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A stochasticity handling heuristic in energy-cost-aware scheduling for sustainable production

Xu Gong*, Toon De Pessemier, Wout Joseph, Luc Martens

Department of Information Technology, Ghent University/iMinds, Gaston Crommenlaan 8 box 201, 9050 Ghent, Belgium

* Corresponding author. Tel.: +32 9 33 14908; fax: +32 9 33 14899. *E-mail address:* xu.gong@intec.ugent.be

Abstract

The emerging energy-cost-aware production scheduling approaches serve as a promising roadmap towards sustainable production. However, they tend to be static. If a schedule encounters stochastic events during its execution, e.g., machine failure and change of a customer order, its energy cost effectiveness is susceptible to be affected. This paper proposes a heuristic to deal with stochasticity for energy-cost-aware production scheduling. In the framework of simulation optimization, stochasticity is generated, and revision of a baseline schedule is triggered upon stochasticity. The investigation results demonstrate the effectiveness of this heuristic to keep a production schedule energy-cost-effective under stochasticity.

Keywords: Sustainable production scheduling; Volatile energy price; Energy cost minization; Stochasticity

1. Introduction

The industry plays a key role in the society's overall energy consumption. For instance, in Taiwan, the industry takes up about 53.8% of the entire country's energy consumption [1]. With the rising energy price, the energy cost is becoming an expenditure that cannot be ignored any more by energy-extensive factories. Besides, the industrial electricity demand is often dynamic, with some peaks that are evidently higher than the normal level [2]. Thermal power plants, which are independent on the weather, are conventionally called on to meet these peak demands. However, they lead to high greenhouse gas (GHG) emissions. As a result, it is of both economic and environmental importance for the industry to incorporate energy-awareness and energy-cost-awareness into its production activities, and to implement further measures for enhancing energy efficiency and energy cost effectiveness.

To this end, energy-aware and energy-cost-aware production scheduling is increasingly proposed in the recent literature. A multi-agent based distributed evolutionary algorithm, proposed in [3], rearranges process steps, so as to shift production loads to the time periods when the electricity price is lower. Energy consumption and tardiness are jointly minimized in multi-machine scheduling in [4] by using particle swarm optimization (PSO). Makespan and electricity cost are optimized in [5] by a new ant colony optimization metaheuristic, in order to carry out hybrid flow shop scheduling under the volatile electricity price. The minimization of electricity consumption and electricity cost is separately investigated in [6]. The optimal scheduling solution for multiple machines is searched by a PSO algorithm. In [7], the production scheduler minimizes the electricity cost while keeping reasonable tradeoffs with production throughput and CO_2 emissions, respectively. A combined minimization of the energy consumption and total weighted tardiness is conducted in [8] for multi-machine scheduling on the shop floor. The electricity cost is minimized by a genetic algorithm (GA) in the single-machine scheduling in [9] by shifting jobs in time while keeping their sequence. An enhanced energy-cost-aware scheduler is proposed in [10] to shift jobs to low-priced periods while simultaneously assigning the job sequence. As an extension work, the energy cost effectiveness of the scheduling method of [10] is further demonstrated under three electricity charging mechanisms, i.e., real-time pricing, time-of-use pricing, and critical peak pricing in [11]. A Pareto trade-off is

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found between the energy cost that is saved and the makespan.

However, none of these sustainable scheduling approaches considers the stochastic events (SEs) which may take place during the execution of a schedule on machines, e.g., machine failure and change of a customer order. The outputs of these approaches are thus deterministic schedules, which can easily shift away from the expected optimal energy or energy cost saving potential due to the disturbance of an SE. To fill this gap, a heuristic for handling stochasticity in energy-cost-aware scheduling is proposed in this paper.

2. Background

The production planning and scheduling hierarchy commonly exists in a manufacturing enterprise. The production planning deals with how and when to produce in the medium term, by considering customer orders (e.g., product type, quantity, delivery time, etc.), as well as material and resource availability, while the production scheduling assigns production resources in the short term on the shop floor, by taking the production plan as general input constraints (e.g., job release time, due dates, etc.).

