Balancing and Configuration Planning of RMS to Minimize Energy Cost

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Abstract. In this paper, we investigate the use of the scalability property of RMS to reduce the energy cost during the production. The corresponding optimization problem is a new Bilevel Optimization problem which combines a line balancing problem with a planning problem. A heuristic based on a simulated annealing algorithm and a linear program is proposed. An illustrative example is presented to highlight the potential of this new approach compared to the cost obtained with a classic production line.

Keywords: Energy · Scalability · Reconfigurable manufacturing systems.

1 Introduction

The industry is responsible for more than 50% of the energy consumption worldwide, and its electricity use is expected to grow as a result of an increase in product demand [17]. Moreover, the societal environmental concern urges companies towards energy-efficient and sustainable production systems. Thus, energy consumption has to be considered from a strategic level to an operational level [8]. The design and management of energy-efficient manufacturing systems (MS) requires to increasingly consider renewable energy sources, whose use alongside classical ones is expected to grow in the next decades [1]. When considering energy consumptions of production systems, three energy measures are usually referred to: (1) total energy consumption; (2) time-of-use pricing (TOU); (3) peak power limit.
Production systems are subject to volatility of the market and need to quickly adapt their throughput to the demand. The notion of Reconfigurable MS (RMS), introduced by [10], aims to achieve such reactivity by reconfiguring the production system. Typical RMS are composed of several workstations organized in serial manner with multiple parallel identical machines used in each workstation, as shown in Figure 1. Parts are moved from a workstation to the next by a conveyor and a gantry. The machines on each workstation are generally computer numerical control machines, reconfigurable machine tools, but can also consist in other types of resources (e.g., workers with cobot). RMS can be an interesting lever to deal with variable energy availability or pricings as it is the

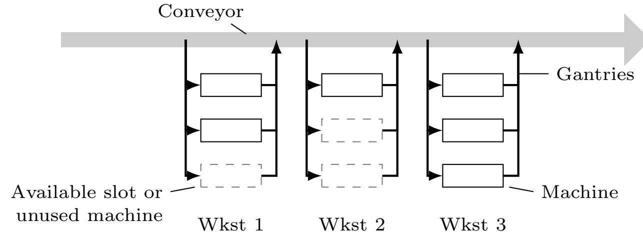

Fig. 1. RMS layout as seen by [9]

case with TOU, which require to modulate the energy consumption. In costlier periods, a less consuming configuration, even with lower productivity, can be used, before switching to a higher-throughput higher-consumption configuration in periods with lower energy prices so as to satisfy a given demand.

In this paper, a Bilevel Optimization problem is addressed, optimizing the energy cost while satisfying a given demand. The upper-level problem is a balancing problem to determine the design of the RMS and thus the set of configurations which can be used. The lower-level problem consists in finding an optimal planning, i.e. an assignment of configurations to energy cost periods that minimizes the total energy cost while meeting the desired demand. A specific iterative heuristic approach to solve the problem is also investigated.

The remainder of the paper is organized as follows: Section 2 introduces the related works. Section 3 formulates the considered problem and its assumptions. Section 4 presents the developed method and Section 5 gives a numerical illustration. Conclusions and perspectives are given in Section 6.

2 Related works

RMS have been introduced in [10]. They aim to reach as high throughput as dedicated lines and as much flexibility as flexible MS. This is enabled by their capacity to integrate new machines and/or change modules on workstations.

The literature on RMS deals with system design, process planning, scheduling and reconfigurable control [2]. RMS rely on specific characteristics such as modularity, integrability, convertibility, diagnosability, customization and scalability [11]. The scalability of RMS is obtained by adding or removing functionalities in order to have a production system that fits the market demand. According to [11], it might be the most important characteristic of RMS. [6] investigated a model for assessing the scalability capacity of a make-to-order RMS considering different demand scenarios and w.r.t. different performance measures. In [18], a scalability planning methodology for reconfigurable manufacturing is explored. Starting with an existing system, the approach consists in changing its capacity by successive reconfigurations. The objective is to minimize the number of machines required to respect a new throughput. The recent survey [14] state that scalability can improve the optimization of MS design, their management and

help to develop new MS paradigms for sustainability and societal challenges.
As to energy consumption, [7] is one of the first papers dealing with energy at the design phase of dedicated lines. For RMS, [4] investigated a multi-objective production planning problem that considers energy consumption, throughput, and inventory holding costs to assess the performance of the planning. A configuration corresponds to a production plan which is adjoined by a total energy consumption. [19] introduced the concept of energy-efficient RMS and investigated a discrete event simulation model to evaluate the systems energy efficiency. In [13], a multi-objective RMS consisting of a rotary table and a set of machines and modules is studied. The approach consists in two stages: the systems design and its control, with the goal to minimize the cycle time and the overall costs that include energy costs. The recent survey [1] showed that few research projects consider reconfigurations to improve energy efficiency and sustainability in production and that RMS have great potential in this respect.
To conclude, as far as we are aware of, no study has considered both scalability and energy consumption in the context of RMS.

