Using Reconfigurable Manufacturing Systems to minimize energy cost: a two-phase algorithm

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Abstract: Energy consumption has become a major concern for society, and since the industrial sector is the largest consumer, companies are urged to improve energy efficiency of their production systems. This paper investigates how Reconfigurable Manufacturing Systems (RMS), and particularly their scalability feature, can be exploited in order to minimize the energy cost in production systems w.r.t. a Time-Of-Use pricing scheme. In the case of RMS, the resulting energy cost optimization problem is a Bilevel Optimization problem, as it jointly considers both the line balancing and the production planning. After introducing the problem and its features, a solving approach based on a simulated annealing algorithm and a linear program is proposed. The approach is then validated on designed instances based on classical test problems taken from the literature. Results show that considerable savings in terms of energy cost can be achieved w.r.t. dedicated lines, even when optimally designed, ultimately showing the great potential of RMS towards energy efficiency.

Keywords: Energy-efficiency, Flexible and reconfigurable manufacturing systems, Process Planning/Equipment Selection

1. INTRODUCTION

Energy consumption worldwide is supposed to rise by nearly 50% by 2050 and the industrial sector is the largest energy consumer, with an electricity usage that is expected to grow by 40% in the projected period (U.S. EIA, 2019). However, the concern of society for the environment is driving companies to adopt more energy-efficient and sustainable production systems. This also implies the design and management of energy-efficient manufacturing systems (MS) to increasingly consider renewable energy sources, which usage is expected to spread in all sectors during the next decades (Battaïa et al., 2020). Consequently, energy efficiency must be considered at all levels, be it strategic, tactical or operational (Giret et al., 2015). When considering energy efficiency of production systems, three measures are usually referred to (see e.g. Masmoudi et al. (2019)): total energy consumption; total energy cost w.r.t. to a given pricing scheme – more often Time-Of-Use (TOU); power peak limitation.

Moreover, world gross output is expected to double worldwide in the next decades, with high volatility of the market which requires production systems to quickly adapt their throughput. The notion of Reconfigurable Manufacturing System (RMS), introduced by Koren et al. (1999), aims to achieve such reactivity by means of efficiently reconfigurable production systems. Typical RMS are composed by several serial workstations with multiple parallel identical machines used at each stage. The machines on each workstation are generally computer numerical control machines or 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 case with TOU, since it allows to change the system structure to better fit energy requirements. 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 and meet the demand. In this paper, we deal with the problem of balancing an RMS in order to define a most fitting set of configurations so as to minimize the energy cost associated with a given demand and w.r.t. a energy cost profile. The problem has been shown to be a Bilevel Optimization problem in Cerqueus et al. (2020b) which first studied it. The authors have proposed a two-phase decomposition approach to tackle it but have only shown its effectiveness on a case study with realistic energy cost parameters. In this work, we extend the two-phase approach and perform an extensive computational experience so as to validate it and better assess the potential gains in terms of energy cost that could derive by the use of RMS.

The plan of the paper is as follows. Section 2 reviews similar works in the literature. Section 3 outlines the problem at study. Section 4 delves into the details of the decomposition approach. Section 5 describes the computational sessions. Finally, Section 6 shows the conclusions and perspectives of this work.

2. LITERATURE REVIEW

RMS have been introduced in Koren et al. (1999). They aim at reaching as much flexibility as flexible MS while keeping as high a production rate as dedicated lines. Specific features of RMS are modularity, integrability, convertibility, diagnosability, customization and scalability (Koren et al., 2017). Scalability is enabled by the capacity to integrate or remove parallel machines on workstations and motivated by the need to adapt the production level to fluctuations of demand or energy price. The literature on RMS mainly deals with system design, layout, process planning, and reconfigurable control (Bortolini et al., 2018), and it seems that few papers consider scalability as a lever for productivity. Deif and ElMaraghy (2007) investigates a model for assessing the scalability capacity of a make-to-order RMS according to different demand scenarios and performance measures. In Wang and Koren (2012) a scalability planning methodology for reconfigurable manufacturing is explored. The approach consists in changing the capacity of an existing system by successive reconfigurations, in order to minimize the number of machines required to respect a new throughput. In Hees et al. (2017), a production planning system that focuses on the scalability of the production capacities and the adaptation of functionalities is investigated. In Moghaddam et al. (2020), two different approaches are considered to design multi-product and scalable RMS for multiple production periods. The objective is to minimize design and reconfiguration costs while fulfilling a given demand. Both approaches are based on the estimated demand of different parts: (i) up- or downgrade the RMS depending on estimates for each production period, or (ii) select and reconfigure the reconfigurable manufacturing tools for all periods based on longer-term estimates.

