to 0.1.

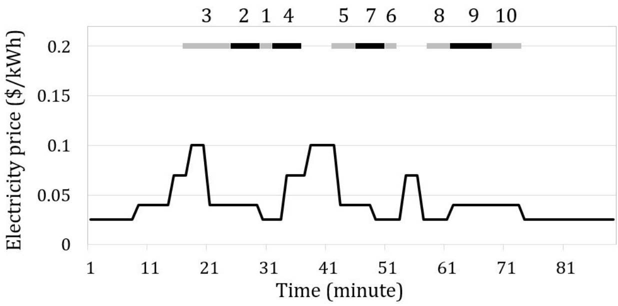
Figure 6 illustrates electricity price fluctuation (solid line) and resulting job schedules of 10 jobs (gantt chart). First, it is shown that absence of the idle time control with S_B (scenario 1, Figure 6(a)) leads to the job schedule with zero due-date deviation (DD) and idle



(a) Scenario 1: schedule by S_B without idle time control



(b) Scenario 2: schedule by S_B with idle time control



(c) Scenario 3: schedule by S_E with idle time control

Figure 6: Scheduling results by different strategies

Table 1: Test results: 10-job case

Scenario	C_j	IT	kWh	DD	EC	TC
1. No idle time control	0.01	8	14.517	0.00	0.117	0.117
2. S_B with idle time control	0.01	0	16.065	4.00	0.103	0.142
3. S_E with idle time control	0.001	0	15.301	31.00	0.098	0.101

Table 2: Electricity price distribution

	off-peak	semi-peak	peak	high-peak	peak	semi-peak	off-peak
Portion over planning horizon (%)	14	14	14	14	14	14	16
Electricity price ($ per kWh)	0.025	0.04	0.07	0.10	0.07	0.04	0.025

time (IT), but about 14% increased energy cost (EC) could be obtained compared to those of scenario 2 as shown in Table 1. The combination of arrival-time and idle time control (scenario 2, Figure 6(b)) contributes to satisfying both the JIT and energy performance by adding positive machine turn-off time segments, resulting in zero idle time and the increment of total due-date deviation from 0.0 to 4.0, compared to scenario 1. Lastly, S_E (scenario 3, Figure 6(c)) yields the job schedule with much higher due-date deviation (31.0), but the energy cost is reduced by about 16% and 9%, compared to the scenario 1 and 2, respectively.

We also conduct experiments for relatively large size datasets based on the given scenarios. A total of 10 replications are made for each dataset with $n = 30, 50, 80, 100, 120, 150$, and average values of energy consumption for normal processing (P_{kWh}) and machine idle (I_{kWh}), due-date deviation, total idle time, and total costs are investigated. For each instance with different planning horizon, electricity prices are sequentially assigned to each time period based on four different price rates and their portions over planning horizon as shown in Table 2. Finally, all experimental results are summarized in Table 3.

Given the significant impacts of different production strategies on performance measures, it is shown that a small penalty for the violation of production due-date makes DIATC focus more on developing job schedules with lower energy consumption as experienced in the previous small instance experiment. Averages of 0.5% and 21% lower energy consumption (kWh) for normal processing and machine idle are observed, respectively, by sacrificing JIT performance; average 4.1% higher due-date deviation could be obtained by S_E compared to

Table 3: Impact of production strategy and idle time control

		Without idle time control					With idle time Control				
n	C_J	J_P	J_I	DD	IT	TC	J_P	J_I	DD	IT	TC
30	0.01	0.41	0.01	27.02	19.90	0.68	0.42	0.02	0.00	23.60	0.44
30	0.001	0.40	0.01	32.36	11.30	0.44	0.42	0.02	0.00	23.60	0.44
50	0.01	0.65	0.00	84.30	10.00	1.50	0.68	0.04	0.00	40.20	0.72
50	0.001	0.65	0.00	87.38	6.60	0.74	0.68	0.04	0.00	40.20	0.72
80	0.01	1.09	0.00	233.73	5.40	3.43	1.12	0.07	0.00	67.10	1.19
80	0.001	1.09	0.00	235.33	5.40	1.33	1.12	0.07	0.00	67.10	1.19
100	0.01	1.40	0.01	331.89	13.50	4.72	1.43	0.09	0.00	82.80	1.52
100	0.001	1.39	0.01	333.67	11.90	1.73	1.43	0.09	0.00	82.80	1.52
120	0.01	1.62	0.00	476.37	1.60	6.38	1.66	0.11	0.00	99.40	1.77
120	0.001	1.62	0.00	476.50	1.80	2.10	1.66	0.11	0.00	99.40	1.77
150	0.01	2.05	0.00	771.79	1.80	9.77	2.10	0.13	0.00	123.10	2.23
150	0.001	2.05	0.00	771.79	1.80	2.82	2.10	0.13	0.00	123.10	2.23

S_B. S_E yields about 22% lower machine idle times, resulting in about 157% lower total cost for the given experimental datasets. It should be noted that all those performance metrics by DIATC without idle time control show no difference regardless of the value of C_J due to zero due-date deviation.

