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Energy- and labor-aware production scheduling for sustainable manufacturing: A case study on plastic bottle manufacturing

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Abstract

Among the potential roadmaps towards sustainable production, the emerging energy-cost-aware production scheduling philosophy is considered as one promising direction. Therein, sustainability objectives, e.g., minimization of energy consumption/cost of production processes and stabilization of the electricity grid, can be achieved by manufacturing enterprises in a low-cost manner. However, these sustainability goals should be integrated with conventional production constraints besides the due date, e.g., reasonable labor cost based on work shifts, no production at weekends, and changeovers for different product types. This paper formulates a mixed-integer linear programming model for energy- and labor-cost-aware production scheduling at the unit process level, considering all the aforementioned constraints. A state-based energy model is used to reveal the energy consumption behavior of a process over time. It thus enables fine-grained energy-aware production scheduling. A case study is conducted for a blow molding process in a Belgian plastic bottle manufacturer. The measured power data enables to build an empirical energy model. The production scheduling is performed under real-time electricity pricing data. As a result, production loads are automatically shifted to the optimal periods. The optimal idle mode is automatically selected between production loads (powering off, idle, etc.). A schedule of joint energy cost and labor cost minimization is demonstrated to reduce 12% and 5% of total cost, compared to schedules that minimize energy and labor cost, respectively. In conclusion, although the labor wage is usually higher during periods with lower electricity price, energy and labor costs can be jointly optimized as a single objective to help factories minimize the production expenditure.

1. Introduction

Factories of the future (FoF) are widely considered as a key economic driver for a society. This is demonstrated by various national programs to re-boost manufacturing [1], e.g., the German industry 4.0 and Industrial Internet in the USA. At European level, FoF are also promoted as public private partnership in research [2]. Among the various aspects of FoF, sustainable manufacturing increases the added value of products by creating sustainable value in manufacturing, while balancing economic, environmental and social impacts [3].

During recent years, energy-cost-aware production scheduling is emerging as a promising roadmap towards sustainable manufacturing. In the hierarchy of a manufacturing enterprise, production scheduling stays at the low level on a shop floor [4] and assigns production jobs for fine-grained machine control to reach the desired production targets.

The early proposition of this idea is found in [5], where the authors pointed out that a significant amount of energy savings can be achieved, if non-bottleneck/underutilized machines are turned off, when they are idle for a certain amount of time. Several job dispatching rules are defined for the machine controller to realize this idea. The authors further integrated maintenance planning into the single machine production planning model [6]. Numerical analyses showed that enforcing more maintenance actions into a production plan decreases the energy cost of a machine, which increases the sensitivity of processing times to machine health status. However, besides the simple job dispatching rules, the authors did not propose any

method to schedule all jobs in advance, nor did they explicitly link energy consumption to energy cost via energy price.

As further progress, Shrouf et al. [7] considered the volatile electricity price, and formulated an integer programming model to schedule jobs by shifting production loads to low-priced periods, without sequencing the jobs. Evidently, a lack of job sequencing capability does not enable a full exploitation of the energy cost saving potential. In their further work [8], they gave some hints on getting energy data on the shop floor by Internet-of-Things (IoT) technologies (e.g., smart meters and sensors). Nevertheless, they did not provide any details on how to associate energy data to the energy and scheduling model.

The aforementioned gaps were filled by Gong et al. [9]. Finite state machines (FSMs, or automata) were used to build an energy model based on empirical power measurements. This energy model can then estimate the power consumption of a machine at the power state level, which is sufficiently fine-grained for production scheduling. Job sequencing was introduced. The effectiveness of whole energy modeling and scheduling method was validated on a surface grinding process, and was further demonstrated with various electricity price data in [4]. Numerical analyses showed that prolongation of production time span contributes to a higher energy cost saving ratio. In their further work [10], a rescheduling heuristic was proposed to handle stochastic events while still keeping the schedule energy-cost-effective. An average energy cost saving ratio between 6% and 19% was demonstrated achieved by using the energy-cost-aware single-machine scheduling approach.