Putnik et al. (2013) states that scalability can improve the optimization of manufacturing system design and management, and help to develop new paradigms for sustainability, but few papers actually consider this last criterion. Zhang et al. (2015) introduces the concept of energy-efficient RMS and investigates a discrete event simulation model to evaluate the systems energy efficiency. For RMS, Choi and Xirouchakis (2015) investigates 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. In Touzout and Benyoucef (2019) a multi-objective problem for sustainable process planning in RMS is addressed. Three optimization criteria are considered: (i) the total production cost, (ii) the total completion time, (iii) the amount of greenhouse gases emitted. Gianessi et al. (2019) is one of the first papers dealing with energy at the design stage for dedicated lines, more precisely by minimizing peak power.

The recent survey of Battaïa et al. (2020) shows that few research projects exploit the capacity of RMS to improve energy efficiency and sustainability in production. To the best of our knowledge, the first study that has considered scalability as a lever to adapt energy consumption in the context of RMS is the one of Cerqueus et al. (2020b).

3. PROBLEM DESCRIPTION

In this work, we consider the optimization problem of determining both a set of configurations of an RMS at the design stage, and the planning of their use. The set of configurations must be large enough so that the RMS can adapt the production planning according to the varying energy costs of a TOU pricing scheme, while fulfilling a demand Δ over a given period T. The planning then consists in selecting which configuration should be used at each moment of the timespan T: the objective is to minimize the total energy cost of production.

This problem, which has first been studied in Cerqueus et al. (2020b), is actually a *Bilevel Optimization problem* (see e.g. Colson et al. (2005), or Moore (1988) for an application to production planning). Indeed balancing and planning problems are usually considered separately by manufacturers with different decision-makers and time horizons – the former is a strategic problem, the latter a tactical/operational issue. In the case of RMS, however, it is useful to design the production system from the start in such a way that its scalability can be exploited as much as possible w.r.t. to a given objective – here energy cost. As a consequence, and regardless of the specific objective, the two decision layers become strongly interconnected: one can easily see that on one hand the performance of a configuration set cannot be assessed without constructing the planning of how configurations are used over the period T, while on the other hand the planning problem cannot be solved if the configuration set is not known in advance. Moreover, the design of an RMS is more complex than that of a dedicated MS. The design decisions of a dedicated MS mainly concern how the n production tasks are assigned to the $m \leq n$ available workstations, so as to comply with technological constraints and optimize production criteria. Even the Simple Assembly Line Balancing Problem (SALBP), that studies a straight paced assembly line in which design decisions only concern the takt time and/or the number of workstations, is NP-Hard and has given rise to a large amount of scientific works (see e.g. Scholl and Becker, 2006). The consideration of a different criterion can only make the problem even harder, as shown for instance in Gianessi et al. (2019) for power peak. With RMS, the task is much harder, as the goal of the design stage is to determine a *set* of line configurations that differ in the assignment of tasks to workstations and in the number of identical resources assigned to each workstation.

In this work, as it has been done in Cerqueus et al. (2020b), we focus on scalability and consider the particular case in which all the configurations of the set share the same balancing, and only differ in the number r_k of resources of each workstation k. As a direct consequence of this assumption, system reconfigurations can be seen as switching on/off resources, and hence reconfiguration times can be neglected since a reconfiguration does not imply a reassignment of tasks and materials to workstations.