3 Problem definition

In this study, we consider a paced production line, dedicated to a single product. The production process is known, i.e. the precedence constraints between the n operations composing it are known and their processing times t_j and their energy consumption e_j are deterministic. The assignment of operations to $K_{\max}$ workstations, i.e. the Assembly Line Balancing Problem (ALBP) defined in [16], is the core strategic decision problem of the production line.
Given a balancing of the line, i.e. such an assignment, a set of parallel machines can be associated with each workstation, so that different configurations can be obtained by turning on/off some of them. We suppose to deal with a RMS with such a feature, i.e. in which all the configurations descend from one balancing and are thus defined by the number r_k of machines turned on for each workstation k. In such a setting, it is reasonable to consider as negligible the time required to reconfigure the system.
A configuration is characterized by two measures: takt time and energy consumption. The takt time is based on the processing time of the operations. The sum of the processing time of the operations assigned to a workstation k is its workload W_k. The cycle time c_k of a workstation k is its workload divided by the number of its parallel machines, i.e. $c_k = W_k/r_k$. It is the average time required to process one piece. The takt time c of a configuration is the maximum cycle time of the workstations. The idle time of the workstation k is $I_k = c - W_k/n_k$.
The energy E consumed during a takt time is the sum of the energy consumed by each workstation. The energy consumption E_k of workstation k is the sum of the energy consumption of operations assigned to it (η_k) and of a residual consumption during idle time that depends by a coefficient α on the number r_k of machines, the idle time I_k and the average consumption per time unit η_k/W_k:

$$E_k = \eta_k + \alpha I_k r_k \frac{\eta_k}{W_k} \tag{1}$$

In this article, we consider the energy consumption by unit of time $Q = \frac{E}{c}$.
Let us now suppose to deal with a TOU pricing scheme with P time periods $p \in \{1 \ldots P\}$, each defined by an energy cost U_p and a duration D_p over a time horizon T, i.e. such that $\sum_p D_p = T$. We want to solve the planning problem of finding the configurations used in each period p that minimize the total energy cost while fulfilling a given overall demand Δ within the timespan T.
Considering the cost of energy since the design stage of the production system gives rise to a *Bilevel Optimization Problem* in which the design (balancing) of the production system is the *upper-level* decision problem, while the planning problem represents the *lower-level* decision-making. The decision variables are:

- upper-level assignment variables $x_{jk} \in \{0,1\}$, $\forall j \in \{1 \ldots n\}, k \in \{1 \ldots K_{\max}\}$
- lower-level planning variables $0 \leq y_{ip} \leq 1$, $\forall i \in \mathcal{C}(\boldsymbol{x}), p \in \{1 \ldots P\}$

where $\mathcal{C}(\boldsymbol{x})$ is the set of configurations that descend from the balancing $\boldsymbol{x}$.
The Bilevel nature of the problem mainly resides in the intertwinement of the two levels, as the suitability of a balancing cannot be evaluated without solving the planning problem, which in turn cannot be solved without knowing the balancing. We refer the reader to [5] for an introduction to Bilevel Optimization. The Bilevel optimization model is the following:

$$\min_{\boldsymbol{x}} \mathcal{T}(\boldsymbol{x}, \boldsymbol{y}^\star);\ \max_{\boldsymbol{x}} \mathcal{R}(\boldsymbol{x}) \tag{2}$$
$$\text{s.t. } \mathcal{B}(\boldsymbol{x}) \leq 0 \tag{3}$$
$$\boldsymbol{y}^\star = \operatorname{argmin}_{\boldsymbol{y}} \mathcal{E}(\boldsymbol{x}, \boldsymbol{y}) \tag{4}$$
$$\text{s.t. } \mathcal{P}(\boldsymbol{y}) \leq 0 \tag{5}$$

where $\mathcal{T}$, $\mathcal{R}$ and $\mathcal{E}$ are, respectively, an overall cost function (which may include cost terms other than energy, related e.g. to workstations and tools), a reconfigurability measure of $\boldsymbol{x}$, and the energy cost of planning $\boldsymbol{y}$ based on the configurations of $\mathcal{C}(\boldsymbol{x})$. $\mathcal{B}(\boldsymbol{x})$ and $\mathcal{P}(\boldsymbol{y})$ are the balancing and planning constraints.