More recent work is seen in academia, pushing forward the boundary of energy-cost-aware production scheduling. Liu et al. [11] proposed a scheduling method for a classical job shop environment, instead of a single machine. Bi-objective optimization was deployed to minimize energy consumption and total tardiness. Yan et al. [12] devised a multi-level optimization approach for energy-efficient flexible flow shop scheduling. Synergistic energy savings were facilitated by enabling cutting parameters optimization at the machine tool level and energy-aware scheduling at the shop floor level. Zhang et al. [12] even proposed a general concept for energy-cost-aware scheduling of multiple factories under real-time electricity pricing. They also investigated in [13] an energy-conscious flow shop scheduling problem, where CO_2 emissions from different electricity sources (natural gas and coal) are incorporated into the scheduling model. They concluded that shifting production loads from on-peak hours to mid-peak hours or off-peak hours can reduce the electricity cost by 6.9%, though this may increase CO_2 emissions in some regions that use gas-fired power plants to meet peak power demands.

Recent relevant literature is also found from industry. Merkert et al. [14] surveyed the available energy-cost-aware production scheduling methods, with a set of real industrial case studies. Hadera et al. [15] considered a steel production scheduling case, where various electricity sources are purchased in a factory, i.e., electricity markets, ToUP (time-of-use pricing), base load contract, and onsite generation. The possibility of offloading surplus power back to the grid was also included. Harjunkoski [16] described the scheduling problem from the industrial perspective. A set of trends affecting scheduling are listed, e.g., IoT, big data, smart grids/renewable

energy, unmanned sites, and service. Weinert et al. [17] used an agent-based approach for peak load management of multiple machines. Peak loads are avoided by shifting production loads under the volatile electricity price. The system run in test mode in a transformer factory showed good results of limiting the overall load under a defined threshold, while the process execution time tended to be prolonged.

Despite of the vast amount of emerging work on energy-cost-aware production scheduling, the labor cost is seldom integrated with the energy cost, although it is a conventional and fundamental factor for production management. Generally, a crucial aspect, which would be a long-term obstacle for the progress of production scheduling, is that current scheduling models rely on more or less simplified assumptions. This is often caused by missing knowledge of a production environment and/or a lack of empirical data (e.g., actual power consumption). The labor aspect falls in this situation.

As pricing follows the general market rule of supply and demand, labor cost will be expensive when the supply is low (e.g., at weekends labor cost can be 20 to 50% higher than on weekdays). Labor cost hence follows the opposite trend of energy cost. The latter is higher in periods of peak demands, i.e., weekly business hours. As such, taking into account labor costs could reduce the energy cost saving potential of energy-aware production planning and scheduling, since shifting to low-cost energy hours implies a higher labor cost.

To this end, this paper integrates the consideration of energy- and labor-cost-awareness into single-machine production scheduling, and analyzes through a case study its performance, in terms of energy cost and labor cost.

2. Model formulation

The production scheduling problem is to automatically assign the sequence (π) and start time (STJ_i) of N_J jobs, as well as the machine power states (s, including the states for an optimal idle mode between two jobs) at the level of a discrete manufacturing machine, under volatile electricity pricing, without breaking the due date (DT) and the labor working rule, i.e., no production at weekends. The scheduling is based on single-objective optimization, namely cost minimization, including energy cost (EC) and labor cost (LC).

One job contains one single product type, while different jobs contain different product types. Then, this requires that a machine changeover for each job needs to be inserted into the schedule. The electricity price (EP) varies with time slots (D), but stays constant within each D. The energy consumption calculation is at power state level. There are $\left| SH \right|$ shift types ($sh \in SH$) within one day. The wage per shift (W_{sh}^{pt}) varies with sh and personnel type (PT). PT varies with s, which are linked to machine operations.