Under this assumption, and by considering the minimization of the energy cost of production as the main objective, the goal of the design stage is to determine the balancing $\boldsymbol{x}$ that gives rise to the most fitting set of descending configurations $\mathcal{C}(\boldsymbol{x})$ in terms of per-time-unit energy consumption Q^i and takt time c^i, $i \in \mathcal{C}(\boldsymbol{x})$. The Bilevel Optimization problem at hand can then be expressed as:

$$\min_{\boldsymbol{x}} \ \mathcal{F}(\boldsymbol{x}, \boldsymbol{y}^\star); \max_{\boldsymbol{x}} \ \mathcal{S}(\boldsymbol{x}) \tag{1}$$

$$\text{s.t. } \mathcal{B}(\boldsymbol{x}) \leq 0 \tag{2}$$

$$\boldsymbol{y}^\star = \operatorname*{argmin}_{\boldsymbol{y}} \ \mathcal{E}(\boldsymbol{x}, \boldsymbol{y}) \tag{3}$$

$$\text{s.t. } \mathcal{P}(\boldsymbol{y}) \leq 0 \tag{4}$$

In the *upper-level problem* (1)-(3), $\mathcal{F}$ is an overall cost function and $\mathcal{S}$ a scalability measure of $\boldsymbol{x}$; (2) enforce the balancing constraints; (3) certifies that planning $\boldsymbol{y}^\star$ has minimum energy cost $\mathcal{E}$, given balancing $\boldsymbol{x}$.
Binary *upper-level variables* x_{jk} take value 1 if task $j \in \{1,\dots,n\}$ is assigned to workstation $k \in \{1,\dots,m\}$ w.r.t. an upper bound $n_{\max}$ on the number of tasks assigned to the same workstation. Each task features a processing time t_j and a total energy consumption e_j (i.e. the integral of the power consumption profile of task j over its processing time). The basic configuration that descends from balancing $\boldsymbol{x}$ has $r_k = 1\ \forall k \in \{1,\dots,m\}$, and workstation k could have takt time $c_k = \frac{W_k}{r_k}$ equal to its workload $W_k = \sum_j t_j\, x_{jk}$. The takt time of the line, c, is then set according to the *bottleneck* workstation $k' = \arg\max c_k$.
Other configurations can be derived from balancing $\boldsymbol{x}$ by increasing the number r_k of resources of workstations, but only those having a higher production rate, i.e. a lower c, are worth being considered. By definition, c can only be reduced by increasing by one the number $r_{k'}$ of resources of the bottleneck station. This can result in a possible new bottleneck station. This process can be repeated until the bottleneck station would exceed the maximum number of resources per workstation $r_{\max}$. By following this reasoning, one can obtain the full set $\mathcal{C}(\boldsymbol{x})$ of configurations originating from $\boldsymbol{x}$, with descending takt time values.
As for energy consumption, we assume that during idle time $I_k = c - c_k$ stations have a residual energy consumption which is proportional by a factor α to I_k, the number of resources r_k and the per-resource, per-time-unit energy consumption of tasks assigned $\frac{\eta_k}{W_k}$, with $\eta_k = \sum_j e_j\, x_{jk}$. Hence, the energy consumption of workstation k during a takt is $E_k = \eta_k(1 + \alpha\frac{r_k\, I_k}{W_k})$. This allows to associate each configuration $i \in \mathcal{C}(\boldsymbol{x})$ with a per-time-unit energy consumption Q^i:

$$Q^i = \frac{1}{c^i}\sum_k E^i_k = \frac{1}{c^i}\sum_k \eta_k\,(1 + \alpha\frac{r^i_k\, I^i_k}{W_k}) \qquad (5)$$

in which η_k and W_k are invariants of the configuration i, while c^i, r^i_k, I^i_k and thus E^i_k depend on i.
The *lower-level problem* (3)-(4) represents the planning decisions, i.e. how configurations of $\mathcal{C}(\boldsymbol{x})$ should be used w.r.t. a given pricing scheme to minimize the production energy cost while ensuring fulfilment of demand Δ. Since we are considering a TOU pricing scheme, the time horizon T is divided in several cost periods and *lower-level variables* y_{ip} represent the portion of period p spent producing according to configuration $i \in \mathcal{C}(\boldsymbol{x})$. Constraints (4) enforce planning feasibility and demand fulfilment, while term $\mathcal{E}(\boldsymbol{x},\boldsymbol{y})$ of (3) is the total energy cost of producing according to configurations $\mathcal{C}(\boldsymbol{x})$ and planning $\boldsymbol{y}$.