As an impact of idle time control in DIATC, average energy consumption cost by normal processing (J_P) with idle time control is about 3% lower than those without idle time control in these particular datasets. It should be noted that such energy consumption levels can vary depending on different distributions of job due-dates and electricity prices, and J_P difference observed in these experiments cannot always be formed and represent complete standard tendency. In the same vein, idle time control should be understood for its impact on job schedules and energy consumption. It is shown that idle time control contributes to decreasing machine idle time and resulting energy consumption; about 81% idle times on average and about 63 $\sim$ 100% energy consumption costs incurred by machine idle and normal processing could be saved by idle time control. It should be noted that due-date deviation for all instances by DIATC without idle time control becomes zero because the JIT penalty dominates the energy consumption costs in these particular datasets. In sum, DIATC without idle time control yields about 36% better performance in average than

DIATC with idle-control in these particular datasets, due to the relatively huge difference in total due-date deviation and resulting JIT penalty. In the next section, we investigate the solution quality of DIATC, compared to the metaheuristic approach.

5.2. Comparison with metaheuristic

In this section, we consider scheduling problems with $10 \sim 300$ production jobs, and the results of PMVS and DIATC are compared. PMVS is obviously a NP-hard problem, and even small-size instances are hard to be solved within a reasonable computational time. To solve large size instances of PMVS, therefore, we apply a metaheuristic approach, PSO.

PSO is a population-based metaheuristic approach motivated by observations of social behaviors of composed organisms. PSO is characterized by the exploring agents, called particles, which adjust their positions according to own experience and communications with others (Eberhart & Kennedy, 1995). Particles update their positions with velocities that include three major components; (i) inertia that is particle's nature to maintain its past velocity, (ii) a component that makes a particle move towards own best position based on own experience, and (iii) a component that makes a particle move towards the best position achieved by any of the exploring particles based on communications with others. Each component has its own weight, and the quantity of velocity is achieved by the weighted sum of three components with some randomness (Tasgetiren et al., 2004). In this experiment, we generate 10,000 particles and set the weight of inertia as 2 and the weights of second and third components as 1.4, which are typically used in PSO to guarantee good performance.

Designing the PSO algorithm, one of the most important issue is the solution representation. In order to solve PMVS, we design the solution representation that is composed of 3 different parts. The first part aims at finding the particle's corresponding job permutation. For this purpose, the smallest position value rule is applied (Tasgetiren et al., 2004). In the second part, the idle time is assigned into either side of each job, so that the solution of the second part becomes $n + 1$ dimensions, given n as the number of jobs (Lu et al., 2008). The last part of the solution representation is used to the get machine shut down index in the idle time set, which satisfies inequalities (17).

Table 4: Experimental results: total cost and CPU time (average value)

	S_B					S_E				
	PSO		DIATC			PSO		DIATC		
n	TC	CPU	TC	CPU	R_{TC}	TC	CPU	TC	CPU	R_{TC}
10	0.15	134.40	0.19	0.03	-33.61	0.13	182.92	0.16	0.04	-20.25
30	0.45	2772.64	0.58	0.12	-28.08	0.43	2383.47	0.45	0.10	-4.34
50	0.92	9864.67	0.96	0.08	-3.70	0.80	9442.94	0.76	0.09	4.78
80	2.10	10157.98	1.87	0.14	10.88	1.60	10192.71	1.27	0.14	20.44
100	3.86	10622.97	2.31	0.17	40.08	1.91	10651.38	1.66	0.17	12.98
150	17.73	10780.45	5.41	0.28	69.47	4.39	10741.72	2.84	0.25	35.37
180	26.57	10752.62	8.50	0.30	68.01	6.58	10529.53	3.57	0.31	45.76
200	47.90	10748.27	4.74	0.33	90.11	8.42	10800.00	3.43	0.33	59.28
250	101.25	10737.60	8.26	0.39	91.84	11.21	10772.18	4.56	0.42	59.31
300	186.76	10791.33	12.13	0.47	93.50	20.59	10791.24	5.64	0.51	72.61

For performance comparison, we particularly focus on the energy consumption costs incurred by machine idle and normal processing, the JIT cost, and the total cost of PSO and DIATC. A common time limit of 10,800.00 seconds (3 hours) is imposed on the solution time for all instances. Instances are generated based on the data generation rules used for the experiments in section 5.1, and a total of 5 replications are made for each size group (i.e., $n = 10 \sim 300$).