When this hierarchy is exposed in a production environment, there are a variety of uncertainties, which may take place in a stochastic manner [12, 13]. In energy-cost-aware production scheduling, it is essential to have, as many as possible, the time periods during which the energy price is low and the resources are available for production. These time periods are referred here as golden periods. For a specific schedule, the longer the length of golden periods within the scheduling time span, the larger energy cost saving potential will be provided, in comparison to a conventional production schedule which has no awareness of the volatile energy price.

Due to this nature, the energy cost effectiveness of a schedule is sensitive to SEs, since SEs may exert an influence on the length of the golden periods within the scheduling time span. Based on the influence which may be negative, positive, or neutral, the following taxonomy is made on SEs.

- Negative influence: SEs are susceptible to decrease the length of the golden periods. These SEs are listed as (1) machine failure, buffer overflow, temporal blackout of power supply, and a late arrival of materials; (2) rework of some products or parts, increased product demand of a customer order, and an urgent new order; (3) an advanced due date; etc. The SEs in (1) lead to machine or resource unavailability for the scheduled production when they have a time overlap with jobs in an original schedule. The SEs in (2) require the insertion of additional jobs into an original schedule. The SE in (3) may remove some golden periods.
- Positive influence: SEs are likely to increase the length of the golden periods. These SEs are, e.g., (1) decreased product demand of a customer order and cancellation of a customer order; (2) a postponed due date; etc. The SEs in (1) directly release more golden periods in the original schedule, thus adding more time to the scheduling. The SE in (2) may provide extra golden periods.
- Neutral influence: SEs of which the trend to increase or decrease the length of golden periods is not evident. Within the demand side management [14], the variability of the electricity price, e.g., real-time pricing (RTP), is specifically viewed as such an SE for energy-cost-aware production scheduling. The electricity price is volatile such that the length of golden periods fluctuates if a scheduling time span shifts in time.

As a result, it is meaningful to properly handle the SEs and further analyze their influence on the energy cost effectiveness of an energy-cost-aware schedule. The energy cost effectiveness is herein quantified as the energy cost saving ratio ($Ratio_{saving}$) of an optimal schedule (OS), compared with a conventional schedule, as defined by Eq. (1),

$$Ratio_{saving} = \frac{ECost_{conventional} - ECost_{optimal}}{ECost_{conventional}} \times 100\% \quad (1)$$

where $ECost_{conventional}$ is the energy cost of a conventional schedule, and $ECost_{optimal}$ is the energy cost of an optimal energy-cost-aware schedule.

3. Heuristic for handling stochasticity in energy-cost-aware production scheduling

The proposed heuristic aims to handle SEs during the execution of an energy-cost-aware production schedule on a single machine. To implement and evaluate this heuristic, a framework of simulation optimization (Sim-Opt) is set up. The energy cost optimization and energy simulation are highly coupled. The optimization procedure uses the energy simulation model to evaluate all candidate schedules and generates an OS. By following the what-if philosophy, the discrete-event energy model simulates the execution of an OS, and generates SEs during the simulation. They may further trigger the optimization procedure for reactive rescheduling. This interaction iterates until an optimal scheduling solution is fully executed without any influence of SEs.

3.1. Framework of simulation optimization

The proposed heuristic to handle SEs is presented in Fig. 1. The key operations are indicated by different numbers. Operation 1 (O1) decides whether the next scheduling starts from a baseline schedule. In the case of stochasticity, a baseline

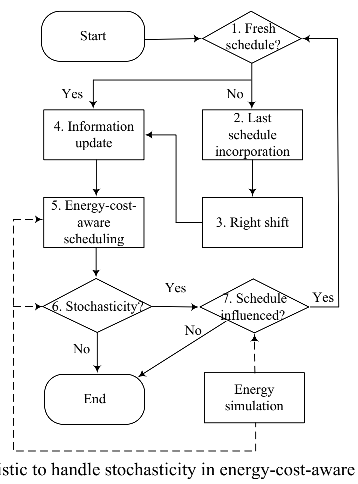

Fig. 1 A heuristic to handle stochasticity in energy-cost-aware scheduling for a single machine (each key operation is indicated by a number)

schedule is the optimal energy-cost-aware schedule whose execution is interrupted by a SE. If a baseline schedule is considered, the next scheduling is not fresh, since the necessary knowledge of the baseline schedule has to be incorporated when the next scheduling starts. Operation 2 (O2) provides this function. The knowledge includes a) name and duration of the SE, b) time when the baseline schedule is interrupted by an SE (i.e., the start time of the SE), c) non-executed jobs that need to be reconsidered in the next scheduling, d) job that is being executed, but is not yet accomplished, upon the occurrence of the SE, and e) total energy cost for the already-executed jobs and last machine energy state before the occurrence of the SE.