4. DECOMPOSITION APPROACH

As in Cerqueus et al. (2020b), the algorithmic approach presented in this paper for the Bilevel Optimization problem is a two stage decomposition approach. Phase 1 addresses the balancing problem through a metaheuristic and yields a balancing $\boldsymbol{x}$, and a set $\mathcal{C}(\boldsymbol{x})$ of configurations generated from it, which seek to optimize both the scalability of the production system and its capacity to fulfill a large range of economical demands. Starting from set $\mathcal{C}(\boldsymbol{x})$, Phase 2 solves the planning problem to minimize the energy cost of the production process needed to satisfy demand Δ over time horizon T. In the following, we describe the two phases in detail.

4.1 Phase 1: Generating a Configuration Set

Phase 1 of the metaheuristic consists in a *Simulated Annealing* (SA) algorithm (see e.g. Aarts et al., 2005). In the two-phase approach for the problem at hand, the SA-based algorithm begins by randomly building a feasible balancing $\boldsymbol{x}$, i.e. that complies with the other previously mentioned constraints, as well as with precedence constraints (here denoted by symbol $\prec$) among tasks:

$$(\forall\, j_1, j_2 \in \{1,\dots,n\} : j_1 \prec j_2)\ \sum_k k(x_{j_2,k} - x_{j_1,k}) \geq 0$$

This also defines the basic configuration, i.e. with $r_k = 1\ \forall k$, of set $\mathcal{C}(\boldsymbol{x})$. Other configurations $i \in \mathcal{C}(\boldsymbol{x})$ are then derived from it as previously described in Section 3.
The neighbors of a balancing $\boldsymbol{x}$ are those which can be obtained by moving one task j from its current workstation k to another $\overline{k} \neq k$, $k_1 \leq \overline{k} \leq k_2$, where

$$(\forall\, j_1 \prec j)\ \sum_k k\, x_{j_1,k} \leq k_1\ ;\ (\forall\, j \prec j_2)\, k_2 \leq \sum_k k\, x_{j_2,k}$$

i.e. such that no precedence constraint involving j is violated. Moreover, a candidate destination workstation cannot be chosen if $n_{\max}$ tasks have already been assigned to it. New workstations can be opened to be assigned tasks, up to a maximum number m.
A balancing $\boldsymbol{x}$ is evaluated by means of a weighted sum $\varPhi(\boldsymbol{x})$ of two terms, namely a *hypervolume metric* $\mathcal{H}(\boldsymbol{x})$ and the production rate $\mathcal{P}(\boldsymbol{x})$ of the most productive among the configurations derived from $\boldsymbol{x}$.
Hypervolume $\mathcal{H}(\boldsymbol{x})$ is computed based on the takt time c^i and per-time-unit energy consumption Q^i of configurations $i \in \mathcal{C}(\boldsymbol{x})$ that are non-dominated configurations w.r.t. c and Q (i.e. those for which no other configuration $i' \in \mathcal{C}(\boldsymbol{x})$ exists s.t. $c^{i'} \leq c^i$ and $Q^{i'} \leq Q^i$). We suppose without loss of generality that configurations $i \in \mathcal{C}(\boldsymbol{x})$ are sorted by decreasing c values. The values of c^i and Q^i are normalized using suitable upper (c_U, Q_U) and lower (c_L, Q_L) bounds: $\tilde{c} = \frac{c-c_L}{c_U-c_L}$ and $\tilde{Q} = \frac{Q-Q_L}{Q_U-Q_L}$. The hypervolume of balancing $\boldsymbol{x}$ is then:

$$\mathcal{H}(\boldsymbol{x}) = (1-\tilde{c}^1)(1-\tilde{Q}^1) + \sum_{i\geq 2}(\tilde{c}^{i-1} - \tilde{c}^i)\cdot(1-\tilde{Q}^i) \quad (6)$$

To have the same order of magnitude, the second part of the weighted sum is also normalized:

$$\mathcal{P}(\boldsymbol{x}) = \frac{c_U c_L}{c_U - c_L}(\frac{1}{c^{|\mathcal{C}(\boldsymbol{x})|}} - \frac{1}{c_U}) \qquad (7)$$

