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Energy-aware decision support for production scheduling[☆,☆☆]

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ABSTRACT

Manufacturing companies are forced to become energy-aware under the pressure of energy costs, legislation and consumers' environmental awareness. Production scheduling remains a critical decision making process, although demanding in computational terms and sensitive on data availability and credibility. Hence the interest in incorporating energy-related aspects in production scheduling. We propose a decision support system (DSS), composed by an Iterated Local Search algorithm that offers hierarchical optimization over multiple scheduling objectives and is energy-aware in terms of both the constraints incorporated and the objectives to be optimized, plus a generic yet concise data model whose entities are extracted from the literature and actual user requirements. The use of this DSS by two textile manufacturers shows that it supports efficiently energy-aware scheduling decisions.

1. Motivation

Public and industry concerns over energy efficiency and environmental sustainability have grown considerably over the last decade. Particularly in the industrial sector, energy efficiency becomes an even more important pillar since it accounts for more than one third of energy consumption worldwide [1] of which the manufacturing sector accounts for about 73%. Despite these numbers, industrial practices towards energy-efficient manufacturing have traditionally been viewed as a 'cost of business', and positioned as the voluntary responsibility of companies. Nowadays, this perception is changing as stricter legislation, industrial standards and energy costs require that companies not only adopt a strategy of minimal compliance, but also treat such a strategy as a catalyst for sustainable practices. Furthermore, consumers are becoming increasingly aware of whether the product they purchase comes from a sustainable source and is produced through eco-friendly methods that, ideally, guarantee minimum environmental impact [2]. Betraying the consumer's confidence can damage a company and its brand image [3]. Altogether, legal compliance, energy costs and customers' increasing ecological awareness [4] are driving companies towards measurable energy improvements, thus strongly motivating our research effort.

Although the manufacturing sector has advanced towards energy efficiency, the derived economic benefits have not been fully exploited [5]. Both academic and business studies indicate that there is an "energy efficiency gap" and highlight that there are strong barriers that impede energy-efficient manufacturing. Systems supporting relevant decisions can help minimize these barriers by monitoring energy consumption and carbon emissions, thus pinpointing areas for savings [6] as a basis for energy-based optimization and intelligent decision making. Several enterprise systems have been enhanced by energy management capabilities, although typically limited to energy monitoring, analysis and reporting [4]. These Energy Management Systems (EMS) do not support management decisions in a coherent way due to a lack of integration of information from shop-floor to top-floor [7]. Apparently, apart from the gap between industrial needs and the academic literature [4,8], there is also a gap between the solutions available and the support of sophisticated decision making such as production scheduling [9].

Indeed, scheduling is an important decision-making process in manufacturing that drills down to deciding on (i) *which* tasks to

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execute, (ii) *where* to process the production tasks and in which sequence and (iii) *when* to execute the production tasks. Typically these decisions are strongly coupled, thus ideally to be taken simultaneously [10]. Due to the complexity and the increasing production volumes, such decisions cannot be addressed without an automated optimization support. This functionality is typically considered part of a Manufacturing Execution System (MES) [10] and is normally supported by an Enterprise Resource Planning (ERP) system through data exchange. Still, scheduling remains computationally complex and data intensive, because it requires not only production data but also the availability status of machines, personnel or energy resources, possibly in real-time. In fact, the more complex a scheduling system is, the more information to be collected and managed [10], and the more competitive the algorithms to be used for obtaining valid schedules of good quality.

Our study focuses on energy-aware flexible shop scheduling environments and is also motivated by the scarce optimization algorithms (and the limited background on the data required) for energy-aware support at the shop floor. The adopted production scheduling framework is as generic as possible and takes into account various operational aspects including constraints on energy consumption (e.g., electricity, gas) and personnel or machine availability. Assuming that a manufacturing process comprises several process steps, the machines of each step share and consume one or more energy resources; hence, relevant constraints can be imposed in one or more process steps, with the maximum level per resource varying across the scheduling horizon (e.g., as implied by flexible electricity pricing). The goal is to find the optimum schedules under different scenarios of resource constraints, accounting for the minimization of both direct and indirect energy consumption.