The full rescheduling starts from the time when the last SE terminates (i.e., the start time plus the duration of the SE). In operation 3 (O3), the right-shift rule postpones all the affected upcoming jobs after the termination of the SE. Depending on the production, an interrupted job has to be totally reproduced (i.e., non-resumable), or just its non-executed part remains to be produced (i.e., resumable). So for an interrupted non-resumable job, its whole part is right-shifted. For an interrupted resumable job, its non-executed part is right-shifted.

In operation 4 (O4), scheduling-related input information is updated and loaded in the scheduler, e.g., energy price, input jobs, start time, due time, optimization configurations, etc. In operation 5 (O5), scheduling is carried out. Operation 6 (O6) judges whether stochasticity is involved in the current simulation. If there is no stochasticity, the simulation terminates. If stochasticity is involved, operation 7 (O7) will further judge whether the SE has an influence on the schedule. This operation is necessary, since it could be that an SE has no influence on the schedule, e.g., a machine failure and recovery in the free period between two consecutive jobs. If the schedule is influenced by the SE, full rescheduling will start by returning to O1. Otherwise, the whole Sim-Opt process terminates.

The energy simulation is involved in O5, O6, and O7, respectively. It is coupled with O5 to make the scheduling energy-aware and energy-cost-aware. It is associated with O6 and O7 to incorporate stochasticity into the simulation evolution in time. The sequential steps “Start-O1-O4-O5-O6-End” form up a conventional scheduling procedure, which leads to static schedules. The cyclic steps “O1-O2-O3-O4-O5-O6-O7-O1-O2-O3…” and “O1-O4-O5-O6-O7-O1-O4…” set up a closed loop to deal with SEs.

3.2. Discrete-event energy simulation

In the discrete-event energy simulation (see Fig. 1) in the heuristic, every action or operation is viewed as an event. Each event is stamped with physical time. The simulation makes its evolution in a chronological order based on the time stamps on events. The total time to run a simulation depends on the total number of discrete events that are involved in this simulation, instead of the physical time length. An SE is designed as a type of events that may cause the simulation to terminate, which mimics the interruption of schedule execution in a production environment. As a result, a production-related energy consumption scenario can be simulated even with SEs.

More specifically, the simulation is enabled by a generic energy model. The generic machine energy model is described by the finite state machine (FSM), as shown in Fig. 2. It comprises five basic elements: a set of states, state transitions, external inputs (e.g., electricity price and production schedule),

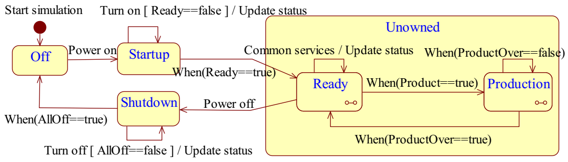

Fig. 2 Energy model for a machine based on finite state machine (FSM)

an explicit initial state when the simulation starts, and an implicit final state when the simulation terminates. The final state can be any one of the defined states, since the simulation can be interrupted by an SE at a random time point. The energy related statistics are collected and reported at the end of the final state, including energy consumption and energy cost at levels of a machine state and a single machine, the production quantity, simulation time, executed jobs, and an SE if it occurs. The machine makes transitions from one state to another in order to model the machine energy consumption behaviour over time, and more specifically to model how a production schedule is executed on a machine.

Besides, each state has a mean power. The machine energy consumption E during a simulation can thus be estimated as:

$$E = \sum_{s \in S} \sum_{t \in T_s} P_s \cdot t \tag{2}$$

where s is a machine state, S is the set of machine states, t is a time period during which the machine stays at state s, T_s is the set of periods during which the machine stays at state s, and P_s is the mean power consumption of state s. A specific set of power states can be defined based on a specific machine. This makes the generic energy model highly extensible.