The fitness $\varPhi(\boldsymbol{x})$ of $\boldsymbol{x}$ (with weight factor λ) is then:

$$\varPhi(\boldsymbol{x}) = \lambda\, \mathcal{H}(\boldsymbol{x}) + (1-\lambda)\, \mathcal{P}(\boldsymbol{x}) \qquad (8)$$

Hypervolume $\mathcal{H}$ allows to use an aggregated criterion to evaluate the scalability of a set $\mathcal{C}(\boldsymbol{x})$ (Cerqueus et al., 2020a). The maximization of $\mathcal{H}$ is meant to hopefully lead to configuration sets whose c and Q values are at the same time as diversified and as low as possible. The latter aspect, in particular, is expected to yield configurations which are both highly producing and energy efficient. Figure 1 depicts the calculation of $\mathcal{H}$ for an example set. The second term of fitness function $\varPhi$ in (8) is proportional to $\mathcal{P}$ to further stress the fact to seek for a configuration with a consistent highest production level.

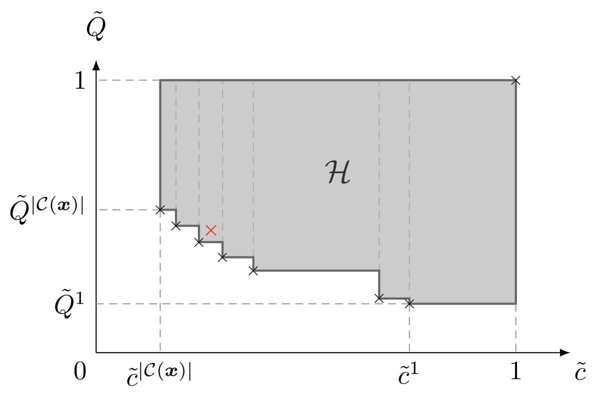

Fig. 1. Hypervolume calculation for a set of 8 configurations (1 dominated, in red).

4.2 Phase 2: Planning Configurations over the Timespan

The planning problem of Phase 2 consists in optimally deploying the configurations of $\mathcal{C}(\boldsymbol{x})$ over a period T to fulfill demand Δ and is solved as a Linear Program (LP). We suppose that the considered pricing scheme is of type TOU, i.e. with a set P of time periods each featuring a energy unit cost U_p; durations of periods D_p are s.t. $T = \sum_{p \in P} D_p$. Lower-level variables y_{ip} are then $[0, 1]$ real variables modeling the portion of time period p spent producing with configuration $i \in \mathcal{C}(\boldsymbol{x})$. The LP model is:

$$\min \sum_{i \in \mathcal{C}(\boldsymbol{x}), p \in P} D_p \cdot U_p \cdot Q^i \cdot y_{ip} \tag{9}$$

$$\text{s.t.} \sum_{i \in \mathcal{C}(\boldsymbol{x}), p \in P} \frac{D_p}{c^i} \cdot y_{ip} \geq \Delta \tag{10}$$

$$\sum_{i \in \mathcal{C}(\boldsymbol{x})} y_{ip} \leq 1 \qquad \forall p \in P \tag{11}$$

$D_p\, y_{ip}$ is the time spent using configuration $i \in \mathcal{C}(\boldsymbol{x})$ to produce during period p. Hence:

- (9) represents the energy cost to minimize, since $Q^i\, D_p\, y_{ip}$ is the associated energy consumption, and
- (10) ensures that demand Δ is satisfied, since $\frac{1}{c^i}\, D_p\, y_{ip}$ is the corresponding produced quantity, resulting from the production rate $\frac{1}{c^i}$.

Finally, (11) impose that production in a period p cannot last more than D_p, $\sum_i y_{ip} < 1$ meaning that production is suspended for a time $(1 - \sum_i y_{ip}) D_p$.