The Iterated Local Search (ILS) used here introduces new compound moves and an adaptive perturbation mechanism to optimize over energy or temporal scheduling criteria. Energy-related criteria include the total energy consumed by machines during production and idle time (direct energy) along with the energy consumed by subsidiary equipment (indirect energy). Temporal criteria include the makespan, the total flow time and the total machine idle time. We note that even temporal criteria target implicitly both the direct and indirect energy consumption. That is, minimizing the makespan increases throughput and reduces the number of shifts thus reducing the indirect energy consumption (e.g., heating); minimizing total flow time reduces production time, hence the direct energy consumption (e.g., machine gas consumption); and minimizing total idle time reduces the energy consumed by machines in idle mode.

Our ILS algorithm can optimize over any subset of these criteria in a hierarchical manner. Indicatively, hierarchical optimization over the three temporal criteria appears both appropriate and sufficient in our two pilots in textile manufacturing, because these end-users wish to target both energy and other production aspects like cost or personnel. What is critical in terms of DSS design is that our algorithmic and modeling approach remains versatile in terms of handling energy-awareness in the objectives to be optimized. Furthermore, by imposing time-varying restrictions on the energy consumption of machines, our algorithm provides schedules that alleviate energy peaks by distributing more ‘uniformly’ the consumption across time. Hence, energy-awareness in our cases amounts not only to energy-driven optimization objectives but also to energy-consumption constraints.

However, even that does not suffice for an energy-aware DSS. To the best of our knowledge, an explicit description of the data entities supporting energy-aware production scheduling is at the moment not available, although scheduling-related entities were presented early enough (e.g., [11]). To identify these data entities, we formulate a set of user requirements as acquired from the academic literature and validated within the textile manufacturing domain. The algorithm is aligned with these entities and remains operative even if certain data (e.g., personnel availability) are missing.

Overall, this paper contributes to decision support for energy-efficient manufacturing by (a) a metaheuristic algorithm that hierarchically optimizes flexible shop scheduling problems, (b) a set of data requirements in the form of a data model, (c) the integrated deployment of the above as a web-service and (d) the evaluation of the proposed DSS in real settings and the tangible benefits obtained by its use.

The remainder of this paper goes as follows; Section 2 provides the background motivating our study. Section 3 presents the production scheduling problem followed by the user and data requirements plus the algorithmic scheme. Section 4 discusses the application of the proposed DSS along with implementation issues and Section 5 presents the evaluation and the benefits using data from a real context.

2. Background

It is being increasingly acknowledged that energy-intensive manufacturers need tools and methods to optimize their processes by considering energy-related criteria [4]. Indicatively, accurate changes on resources or processes can reduce energy usage [12]. Prior studies have been conducted to evaluate the energy-burden of different process steps [13] and then used as a roadmap to identify modifications in these steps; however, such modifications impose a significant investment because they involve radical changes in the manufacturing process [14]. A less costly alternative is the modification of production settings like the temperature of machines; although several studies focus on such changes [14], these changes usually concern specific processes and have side-effects such as lower product quality [8].

The optimization of energy use via production scheduling has received attention only recently. An early attempt formulates a multi-objective optimization problem for an electroplating line [15]. Another study has shown that up to 65% of the energy consumption comes from non-productive machine modes (e.g., stand-by or idling) [16]. Embedding energy aspects into scheduling can be tackled by both exact and heuristic approaches. Exact methods like mathematical programming obtain optimal solutions but require considerable time given that the job-shop and flow-shop scheduling problems are $\mathcal{NP}$-hard [17]. Indeed, by integrating energy constraints in a set of 100 instances, Artigues et al. [18] show that the solution time for a mixed integer programming model is high. This is also outlined by Fang et al. [19] by testing an exact method against heuristic algorithms to minimize the makespan, the peak consumption and the carbon footprint of the production process.

Metaheuristic methods trade optimality for time, i.e., they provide high-quality solutions within reasonable time. Their current state-of-the-art for production scheduling algorithms includes genetic and hybrid evolutionary algorithms [8,20]. Indicatively, Shrouf et al. [21] focus on scheduling on a single machine, taking into account the variable energy cost during daytime, and use a genetic algorithm. Rager et al. [20] use a combination of genetic and memetic algorithms to acquire schedules minimizing the energy demand of multiple parallel machines by first splitting production orders into operations that have constant energy demand; this results in a schedule defined by the underlying ‘identical parallel machine’ environment and the resource-leveling objective. Notably, the approach of Rager et al. [20] has been tested in textile manufacturing, i.e., the dying stage of yarns.

The problem addressed here is more generic: it includes various operational constraints (e.g., parallel unrelated machines, sequence-dependent set-up times) and is applicable with minor modifications to most shop scheduling environments with multiple process steps. Also, the proposed algorithm incorporates novel local search