4 Proposed method

In the following, we propose a sequential, two-phases decomposition heuristic to the Bilevel Optimization problem proposed in Section 3. Phase 1 addresses the design problem to obtain a candidate balancing $\boldsymbol{x}$ and a set $\mathcal{C}(\boldsymbol{x})$ of configurations from it. These are used in the Phase 2 to find a planning that fulfils a demand Δ over a timespan T at a minimum energy cost w.r.t. a given TOU pricing scheme. Since the number of workstation is bounded, we will not consider it in the cost function and $\mathcal{T}$ will be reduced to the energy cost.

4.1 Phase 1: generation of a set of configurations

This phase assigns operations to workstations so as to define the type of machines needed for each workstations. The configurations derived from a balancing offer different levels of productivity with different energy consumption. To increase

the productivity of the system, an additional machine have to be turned on for the bottleneck workstation, which has the highest cycle time c_k. This property defines a method to derive configurations from a balancing: allocate one machine to each workstation to define the first configuration, then iteratively add a machine in the bottleneck workstation.
Further restrictions are needed to avoid unrealistic situations (all operations assigned to the same workstation, an infinity of machines on a workstation...) and conform to industrial constraints:

- There is at least one machine per workstation.
- There is no more than $r_{\max} = 3$ machines per workstation.
- The maximum number of machines in a configuration, $R_{\max}$, is $n/2$.
- The maximum number of operations per workstation is $n_{\max} = 40\%n$.

The definition of configurations is the same as in [3], in which the authors studied the scalability of different derived configurations. They showed that the scalability is not correlated with the classical line balancing indicators (takt time, smoothness ratio...). They proposed to evaluate the scalability by a bi-objective analysis (takt time, number of machines) of the balancing and by computing a hypervolume metric $\mathcal{H}$. We adopt this approach here and compute such a metric on takt time and per-time-unit energy consumption of the configurations. Note that by doing so the metric $\mathcal{H}$ actually aggregates a reconfigurability measure ($\mathcal{R}$) with an energy consumption measure ($\mathcal{T}$).
Let c^i and Q^i be the takt time and energy consumption per time unit of the $|\mathcal{C}(\boldsymbol{x})|$ configurations derived from a same balancing and sorted by decreasing takt time. The hypervolume measures the area above the points (c^i, Q^i):

$$\mathcal{H} = \left(p_c - c^1\right)\left(p_Q - Q^1\right) + \sum_{i=2}^{|\mathcal{C}(\boldsymbol{x})|} \left(c^{i-1} - c^i\right)\left(p_Q - Q^i\right) \tag{6}$$

A reference point (p_c, p_Q) is used as an upper bound on the values of takt time and energy consumption, with $p_c = \sum_j t_j + 1$ and $p_Q = R_{\max} \max_j \frac{e_j}{t_j} + 1$. We refer the reader to [3] for further explanations of the hypervolume.
In order to find the line balancing maximizing the hypervolume computed on its derived configurations, we implemented a simulated annealing [12]. The generation of an initial balancing is random, taking into account the precedence constraints, $n_{\max}$, and limiting the number of workstations to $R_{\max}$. Two balancings are neighbors if all operations are assigned to the same workstation, except one. The neighborhood search randomly selects one neighbor of the current balancing. At the end of the simulated annealing execution, the configurations derived from the best balancing are given to Phase 2.

4.2 Phase 2: assignment of configurations

We set up a Linear Program (LP) in order to decide how to deploy the configurations, returned by the Phase 1, over a given time horizon T. The objective is to fulfill a given demand Δ while minimizing the overall economic cost of the associated energy consumption. The associated decisions can be represented by nonnegative real variables $y_{ip} \geq 0$, equal to the percentage of the period $p \in \{1...P\}$ allocated to configuration $i \in \mathcal{C}(\boldsymbol{x})$. The proposed LP model is:

$$\min \sum_{i \in \mathcal{C}(\boldsymbol{x}), p \in \{1...P\}} D_p \cdot U_p \cdot Q^i \cdot y_{ip} \tag{7}$$

$$\text{s.t.} \sum_{i \in \mathcal{C}(\boldsymbol{x}), p \in \{1...P\}} \frac{D_p}{c^i} \cdot y_{ip} \geq \Delta \tag{8}$$

$$\sum_{i \in \mathcal{C}(\boldsymbol{x})} y_{ip} \leq 1 \qquad \forall p \in \{1...P\} \tag{9}$$

Term (7) represents the economic cost to minimize. Inequality (8) is the demand fulfillment constraint, and relations (9) enforce the fact that the use of some configurations over an energy cost period must not exceed its duration.