5. COMPUTATIONAL EXPERIENCE

We tested our approach on benchmark SALBP instances derived from Scholl (1995) and Otto et al. (2013). For the instances of Scholl (1995), since the author provides sets of instances with same tasks and different c values, we derived one instance per set, with median takt time value. The obtained SALBP instances are enhanced with energy, demand, time horizon and TOU pricing features. The demand is directly derived from the takt time of the SALBP instance. The energy consumption e_j of each task j is computed as the product of its processing time t_j and a randomly generated average power consumption (uniform distribution in [5;50]). We considered a energy cost profile in which a time horizon T of 24h (hours) is subdivided in 6 periods: 1 low-cost period of 8h with a (energy) unit cost of 18, 3 medium-cost periods of total 10h with unit cost 65, and 2 high-cost periods of total 6h with unit cost 108. In order to have (for comparison purposes) a *reference dedicated line* we run a SALBP-1 model on IBM CPLEX with a 3 hours time limit. We discarded Scholl instances for which no SALBP-1 feasible solution could be found within time limit (namely two instances, called Scholl and Barthol2). We only considered 36 instances of Otto et al. (2013), 18 of which are taken from the set of instances with $n = 20$ tasks and 18 from the set with $n = 50$ tasks, evenly distributed in order to have a representative sample of each of the parameter values that the authors of Otto et al. (2013) used for the generation of the instances. All of such Otto instances have a SALBP-1 feasible solution within time limit and are thus considered here. The determination of the reference dedicated line also allows to complete the instances with the upper limit on the number of stations, which is fixed to one third higher than the number of stations obtained when solving the SALBP-1 version.

As for the simulated annealing, the descent factor for the temperature is 0.98 and the initial temperature is set to 10. The weight factor in the fitness function Φ (see (8)) is $\lambda = 0.5$. The total number of iterations and the length of the steps are proportional to the number of tasks in the instance (resp. $1250n$ and $5n$). The simulated annealing having a random component, for each instance the whole of SA and LP is replicated 10 times. Table 1 compares our approach with the performance in terms of energy cost saving that could be achieved w.r.t. the reference dedicated line. Two levels of demands are considered, “lower demand” is the demand directly derived from the takt time of the instances and “higher demand” is a demand 25% higher. Phases 1 and 2 of the metaheuristic use the same set of configurations for both lower and higher demands, as demand is not a parameter of the metaheuristic (contrary to SALBP-1 which considers the demand as known). The value N/A for the higher demand for Bowman denotes that the demand is higher than what could be achieve by the reference dedicated line (the desired takt time is smaller than the higher task processing time). However, our approach finds a solution, since it can use parallel resources on the stations. Instances with name marked by a '*' are those for which the solution of the SALBP-1 with higher demand is not optimal (due to exceeded time limit). For lower demands, using our planning instead of a dedicated line results in an overall 65% average reduction in cost. This does not seem to depend on the dataset, nor on the instance size (69% for Otto with $n = 20$, 64% for Otto with $n = 50$, 63% for Scholl). For higher demands, the cost reduction is lower (56% on average). For all instances but six, the reduction of cost by our approach is significantly lower for higher demands than for lower demands. The difference between categories and size of instances is more visible than for lower demands (64% for Otto with $n = 20$, 54% for Otto with $n = 50$, 51% for Scholl).

As for the occupation rates of the different time periods of the TOU scheme, without surprise the dedicated lines use almost all of the time horizon T. Only high-cost periods are used less than 100% (95% on average for lower demands, 97% for higher demands). For the RMS, low-cost periods are densely used (96% on average for lower demands, almost 100% for higher demands), medium-cost periods are scarcely used (average 3% for lower demands, 14% for