3.3. Full rescheduling

In the heuristic (see Fig. 1), O3 and O5 jointly set up a full rescheduling policy, instead of the schedule pair [15]. The latter approach uses simple control rules, such as the well-known right-shift rule [16, 17]. It shifts forward in time all the jobs that are affected by the schedule breakdown, while keeping the same job sequence. For energy-cost-aware scheduling, this is very likely to reduce energy cost effectiveness, since it does not adapt the shifted jobs to the new periods during which the electricity price may change. However, the right-shift rule provides an initial idea to reactively deal with SEs.

The optimization model stays deterministic and tractable for each full rescheduling due to the contribution of O2, O3, and O4. As a result, the full rescheduling is able to keep the schedule energy-cost-effective after the SEs’ occurrence. The mathematical formulation of the energy-cost-aware single-machine scheduling problem is described in [10], which takes the energy cost as the optimization objective and schedules all jobs before the due date. The OS can be found by using a metaheuristic, e.g., PSO, GA, and ACO (see Sect. 1).

4. Case study

For demonstrating the proposed heuristic, a clamp-on power meter (Yokogawa CW240) was connected between a surface grinding machine (Paragon RC-18CNC) and its power supply. This enables to build a specific energy model for the surface grinding process. The day ahead market price from the Belgian electricity spot market (Belpex) was used as RTP data, where

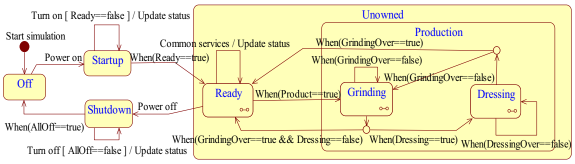

Fig. 3 Energy model for the surface grinding machine

the electricity price is known 24 hours in advance and varies every hour. This facilitates the energy-cost-aware scheduling. The rescheduling was carried out on various SEs based on the taxonomy made in Sect. 2. Details are described as follows.

4.1. Configurations of the heuristic

Six energy states are identified for the surface grinding process, as illustrated by Fig. 3. Their mean power and cycle durations are indicated in Table 1. Compared to the generic model (see Fig. 2), the *Production* state further contains *Grinding* and *Dressing* sub-states. The grinder periodically shifts from *Grinding* to *Dressing* for sharping and regularizing the grinding wheel, and cleaning the impurities coming from the chips. In this case study, the grinder is assumed to shift from *Grinding* to *Dressing* after completing 14 consecutive jobs.

Besides the energy simulation enabled by the above energy model, a GA optimization is used to search for the optimal energy-cost-aware schedule. A population stands for a set of candidate schedules. A chromosome represents an energy-cost-aware schedule. A gene corresponds to a job within a schedule. The population size, elitism rate, crossover rate, mutation rate, and maximum iteration were set as 140, 10%, 95%, 7%, and 100, respectively. A list of grinding jobs, which are involved in the case study (Sect. 4.2, 4.3, & 4.4), is indicated in Table 2.

The "as-early-as-possible" (AEAP) schedule is considered in the following subsections, in order to quantitatively evaluate the energy cost effectiveness of our energy-cost-aware production scheduling method with the capability of handling stochastic events. It is an intuitive schedule by following the idea of completing production as early as possible. It is not the worst case for energy cost saving, since in all the investigations in this paper, it starts from 0 AM of a day which is the start of the night period, and thus automatically makes use of the pricing valley within a day. More schedules are considered in Sect. 4.4 for a thorough evaluation of the energy cost effectiveness of our scheduling method, where the variation of electricity price is considered as a neutral-influence SE.

Table 1 Energy consumption states of the surface grinder

Energy state (one cycle)	Mean power (kW)	Cycle duration (s)
Off	0	Arbitrary, depending on the schedule
Startup	3.55	652
Ready	5.93	25 (default)
Grinding	9.49	25
Dressing	6.72	125
Shutdown	1.00	362

Table 2 Grinding jobs for energy-cost-aware scheduling

Job ID	Number of steel workpieces	Required production time (grinding + dressing)
1	50	1625 s (27 m 5 s)
2	100	3375 s (56 m 15 s)
3	200	6750 s (1 h 52 m 30 s)
4	300	10,125 s (2 h 48 m 45 s)
5	400	13,500 s (3 h 45 m)
6	500	16,875 s (4 h 41 m 15 s)
7	80	2625 s (0 h 43 m 45 s)

4.2. Negative influence

Machine failure is investigated as an example of SEs that have negative influence on the energy cost effectiveness of a production schedule. Machine failure is supposed to occur at 2 h 23 m 20 s and lasts one hour before the grinder restarts normally for continuing the production according to the schedule. If a job is interrupted by machine failure, it is resumable and must be continued ahead of all the upcoming jobs when the machine recovers from the failure.