2.1. Objective

Three objective functions are formulated by Eqs. (1-3), i.e., minimization of joint EC and LC (schedule1), minimization of EC (schedule2), and minimization of LC (schedule3), respectively. The major variables for optimization are s, π, and $STJ_i (i \in [1, 2, ..., N_J])$. For the joint optimization in

Eq. (1), it is clear that the relative percentage of both types of costs is variant and can impact the overall scheduling outcome. Energy cost, for example, can make up less than 10% of overall production cost in automotive manufacturing industries, but also up to 70% in industrial gas production [18].

$$\min_{s,\pi,STJ_i}(EC+LC) \tag{1}$$

$$\min_{s,\pi,STJ_i}(EC) \tag{2}$$

$$\min_{s,\pi,STJ_i}(LC) \tag{3}$$

Evolutionary algorithms (EAs) have been used to successfully solve energy-aware single-objective production scheduling problems. They are illustrated as (1) genetic algorithm [9], where the objective is to minimize energy cost for producing a set of jobs on a unit process; (2) particle swarm optimization [19], where the objective of minimizing energy consumption and energy cost of a line of manufacturing machines is investigated, respectively; (3) ant colony optimization [20], integrated with two local search strategies to minimize the weighted energy consumption and total tardiness of parallel machines.

2.2. Energy cost (EC) constraints

The calculation of *EC* is indicated by Eq. (4). It consists of three subparts: energy cost for processing jobs (CJ_i), energy cost for performing changeovers (CC_i), and energy cost for keeping a machine in an idle mode between two jobs (CI_i).

$$EC = \sum_{i=1}^{N_J} CJ_i + \sum_{i=1}^{N_J-1}(CC_i + CI_i) \tag{4}$$

Eqs. (5-7) provide detailed methods to calculate the three subparts, respectively. In principle, the calculation is based on time slot (*ts*), which is the smallest scheduling time granule. A standby mode enables a machine to keep its power consumption at a level lower than that of production, but higher than zero (without powering off). Next to this, an idle mode is defined. It includes the possibility for a machine to stay in a standby mode and to be completely powered off.

$$CJ_i = \sum_{ts=STSJ_i}^{ETSJ_i} EP_{ts}\left(\beta_{ts}\sum_{t=STJ_i}^{ETJ_i} P_p^t t\right) \tag{5}$$

$$CC_i = \sum_{ts=STSC_i}^{ETSC_i} EP_{ts}\left[\beta_{ts}\sum_{t=STC_i}^{ETC_i}\left(\sum_{s\in S_C} P_s^t t\right)\right] \tag{6}$$

$$CI_i = \begin{cases} \sum_{ts=ETSC_i}^{STSJ_{i+1}} EP_{ts}\left[\beta_{ts}\sum_{t=ETC_i}^{STJ_{i+1}}\left(\sum_{s\in S\alpha_i} P_s^t t\right)\right], \alpha_i \in [1,2,\ldots,N_S] \\ \sum_{ts=ETSC_i}^{STSJ_{i+1}} EP_{ts}\left[\beta_{ts}\sum_{t=ETC_i}^{STJ_{i+1}}\left(\sum_{s\in S_o} P_s^t t\right)\right], \alpha_i = N_S+1 \\ 0, \alpha_i = N_S+2 \end{cases} \tag{7}$$

In Eq. (6), S_c is the set of power states (*s*) involved in a changeover. In Eq. (7), α_i is the machine idle mode indicator for the *i*th job. $S\alpha_i$ is the set of *s* for switching to, staying at, and recovering from the α_i th idle mode of a machine

($\alpha_i \in [1,2,\ldots,N_S]$). S_o is the set of *s* for switching to, staying at, and recovering from off state between jobs ($\alpha_i = N_S+1$). The case where there is no idle period between two jobs (i.e., the next job will just follow the end of the current job) is also included (N_S+2), which of course has zero electricity cost.