Name	n	$\overline{t_{SA}}$	# conf created	lower demand		higher demand	
				# conf used	Cost (%)	# conf used	Cost (%)
Otto-20-10	20	0.34	8.80	1.90	-68	1.90	-70
Otto-20-40	20	0.58	23.60	1.30	-70	1.30	-56
Otto-20-70	20	0.32	8.80	1.90	-70	1.90	-70
Otto-20-100	20	0.52	22.70	1.80	-70	1.80	-57
Otto-20-130	20	0.41	16.10	1.50	-69	1.50	-69
Otto-20-160	20	0.31	8.80	1.60	-70	1.60	-70
Otto-20-190	20	0.65	21.70	1.10	-68	1.30	-55
Otto-20-220	20	0.31	9.00	1.80	-70	1.80	-70
Otto-20-250	20	0.49	20.10	1.50	-69	1.60	-54
Otto-20-280	20	0.33	12.90	1.40	-70	1.20	-67
Otto-20-310	20	0.32	8.40	1.70	-70	1.70	-69
Otto-20-340	20	0.53	21.20	1.30	-69	1.30	-54
Otto-20-370	20	0.32	8.40	1.70	-70	1.70	-70
Otto-20-400	20	0.59	20.80	1.10	-69	1.10	-53
Otto-20-430	20	0.41	12.60	1.50	-70	1.50	-70
Otto-20-460	20	0.34	9.00	2.00	-70	2.00	-70
Otto-20-490	20	0.61	21.70	1.10	-70	1.10	-56
Otto-20-520	20	0.35	8.80	2.00	-70	2.00	-70
Otto-50-10	50	1.46	17.60	1.20	-70	1.20	-66
Otto-50-40*	50	3.27	41.10	1.60	-52	1.60	-40
Otto-50-70	50	1.57	22.80	1.50	-69	1.60	-55
Otto-50-100	50	1.20	17.30	1.10	-69	1.20	-67
Otto-50-130	50	1.85	25.90	1.30	-67	1.30	-51
Otto-50-160	50	1.45	19.50	1.40	-69	1.60	-63
Otto-50-190	50	3.58	44.40	1.60	-53	1.60	-41
Otto-50-220	50	1.68	24.10	1.60	-69	1.60	-53
Otto-50-250	50	1.18	17.80	1.00	-70	1.30	-63
Otto-50-280	50	1.85	26.50	1.40	-66	1.40	-51
Otto-50-310	50	1.42	19.70	1.20	-70	1.50	-61
Otto-50-340	50	3.52	42.40	1.70	-53	1.70	-41
Otto-50-370	50	1.98	24.80	1.30	-69	1.40	-55
Otto-50-400	50	1.37	19.10	1.00	-70	1.20	-63
Otto-50-430	50	1.94	28.10	1.60	-60	1.60	-46
Otto-50-460	50	1.20	17.00	1.20	-70	1.60	-62
Otto-50-490	50	3.08	38.90	2.00	-48	2.00	-38
Otto-50-520	50	1.46	21.90	1.50	-68	1.50	-52
Mertens	7	0.11	6.00	1.00	-67	1.00	-71
Bowman	8	0.12	6.00	1.00	-71	N/A	N/A
Jaeschke	9	0.15	8.00	1.00	-71	2.00	-59
Jackson	11	0.18	8.00	1.10	-70	1.10	-62
Mansoor	11	0.16	5.00	2.00	-70	1.00	-54
Mitchell	21	0.36	9.00	1.60	-70	1.40	-57
Roszieg	25	0.51	11.70	1.50	-70	1.90	-59
Heskiaoff	28	0.55	11.90	1.60	-70	1.20	-65
Buxey	29	0.75	15.70	1.40	-69	1.60	-55
Sawyer	30	0.79	16.20	1.10	-69	1.30	-53
Lutz1	32	0.80	20.00	1.30	-69	1.40	-58
Gunther	35	0.91	17.70	1.40	-67	1.50	-52
Kilbridge	45	1.15	16.00	1.00	-70	1.20	-60
Hahn	53	1.01	12.80	1.30	-70	1.50	-63
Warnecke	58	2.93	29.20	1.50	-49	1.50	-37
Tonge	70	2.65	26.90	1.30	-60	1.30	-45
Wee-mag	75	7.95	26.30	1.40	-55	1.40	-41
Arcus1	83	2.65	24.50	1.30	-61	1.30	-45
Lutz2*	89	5.49	19.10	1.70	-41	1.70	-29
Lutz3	89	3.64	24.10	1.70	-50	1.70	-38
Mukherje	94	2.92	27.50	1.40	-51	1.40	-39
Arcus2	11	4.53	29.80	1.40	-51	1.40	-37
Barthold	148	5.98	23.80	1.50	-67	1.50	-53