The investigation date is 17-Oct-2015, during which the electricity price (see Fig. 4) is low in the late evening and early morning, and is high around the noon and in the early evening. Without considering any SE, the baseline schedule, which includes job1 to job6 (see Fig. 4), is obtained by following the steps in the heuristic "Start-O1-O4-O5-O6-End" (see Fig. 1). Its energy cost is 5.39 €.

Upon the machine failure at 2 h 23 m 20 s, the full rescheduling is triggered, (i.e., "O6-O7-O1-O2-O3-O4-O5" in the heuristic). An updated schedule is then got and continues to be executed in the simulation. As shown in Fig. 4, the updated schedule effectively reassigns the upcoming jobs such that the low-priced periods are fully made use of, and the high-priced periods are avoided. The actual energy cost is comprised of two parts: (1) the energy cost of grinding jobs before the occurrence of machine failure (0.76 €), and (2) the energy cost of rescheduled grinding jobs after the end of the machine failure (4.90 €). The actual total energy cost is thus 5.66 €.

For comparison, a simple right-shift policy is assumed to be applied to the AEAP schedule under the same machine failure. When the grinder recovers from the failure, it continues to work by following the same job sequence in the baseline schedule, while all the upcoming jobs are delayed by one hour because of the machine failure. Consequently, the energy cost is 5.84 €.

Therefore, the reschedule successfully reaches a $Ratio_{saving}$ (see Eq. 1) of 3.1% upon the occurrence of machine failure. The $Ratio_{saving}$ is not impressively high due to the electricity price profile. The price on the specific day has a long valley that starts from the beginning, such that it occupies more than half of all the low-priced periods that exist in the scheduling time span (27-Oct-2015). So the AEAP schedule naturally

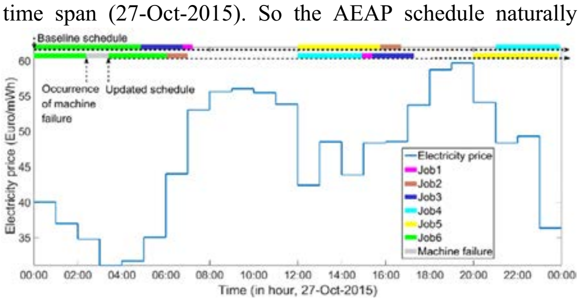

Fig. 4 Energy-cost-aware rescheduling upon machine failure

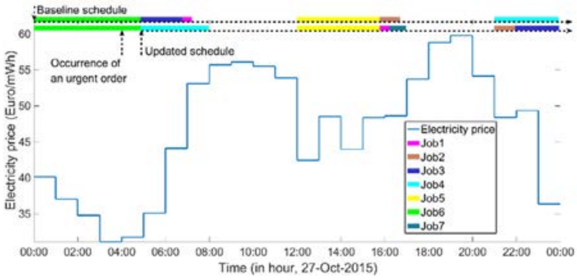

Fig. 5 Energy-cost-aware rescheduling upon an urgent order

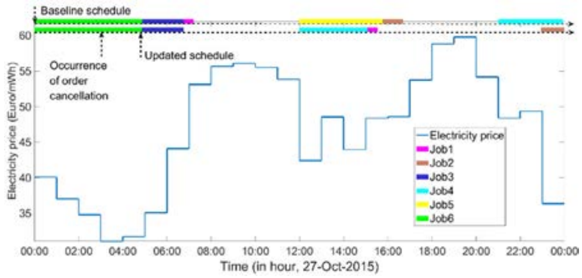

Fig. 6 Energy-cost-aware rescheduling upon order cancellation

makes use of this long valley. However, this does not hint that the scheduling cannot contribute to significant energy-cost-effectiveness. A further investigation will be carried out in Sect. 4.4. Besides, the reschedule leads to a higher energy cost, compared to the baseline schedule (5.66 € versus 5.39 €). This is because the machine failure takes up one hour of low-priced periods, and there are no additional low-priced periods in the scheduling time span to accommodate all the rescheduled jobs.