As a relative performance indicator between DIATC and PSO, we calculate the relative percent deviation of total cost such that

$$\mathrm{R}_{TC}(\%) = \frac{TC_{\mathrm{PSO}} - TC_{\mathrm{DIATC}}}{TC_{\mathrm{PSO}}} \times 100. \tag{26}$$

Similarly, relative percent deviations of the energy consumption cost and the JIT cost are denoted as R_E and R_J, respectively.

The computational results of S_B and S_E are summarized in Tables 4. Overall, DIATC shows its superiority for the large size datasets. Specifically, for S_B, approximately $10 \sim 94\%$ better performance can be achieved by DIATC for $n \geq 80$ instances. For the same datasets, $13 \sim 73\%$ lower total costs can be obtained by DIATC when S_E is implemented. For relatively small size instances (i.e., $n \leq 50$), however, PSO shows better performance than DIATC; PSOs by S_B and S_E yield, on average, $4 \sim 33\%$ and $-5 \sim 20\%$ better performance compared to DIATC, respectively.

Performance on energy and JIT costs are also compared, and results are summarized in Table 5, in which the relative difference between S_B and S_E is denoted by R_{BE} for the given measures (values in parentheses indicate energy costs incurred by machine idle). It is shown that S_E by PSO and DIATC yields about up to 13.3% and 6.3% lower energy consumption costs than those by S_B, respectively. The JIT costs by S_B are about up to 92% and 100% higher than S_E for both PSO and DIATC, respectively. It should be noted that such unexpected results are caused by the relatively small penalty (i.e., $C_J = 0.001$) given for S_E compared to S_B, even though real MSEs of S_B are much smaller than those of S_E. As a result, for large size data groups (i.e., $n \geq 80$), about up to 11% higher energy consumption cost is incurred by DIATC for both S_B and S_E. However, DIATC yields, on average, about $30 \sim 99\%$ lower JIT costs for both strategies, which offsets such energy cost gaps, finally resulting in up to 94% and 73% lower total costs for S_B and S_E, respectively.

One obvious observation in PSO and DIATC is that the computational time (CPU) of PSO dramatically increases, and even 80−job instances take about 3 hours to give solutions; most of instances with $n \geq 200$ cannot be solved within the 3−hour time limit. On the contrary, DIATC gives all solutions within about 0.5 seconds, which is an extremely short computational time compared with those of PSO. It should be emphasized that DIATC is performed based on a time-scaled approach that eliminates the need for directly synchronizing events and thereby eliminates the complexity associated with discrete event distributed simulation approaches. The control laws in arrival time and idle time control assure stability and convergence, while allowing the production system to be effectively controlled with minimal global information, and minimize system complexity. In particular, most of the computational complexity of DIATC is related to sorting arrival times of production jobs and machine vacations, which is known as $O(n^2)$. Such low computational complexity guarantees system scalability, yielding an advantage for solving larger size problems.

The decision-making processes of DIATC and PMVS are based on complicated mechanisms that are mainly affected not only by due-date and idle time distributions of jobs but also by electricity price rate distributions, possibly resulting in irregular trends on the