5 Numerical example

To illustrate our approach, in this section we present the result obtained for the instance Heskia [15], which features 28 tasks, for which we generated energy consumption values. LP Model of Phase 2 is solved using IBM ILOG CPLEX. A balancing of operations of five workstations (named S_1 to S_5), with a takt time of 309 s, is output by simulated annealing in Phase 1. Eight configurations are derived from this balancing: Table 1 shows their takt time and energy consumptions. Figure 2 depicts configuration $i = 2$ and gives the values of W_k, I_k and η_k for each workstation k (which are common to all configurations). For this configuration, the takt time is 284 s. From (1), and using $\alpha = 0.1$, the energy consumption of S_1 is $4382 + 0.1 \times 104 \times 1 \times \frac{4382}{180} = 4.635$. Similarly we get 8.392 for S_2, 6.929 for S_3, 4.153 for S_4 and 1.310 for S_5. Thus the total energy consumption of configuration $i = 2$ is $E^2 = 25.419$, and $Q^2 = 89.51 \times 10^{-3}$.

i	1	2	3	4	5	6	7	8
$c^i(s)$	309	284	180	154.5	142	135	116	103
$Q^i(\times 10^3)$	80.88	89.51	135.64	157.76	172.51	182.79	209.72	236.21
E^i	24.992	25.419	24.414	24.374	24.495	24.676	24.327	24.329

Table 1. Features of the eight configurations from the instance Heskia

As to Phase 2, we defined $P = 6$ periods over a 24 hours time horizon, the duration and the cost of energy of which are shown in Figure 3, along with the planning returned by Phase 2 for a demand $\Delta = 601$. Grayed areas represent production interruptions. The optimal energy cost is 175.186. Only two configurations are used. Configuration 8 (with the lowest takt time) is used in the first period and 47% of the second, allowing to stop production during the costliest periods. Configuration 7, with the lowest E^i value, is used to produce the remaining demand. In this example, periods are either used fully or not at all: this

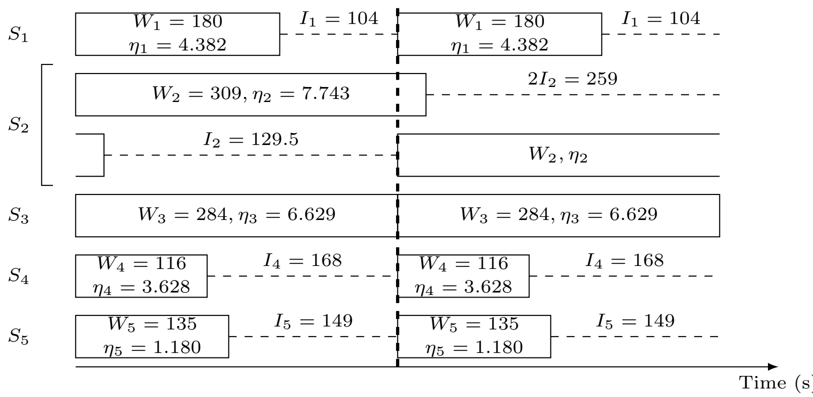

Fig. 2. The second configuration for the instance Heskia

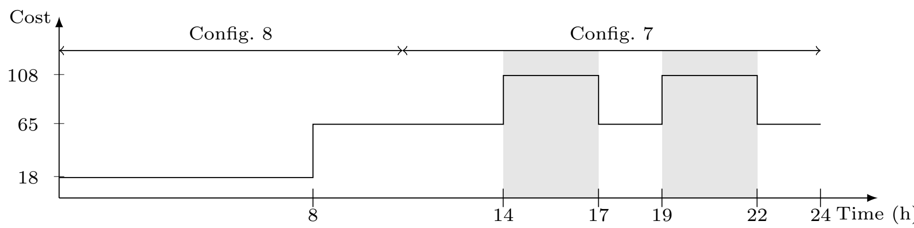

Fig. 3. Pricing scheme over the 24 hours time horizon and planning output by Phase 2.

is not a constraint of the LP, and not all instances show this behaviour.
A dedicated line with one machine per workstation would require 8 workstations and have a takt time of 143 s. If such a line was used during the 24 hours to satisfy the demand, the energy cost would amount to 242.573. Our method enables an almost 30% energy cost reduction by using a RMS instead.

6 Conclusion and perspectives

In this article, we studied the Bilevel optimization problem of balancing and configuration planning of a RMS to satisfy a given demand with minimum energy cost w.r.t. a TOU energy pricing scheme. The main motivation of this work is to show how RMS can be beneficial when dealing with questions arising from more variable energy sources, an issue nowadays more and more sensitive.
To solve this problem, we defined a two-phases method. We developed a simulated annealing for Phase 1 that evaluates the different configurations derived from a same balancing, taking simultaneously into account their takt time and energy consumption. A linear programming model is used in Phase 2 to plan the use of the configurations over a time horizon. The numerical example showed that increasing the production on low-cost periods and not producing on high-

cost periods can lead to a significant reduction of the overall energy cost. Further tests on a wider instance set would allow to better assess the potential savings that could be achieved using this approach. Moreover, it would be interesting to consider some industrial constraints, such as a power peak limit.

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