Furthermore, the rescheduling upon an urgent order is demonstrated with the same baseline schedule. Job7 is assumed to be an urgent order, which occurs at 4 h during the execution of the baseline schedule. The updated schedule (see Fig. 5) is obtained by following the steps "O6-O7-O1-O2-O3-O4-O5" in the heuristic (see Fig. 1). Its total energy cost is 5.79 €. Obviously, the energy cost increases in comparison with the baseline schedule (5.39 €), as job7 is newly inserted. However, the contribution of the energy-cost-aware rescheduling is two-fold. First, as demonstrated by Fig. 5, the updated schedule is still energy-cost-effective, in the sense that it assigns the jobs to the low-priced periods and effectively avoids the high-priced periods. Second, the updated schedule is able to complete all the jobs before the due time, while job7 will surely be processed in tardiness in the baseline schedule, causing additional tardiness penalty.

4.3. Positive influence

Cancellation of a customer order is investigated as an example of SEs that have positive influence on the energy cost effectiveness of a production schedule. If an order is cancelled during the execution of a job, this job is supposed to continue to be completed before the start of the updated schedule. Job5 is assumed to be cancelled at 3 h during the execution of the baseline schedule. The same baseline schedule and scheduling time span in Sect. 4.2 are used.

The updated schedule (see Fig. 6) is given by following the steps "O6-O7-O1-O2-O3-O4-O5" in the heuristic (see Fig. 1). The corresponding energy cost is 3.80 €. For comparison, the AEAP schedule is assumed to follow the same schedule (i.e., the same job sequence and job start time) even when job5 is cancelled. Its energy cost is 4.11 €. The $Ratio_{saving}$ is thus 7.5%, indicating an interesting potential for energy cost saving.

In addition, if the baseline schedule is executed by keeping its job sequence and start time with the same order cancellation, the energy cost is 3.89 €. It is higher than the energy cost of the updated schedule (3.80 €), due to the low-priced periods released by job5. This demonstrates the robust energy-cost-effectiveness of the full rescheduling policy.

4.4. Neutral influence

The variability of the electricity price is viewed as a special SE that has neutral influence on the energy cost effectiveness of a schedule (see Sect. 2). To this end, the RTP data from Belpex during a whole year (4-Nov-2014 to 3-Nov-2015) was used. The time duration of energy-cost-aware scheduling is set as 24 hours within the same day. So there are in total 365 sets of electricity prices to exhibit the variability of the electricity price during different scheduling time spans while keeping the same time span length.

As a result, 365 energy-cost-aware schedules for 356 different days are obtained by iteratively following the closed loop "O1-O4-O5-O6-O7-O1-O4…" in the heuristic (see Fig. 1). In comparison, the energy costs of the schedules AEAP, "as-late-as-possible" (ALAP), "start-from-*n*AM" (SF*n*AM) (n = 1, 2, 3, …, 9) are respectively calculated on each day. An SF*n*AM schedule means that the entire production starts at *n*AM of a day, and continues without idling between jobs until all the jobs are completed. They serve as intermediate cases between the AEAP and ALAP schedules, in terms of the start time of the whole production.

As indicated by the box plot in Fig. 7 and by the corresponding statistics in Table 3, the OS given by our energy-cost-aware production scheduling method achieves a $Ratio_{saving}$ which is averaged between 6% and 19%. The OS tends to save more electricity cost if the comparison schedule starts the whole production in the early morning (6AM to 9 AM). This is explained by the electricity price profile which tends to rise from the valley during this period, and is followed by peaks (see the electricity price profile in Fig. 6 for an example).

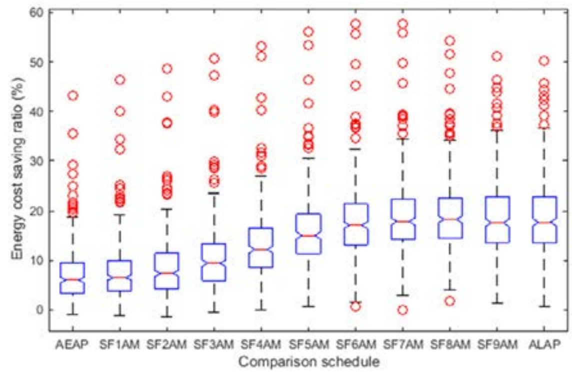

Fig. 7 Box plot of the energy cost saving ratio of the energy-cost-aware production scheduling method under RTP at 365 different days. The central red line, upper edge, and lower edge of each box are median, 75th percentile (Q3), and 25th percentile (Q1), respectively. The red circles are outliers. The whiskers (black dash lines) are set as 1.5(Q3-Q1).