For multiple standby modes, Eq. (8) enforces there must be one and only one idle mode between two adjacent jobs.

$$\forall \alpha_i \wedge \left(\exists! \alpha \in [1,2,\ldots,N_S+1, N_S+2]\right): \alpha_i = \alpha \tag{8}$$

Eqs. (9-10) map the current time in *ts* to electricity pricing time slots (*D*). This mapping is frequently used in Eqs. (5-7), since energy calculation is based on *ts* (fine-grained), while energy cost calculation is based on *D* (coarse-grained). In this model, fined-grained energy calculation is necessary to enable energy modeling by FSMs [9].

$$\beta_{ts} = \begin{cases} 1, if\ t \in [ts \cdot D, (ts+1) \cdot D) \\ 0, otherwise \end{cases} \tag{9}$$

$$ts = \lfloor (t-T_s)/D \rfloor, t \in [T_s, T_s+\delta t\ldots, DT-\delta t, DT] \tag{10}$$

2.3. Labor cost (LC) constraints

LC is calculated by Eq. (11), and dependent on shift (*sh*) type. A shift increment in hours (δsh) is defined in Eq. (12).

$$LC = \sum_{sh=ST}^{DT}\sum_{pt\in PT} W_{sh}^{pt} \cdot \theta_{sh}^{pt} \tag{11}$$

$$\delta sh = 24/|SH| \tag{12}$$

Within one *sh*, once a personnel type (*pt*) is required by an involved power state (*s*), this *pt* will be included in this *sh* ($\theta_{sh}^{pt} = 1$). Otherwise, the binary personnel occupation indicator θ_{sh}^{pt} is zero. In other words, once a person is needed sometime in a shift, this person will work during the whole shift, regardless of the actual workload. Consequently, the number of "man-shifts" is used in this model to measure the personnel resources required for a production schedule, although the cost of a man-shift may vary a bit by *pt*. As FSMs enable *s* to make transitions step by step, this make FSMs fit quite well to determine θ_{sh}^{pt} over time. Readers are referred to [9] for details on machine energy modeling by FSMs.

2.4. Sequence constraints

Job precedence constraints are made according to scheduling positions. Eq. (13) defines that the end time of the first job (ETJ_1) with job ID *j* should include job start time (STJ_1), duration for starting a machine (*TSU*), and production duration (DJ_j^1). For jobs in middle positions (i.e., all except the first and last positions) in Eq. (14), the start time and production duration are accounted for. For the last job defined in Eq. (15), the end time should consider the start time, production duration, and duration for shutting down (*TSD*) the machine from production state. Besides, a job should have

a unique scheduling position, as required by Eq. (16).

$$ETJ_1 = STJ_1 + TSU + DJ_j^1, \, j \in J \tag{13}$$

$$ETJ_i = STJ_i + DJ_j^i, \, i \in [2,3,\ldots,N_J-1], \, j \in J \tag{14}$$

$$ETJ_{N_J} = STJ_{N_J} + DJ_j^{N_J} + TSD, \, j \in J \tag{15}$$

$$\exists! i \in I : i = j, \, \forall j \in J \tag{16}$$

For a changeover, its duration (DC_i) is inserted at the end of the ith job to get prepared for the $(i+1)$th job. Thus its start time (STC_i) in Eq. (17) is the end time of the ith job (ETJ_i). Its end time (ETC_i) defined in Eq. (18) is STC_i plus DC_i.

$$STC_i = ETJ_i, \, i \in [1,2,\ldots,N_J-1] \tag{17}$$

$$ETC_i = STC_i + DC_i, \, i \in [1,2\ldots,N_J-1] \tag{18}$$

2.5. Production resource constraints

Eqs. (19-20) require that at the end of the ith job, a selection of an idle mode must ensure a sufficient accommodation period between the end time of the current changeover (ETC_i) and the start time of next job (STJ_{i+1}).

$$\forall \alpha_i \in [1,2,\ldots,N_S]: \sum_{s \in S_{\alpha_i}} D_s \leq STJ_{i+1} - ETC_i \tag{19}$$

$$\sum_{s \in S_O} D_s \leq STJ_{i+1} - ETC_i, \, if \, \alpha_i = N_S + 1 \tag{20}$$

Eqs. (21-22) define that only one job can be produced at one time and preemption is not allowed.

$$STJ_i < ETJ_i, \, i \in I \tag{21}$$

$$ETC_i \leq STJ_{i+1}, \, i \in [1,2,\ldots,N_J-1] \tag{22}$$

Eq. (23) requires that a machine should only have one power state at a point of time. Each state has constant power.

