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Procedia CIRP 61 (2017) 387 - 392



The 24th CIRP Conference on Life Cycle Engineering

## 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.

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Peer-review under responsibility of the scientific committee of the 24th CIRP Conference on Life Cycle Engineering

Keywords: Sustainable production scheduling; Personnel scheduling; Energy modeling; Volatile energy price; Demand side management; Cost estimation

#### 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 finegrained 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 energycost-aware scheduling of multiple factories under real-time electricity pricing. They also investigated in [13] an energyconscious flow shop scheduling problem, where CO<sub>2</sub> 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<sub>2</sub> 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 energyand 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 ( $\pi$ ) 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 ( $W_{sh}^{pr}$ ) 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,  $\pi$ , and  $STJ_i(i \in [1,2,...,N_J])$ . For the joint optimization in

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