The maximal $Ratio_{saving}$ tends to reach 50% or even more. The minimal $Ratio_{saving}$ tends to be slightly higher than 0 in most cases and to be slightly lower than 0 in a few cases (i.e., schedules starting from the night, i.e., 0 AM, 1 AM, 2AM, and 3 AM). The latter phenomenon is again explained by the electricity price profile, which usually has a large valley from the beginning (see the price profile in Fig. 6 for an example). These schedules starting from the night thus naturally make use of the valley to achieve a low electricity cost, which is comparative to the electricity cost of the OS. Furthermore, the 25% best $Ratio_{saving}$ tends to achieve 23%, while the 75% best $Ratio_{saving}$ has the trend to approach 15%. All the outliers are beyond the 1.5 interquartile range of Q3 (75^{th} percentile), except the three that are around 0. Overall, these statistics demonstrate the high potential of our scheduling method for helping plants to reduce their energy cost of production.

Table 3 Statistics of the energy cost saving ratio of the proposed energy-cost-aware production scheduling method (Q3: 75^{th} percentile, Q1: 25^{th} percentile)

Schedule	Max (%)	Min (%)	Median (%)	Q3	Q1	Outlier (%)
AEAP	43.24	-0.86	6.02	9.53	3.28	3.02
SF1AM	46.43	-1.09	6.52	10.02	3.77	3.02
SF2AM	48.59	-1.47	7.34	11.43	4.25	3.30
SF3AM	50.60	-0.41	9.45	13.43	5.96	3.02
SF4AM	53.13	0.02	12.21	16.48	8.57	2.75
SF5AM	56.03	0.77	15.03	19.39	11.34	2.75
SF6AM	57.79	0.59	17.11	21.41	13.21	3.02
SF7AM	57.80	0.04	17.87	22.41	14.26	3.02
SF8AM	54.39	1.77	18.31	22.58	14.39	3.85
SF9AM	51.03	1.23	17.62	22.82	13.67	2.47
ALAP	50.19	0.74	17.72	22.88	13.50	2.20

5. Conclusion

This paper proposes a heuristic to handle stochasticity that may occur during the execution of an energy-cost-aware production schedule. This heuristic adopts a reactive full rescheduling policy to fully revise the baseline schedule upon stochasticity in a reactive manner. Therefore, a schedule that is affected by a stochastic event (SE) can be robust and still keep energy-cost-effective. To enable the implementation and performance analysis of this heuristic, a framework of simulation optimization (Sim-Opt) is built up.

The effectiveness of this heuristic is fully demonstrated upon a number of SEs, and by using measured power data from a surface grinding machine and real time pricing (RTP) data from the Belgian electricity spot market. The conventional "as-early-as-possible" and "as-late-as-possible" production schedules are used to evaluate the energy cost saving potential of an energy-cost-aware production schedule. The demonstration under machine failure, an urgent order, and order cancellation, respectively, proves that the heuristic keeps the energy-cost-aware production scheduling approach energy-cost-effective upon stochasticity. Besides, the variability of electricity price during different scheduling time spans is considered as a special SE. By applying the heuristic, the robust energy cost effectiveness of the energy-cost-aware production schedule under volatile electricity price is also demonstrated.

The proposed heuristic fills the gap in literature where the existing energy-aware or energy-cost-aware production scheduling approaches are static without considering the SEs that may take place in a production environment. As energy-cost-aware production scheduling helps manufacturing factories to save energy cost and supports power plants to reduce greenhouse gas (GHG) emissions within the demand side management (DSM) framework, this heuristic enhances the potential economic and environmental contributions provided by energy-cost-aware production scheduling.

Future work includes quantification of GHG emissions and extension of the energy-cost-aware scheduling approach to a larger scale in order to make it a meaningful solution for industrial energy consumption optimization.

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