$$P_s^t = P_s = \sum_{s \in S} P_s^t, \, t \in [T_s, T_s + \delta t, \ldots, DT - \delta t, DT] \tag{23}$$

Eqs. (24-25) enforce that the machine should be completely powered off before the due date, and before the start of the weekend within a week.

$$P_s^{T_s} = 0, \, ETJ_{N_J} + TSD \leq DT \tag{24}$$

$$P_s^t = 0, \, \forall t \in weekend \tag{25}$$

3. Empirical site survey

The case study was conducted in a Belgian plastic bottle manufacturer. Various extrusion blow molding (EBM) processes were deployed on the shop floor, so as to produce different types of bottles at the same time. The final bottles vary in shape, volume, color, etc. A full lifecycle production cost analysis [21] showed that, labor costs thereof take up a significant portion of 10% of total production cost, while the energy cost is limited to 3%. The raw material cost occupies over 50%, showing up as the main cost driver of this factory.

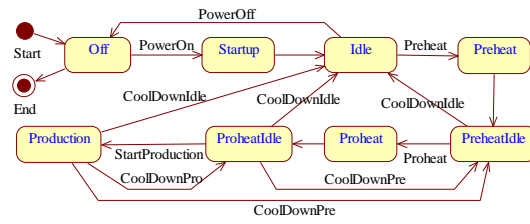One of the EBM processes is taken as the application target

Fig. 1. State-based energy model of extrusion blow molding processing

of the model in Sect.2. It comprises of three major electricity consumers: a main system, an extruder and a hydraulic system. The main system has a general power demand, which drives a set of energy-intensive operations, e.g., cutting, mixing, grinding, and pushing the input materials (plastic and color granules, and recycled plastic chips), heating and melting. The extruder continuously pushes melted plastic through a die, in order to produce the parison. The hydraulic system consumes power for provisioning mechanical movement of the process: clamping and closing the mold and cutting the parison.

Power measurements on this EBM process were performed by three Siemens® PAC 3200 power monitors on the three major electricity consumers. A set of eight power states were identified from the collected power data. The states, state transitions and triggering events for state transition are presented by FSMs in Fig. 1. The power profile of each state and the required personnel type are indicated in Table 1.

When the EBM machine is manually powered on by an operator at 6 am on Monday, it goes through Startup state and stays at Idle. This is followed by transitioning to Preheat, which is also initiated by the operator. The plastic is heated in the barrel until reaching the temperature of 140 °C. The machine then stays at PreheatIdle and keeps the temperature until the operator starts the Proheat command. The temperature then rises to a higher level between 140 °C and 200 °C, depending on the type of bottles to be produced. Once the temperature level is achieved, the machine transitions to ProheatIdle. If the retention time of ProheatIdle surpasses 30 min, additional cooling should be activated to avoid a further rise of the temperature. Once the operator gives command to start the production, the machine transitions to Production state, starting to actually produce bottles according to the schedule.

Once the current production is completed, an operator can

Table 1. Power profile of extrusion blow molding process and required personnel of each power state

State	Power (kW)	Duration (Sec)	Required personnel (one person for each type)
Off	0	≥ 0	Operator
Startup	3.51	442	Operator
Idle	1.19	≥ 0	Operator
Preheat	17.52	1395	Operator
PreheatIdle	8.15	≥ 0	Operator
Proheat	16.95	810	Operator
ProheatIdle	9.00	≥ 0, and ≤ 1800 if no cooling	Operator
Production	46.35	17.92/bottle	Operator, technician, packer, quality checker

Table 2. Time for shifts and working days

Early shift	Late shift	Night shift	Start of a week	End of a week
6 h ~ 14 h	14 h ~ 22 h	22 h ~ 6 h	6 h Monday	6 h Saturday

make the EBM machine transition to Idle, PreheatIdle, or ProheatIdle before starting the next job. This intrinsically provides multiple standby modes, in terms of saving energy consumption and cost. Furthermore, the transition from Production to Off via Idle offers the possibility to stay powered off between two jobs. For this reason, the duration of Off, Idle, PreheatIdle, and ProheatIdle is arbitrary in the energy model (Table 1). It then depends on the scheduler to automatically give the optimal idle mode between jobs.