Table 5: Relative performance on energy and JIT costs: average values

		Energy cost		JIT cost			
n		PSO	DIATC	PSO	DIATC	R_E (%)	R_J (%)
10	S_B	0.15 (0.00)	0.16 (0.01)	0.00	0.04	-6.67	-
	S_E	0.13 (0.00)	0.15 (0.01)	0.01	0.00	-15.38	100.00
	R_{BE} (%)	13.33	6.25	-	100.00		
30	S_B	0.43 (0.01)	0.44 (0.04)	0.03	0.13	-2.33	-333.33
	S_E	0.40 (0.00)	0.44 (0.03)	0.03	0.02	-10.00	33.33
	R_{BE} (%)	6.98	0.00	0.00	84.62		
50	S_B	0.72 (0.02)	0.74 (0.05)	0.20	0.21	-2.78	-5.00
	S_E	0.69 (0.01)	0.74 (0.05)	0.11	0.02	-7.25	81.82
	R_{BE} (%)	4.17	0.00	45.00	90.48		
80	S_B	1.15 (0.03)	1.22 (0.11)	0.95	0.66	-6.09	30.53
	S_E	1.12 (0.04)	1.20 (0.10)	0.48	0.07	-7.14	85.42
	R_{BE} (%)	2.61	1.64	49.47	89.39		
100	S_B	1.52 (0.04)	1.59 (0.15)	2.34	0.72	-4.61	69.23
	S_E	1.47 (0.05)	1.59 (0.15)	0.44	0.07	-8.16	84.09
	R_{BE} (%)	3.29	0.00	81.20	90.28		
150	S_B	2.34 (0.12)	2.55 (0.32)	15.38	2.86	-8.97	81.40
	S_E	2.29 (0.10)	2.55 (0.32)	2.10	0.29	-11.35	86.19
	R_{BE} (%)	2.14	0.00	86.35	89.86		
180	S_B	2.76 (0.11)	3.02 (0.27)	23.82	5.48	-9.42	76.99
	S_E	2.72 (0.11)	3.02 (0.27)	3.86	0.55	-11.03	85.75
	R_{BE} (%)	1.45	0.00	83.80	89.96		
200	S_B	2.96 (0.13)	3.29 (0.37)	44.94	1.45	-11.15	96.77
	S_E	2.96 (0.14)	3.28 (0.37)	5.46	0.15	-10.81	97.25
	R_{BE} (%)	0.00	0.30	87.85	89.66		
250	S_B	3.80 (0.18)	4.15 (0.54)	97.45	4.11	-9.21	95.78
	S_E	3.79 (0.18)	4.15 (0.53)	7.42	0.41	-9.50	94.47
	R_{BE} (%)	0.26	0.00	92.39	90.02		
300	S_B	4.42 (0.19)	4.92 (0.56)	182.34	7.21	-11.31	96.05
	S_E	4.42 (0.19)	4.92 (0.56)	16.17	0.72	-11.31	95.55
	R_{BE} (%)	0.00	0.00	91.13	90.01		

energy consumption and JIT cost variations. It is worthwhile to note that DIATC can possibly yield unstable results for JIT and energy perspectives, depending on different production settings on electricity prices, due-date distribution, and JIT penalty. Nevertheless, the significance of the DIATC approach under such dynamic causal relationships is that the trade-off among these metrics can be efficiently tested in advance thanks to its extremely short computational time, and proper strategies can be flexibly selected and implemented for different production settings.

6. Conclusion

In this paper, we investigated a single machine scheduling problem with time-varying electricity pricing to minimize the total production costs of JIT penalty and energy consumption. A new MINLP model that determines job arrival times and machine turn-off times was developed, and a continuous-time variable control models and algorithm were proposed to solve the investigated problem. Specifically, arrival time and idle time controllers were modeled to manage job arrivals and machine idle so as to improve both JIT and energy performance, simultaneously. HASS VF0 machine profiles were used for the numerical experiments with randomly generated instances. Computational results showed that idle time control contributes to about 81% decreased machine idle times and about $63 \sim 100\%$ decreased energy consumption costs compared with the algorithm without idle time control. Energy-focused and balanced production strategies are also tested by the proposed algorithm, and their trade-offs were investigated in terms of JIT and energy performance. For relatively large size data groups, the proposed approach incurs about $4 \sim 11\%$ higher energy consumption costs on average, which are offset by about $30 \sim 99\%$ lower JIT costs, resulting in $10 \sim 94\%$ lower total costs on average compared to the metaheuristic approach.

Computational complexity of solving the given MINLP is extremely high, due to complicated decision-making procedures under the integrated consideration of time-varying electricity pricing, requested due-date, and energy consumption cost. The discrete time control mechanism of the proposed approach led the production system to be effectively managed with minimal global information, finally resulting in minimizing system complexity.

However, algorithmic improvement of DIATC in both JIT and energy performance is still crucial, especially when the problem size increases. One of the technical limitations existing in the proposed approach is that the final energy consumption cost for normal machine processing is determined by the result of arrival time control, resulting in relatively loose decision-making processes rather than an active approach. One possible solution will be embedding a derivative controller that more clearly affects job arrival times while considering the time-varying electricity cost. Furthermore, advanced idle time control for more effectively deciding the number of machine vacation objects and their positions will be required to bridge performance gaps.

For the machine power switch strategy, as mentioned in section 1, machine speed control (i.e., capacity control) can be an alternative approaches that replaces the machine turn-off strategy, especially when machine specifications cannot support flexible power switch during operations. However, such a capacity change from this nominal value may result in deterioration of product quality as well as of the machinery itself, thereby increasing machine maintenance costs. Therefore, integrated decision-making processes considering these performance conflicts will be able to more accurately incorporate real-world conditions in the machine power switch strategy. Lastly, extensions of the proposed control models and algorithm for job-shop or flow-shop production systems with multiple machines require additional research.

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