Table 1. Energy cost of the planning of an RMS yielded by our method (SA and LP), compared with that of a dedicated line. Term $\overline{t_{SA}}$ is the solving time of our approach. Columns 4, 5 and 7 are resp. the number of configurations output by the SA and the average number (over 10 replications) of those used during the planning to satisfy lower and higher demands. *Cost* columns are energy cost percentage decrease values, i.e. the energy cost of the RMS, minus that of the dedicated line, divided by the latter.

higher demands), high-cost periods are never used. The average number of used configurations is always below 2. The typical planning generated for the RMS has the following structure. Let $j, k \in \mathcal{C}(\boldsymbol{x})$ be the configurations with lowest per-takt energy consumption and highest productivity, respectively. Then:

- if the demand can entirely be fulfilled during the low cost period, then the configuration j and k are used so that the per-produced-item energy consumption is minimized and the demand is answered;
- if the demand is greater than such limit, then configuration k is used for the full low-cost period and the exceeding demand is fulfilled in priority during the medium-cost periods, according to the same scheme.

This planning profile is a consequence of the fact that there is only a 5% difference in terms of per-produced-item energy consumption between the most and the least consuming configurations, which is largely smaller than the difference of per-time-unit energy cost between low-, medium- and high-cost periods (40%).
Few replications (8 out of 610) use a configuration that is neither the most productive, nor that with the lowest per-takt energy consumption, but instead offers an interesting tradeoff between productivity and energy cost.
Since this solution structure is recurring, simple heuristics could be derived to easily build the production planning of an RMS and achieve significant cost economies.

6. CONCLUSION

In this article, we address the Bilevel Optimization problem of balancing a Reconfigurable Manufacturing System (RMS) and derive a set of system configurations that would allow to obtain a production plan of minimum energy cost w.r.t. a Time-Of-Use (TOU) pricing scheme and capable of meeting a given demand over a given time horizon. The purpose of this study is to show the relevance of RMS when dealing with energy-efficient production, an issue nowadays more and more sensitive.
The problem has been first studied in Cerqueus et al. (2020a), which investigated whether the scalability of RMS can be a lever for energy efficiency. We deal here with the same problem and propose an extended version of the two-phase metaheuristic. A thorough computational experience is performed to better assess both the problem interest and the approach effectiveness. In Phase 1, a Simulated Annealing seeks for a balancing of the production line. A balancing is evaluated by assessing the quality of the derived configuration set via a weighted sum of the highest attainable production rate and of the scalability of the production system (defined as the diversity and the performance of its configuration set). Phase 2 solves a Linear Program to optimally use the configurations derived from such balancing over the considered time horizon.
Tests have been run on benchmark instances of the SALBP, enhanced with problem-specific features, and results have been compared with dedicated lines composed of optimal or near-optimal SALBP solutions. The comparison shows that substantial savings can be achieved in terms of energy costs, even with tight levels of demand, by using a low number of configurations on average.
Many future research paths can be outlined.
First, Phase 1 could benefit from the use of other neighborhood operators or metaheuristic schemes, e.g. Variable Neighborhood Search. Moreover, the proposed metaheuristic can be improved by a feedback mechanism so as to include in the evaluation of a balancing the optimal cost of a planning made up of the configurations derived from it. A feedback mechanism would also allow to better exploit the

Bilevel nature of the problem, as opposed to the two-steps hierarchization considered here, and ultimately lead to algorithms capable of achieving globally better solutions. To this end, the most promising direction seems the design of an exact Bilevel Optimization algorithm. The multi-objective nature of the upper-level problem also deserves further investigations.

The structure of solutions could be studied from a theoretical point of view to seek for properties (e.g. in terms of dominance w.r.t. takt time and energy parameters) that could help design even more performing algorithms to obtain energy-efficient RMS.

By removing the same-balancing assumption of Cerqueus et al. (2020a), a far wider range of industrial cases could be considered, as well as potentially better (since less constrained) configuration sets. In this case, reconfiguration times could not be neglected anymore in the planning problem but more energy-efficient configurations could be available and ultimately allow larger economic savings.

Lastly, future research works could also consider some other industrial constraints, such as a power peak limit.

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