The exact labor costs cannot be disclosed due to confidentiality. But all staff is paid on an hourly basis (€/h), where a bonus is paid for night shifts. The variation exists in a night shift, where a rise of 10% wage is observed, in comparison to the wage of an early or late shift. Table 2 shows the period covered by each shift, as well as the period of a working week. This implies the factory is closed at weekends, and the EBM process should be powered off before a weekend.

A mold or color changeover is required when the machine produces a distinct type of bottles. As a changeover is conducted at ProheatIdle or PreheatIdle state, a limited variation is produced in power consumption. Statistically, a moderate variation of 22% was observed in power consumption of the machine. In comparison, a high variation of 85% was found in the changeover time. This can be explained by the manual labor involved, which depends on the person and the specific production environment during the changeover. The model in this paper assumes that the EBM machine is always shifted to ProheatIdle for a changeover over 13309 sec, which is the average level of the collected data.

4. Performance analysis

The scheduling model formulated in Sect. 2 was implemented and optimized by a genetic algorithm [9]. The scheduling time span lasts two weeks, from 19 Oct. to 1 Nov. 2015. The electricity price, which varies each hour, was taken from Belpex [22], the Belgian electricity spot market.

Three optimal production schedules were obtained, by optimizing respectively the objective functions of Eqs. (1-3). The three schedules are named schedule1, schedule2, and schedule3. They further go through discret-event simulation along the scheduling time span. The simulation data of scheduled personnel shifts are gathered in man-shift and illustrated in Fig. 2. The key energy- and cost-related performance of the three schedules is demonstrated in Fig. 3.

Schedule2 (Fig. 2b) requires the most total man-shifts (89), morning man-shifts (32), and night man-shifts (29). In comparison, schedule1 (Fig. 2a) needs the least total man-shifts (78); both schedule1 and schedule3 require the least night man-shifts (24). This is explained by the effectiveness of the model and optimization as follows.

In optimization of sole energy cost (schedule2), the GA search makes a progress without any awareness of shift-based labor cost. It schedules more night periods for production,
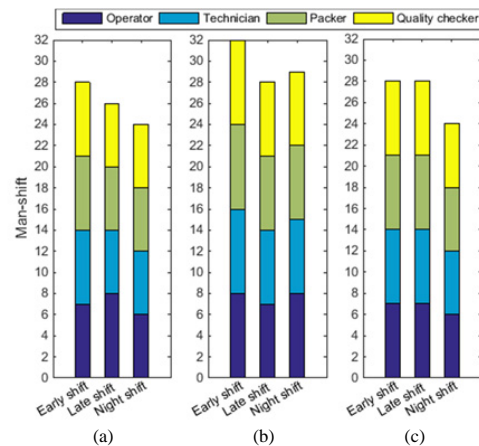

Fig. 2. Optimal personnel planning per shift under three different optimization objectives. Subfigure (a), (b) & (c) corresponds to minimization of joint energy and labor cost, minimization of energy cost, and minimization of labor cost, respectively.
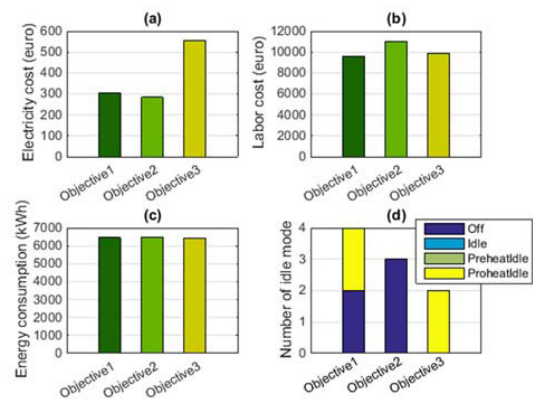

Fig. 3. Simulation results of optimal schedule by three different objectives. Objectives1-3 are minimization of joint energy and labor cost, minimization of energy cost, and minimization of labor cost, respectively. Subfigure (a): energy cost. Subfigure (b): labor cost. Subfigure (c): energy consumption. Subfigure (d): number of idle mode (Four possible idle modes are available, i.e., Off, Idle, PreheatIdle and ProheatIdle, for optimal selection of an idle mode between jobs. If there is no actual bar for an idle mode, it means this mode is never selected in a schedule).

during which the electricity price is low. As observed, all the scheduled power-off periods in schedule2 are long enough (2 h 42 m 3 sec, 43 h 22 m 10 sec, and 9 h 20 m 51 sec) to skip some high-priced periods where the electricity price varies each hour. But this in turn incurs not only more night shifts, but also more early shifts, because a changeover and other machine idling-related state transitions need to follow an accomplished job, which may expand the work period from a night shift to a new morning shift. As a result, schedule2 achieves the lowest electricity cost (284 €, Fig. 3a) by performing the highest number of power-off between jobs (3, Fig. 3d), while it causes the most expensive labor cost (Fig. 3b) and total cost.

In the optimization process to get schedule1 and schedule3, the GA search advances in a direction of the solution space, such that the work periods are compressed in a number of shifts which is as small as possible. The number of night man-shifts is minimized (24, Fig. 2ac), so as to reduce the labor cost over

the night as this is more expensive. This links back to the relative weight both types of costs have in the total production cost (10% and 3% for labor and energy costs, respectively): in this specific case study, the portion of the labor cost is significantly higher than the energy part, hence titling the scheduling engine to favor a lower number of man-shifts over a lower overall energy cost.

Since there is no energy-cost-awareness in schedule3, no machine power-off is scheduled (Fig. 3d), and only the idle mode of staying ProheatIdle is scheduled twice during a very short period of 27 m 30 sec and 23 m 31 sec, respectively, which is not effective to skip high-priced periods. Consequently, the energy cost of schedule3 is the highest (556 €, Fig. 3a), while the labor cost is moderate (Fig. 3b).

Schedule1 is considered the best for two reasons. First, it has the least man-shifts (78), and least total energy and labor cost, which is 12% and 5% lower than schedule2 and schedule3, respectively. Second, its performance indicators in energy cost (307 €, Fig. 3a), energy consumption (6456 kWh, Fig. 3c), and optimal selection of idle mode (2 power-off modes and 2 ProheatIdle modes, Fig. 3d) are all moderate, without any obvious gap compared to the other two schedules. This implies that the integration of energy- and labor-cost-awareness is effective in both energy and labor performance, without greatly jeopardizing either of the two aspects.

Another observation is the more or less equal energy consumption of the three schedules (Fig. 3c). This is explained by the equal number of jobs and total bottles to be produced. Although the number and type of selected idle mode vary in schedules, the energy consumption for the state transition between the Production state and an idle mode is minor, in terms of both power and state retention time (Table 1).

Last but not the least, although this paper focuses on single-machine scheduling, the proposed scheduling method is still nontrivial, as it can be simultaneously applied to multiple single machines. For instance, the factory under investigation has 17 EBM machines in total, which evidently amplifies the cost saving potential of this scheduling approach.

5. Conclusion

Aiming at enhancing the economic and environmental impact of manufacturing processes, this paper formulated a single-machine production scheduling model that considers energy and labor cost involved in production on the shop floor. Compared to the existing energy-aware production scheduling models, the proposed model takes into account machine changeovers for producing distinct product types, as well as the labor aspect which regroups the scheduling time horizon into work shifts and makes the labor cost also changing over time.

The question that this paper addresses is: which economic influence will be brought by incorporating the labor into the energy-aware production scheduling model? A case study was performed at an extrusion blow molding process of a Belgian plastic bottle manufacturer. Empirical power measurements, on-site survey and the Belgian electricity spot market provide rich and real data to this novel scheduling model. Numerical analyses show that although incorporation of labor increases the energy cost by 9%, it reduces the joint energy and labor cost

by 12%. The absolute joint cost is reduced significantly, as the energy cost takes up only around 3% of the total in the case studied. In conclusion, energy and labor cost can be jointly optimized in production scheduling.

Acknowledgements

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