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Abstract

Among the many changes in industrial production brought by Industry 4.0, product shorter lifetime and wider variety are two of the hardest challenges that manufacturing systems must face to stay competitive. To this end, Reconfigurable Manufacturing Systems (RMS) are among the most valuable tools, mainly due to being highly scalable, i.e. production tasks and/or resources can be reorganized in very reasonable time to promptly adapt the throughput to quick demand changes.

The use of the Scalability property of RMSs can be generalized to achieve efficiency and responsiveness in many situations displaying variability in some form. Such is the case of a variable energy cost profile: e.g. with Time-Of-Use pricings, an RMS allows to use lower-consumption, lower- throughput configurations in costlier periods, and higher-consumption, higher-throughput configurations in off-peak periods, hence to fulfill a given demand with minimum energy-related costs.

However, designing an RMS to achieve this goal is difficult, as two decision problems must be faced together that are hierarchically related, usually tackled in distinct moments, and yet strongly intertwined: line balancing and production planning. Moreover, several criteria can be considered to assess the suitability of a design, giving rise to a Multi- Objective Bilevel Optimization Problem, balancing and planning being the upper- and lower-level.

We consider here three criteria, namely the number of workstations and -to take into account demand uncertainty- the expected values of service level and energy cost w.r.t. a set of demand scenarios. We propose a three-phase matheuristic and discuss its economical impact on instances derived from the literature.

Keywords: Reconfigurable Manufacturing Systems, Scalability, Energy Cost, Demand Uncertainty, Bilevel Optimization

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1. Introduction

The energy consumption is a worldwide concern nowadays and the society is pushing companies toward more energy-efficient and sustainable production system. According to the international energy outlook report of the U.S. Energy Information Administration (U.S. EIA, 2019), the industrial sector is expected to be the largest energy consumer by 2050 with 40% of the worldwide consumption and this latter should increase by nearly 50% in this time horizon.

This concern in energy-consumption should also gain interest in the processes of design and management of manufacturing systems (MS), for which an increasing interest for renewable energy sources in all sectors is expected in the next decades (Battaïa et al., 2020). Over time, energy consumption must be considered from the strategic to the operational level (Giret et al., 2015). Three measures are usually used for energy consumption in production systems: the total energy consumption, the peak power limitation and the Time-Of-Use (TOU) pricing.

From another side, the world gross output is facing an important growth, with a high volatility of the market. This requires the production systems to be able to quickly and efficiently adapt. The reconfigurable manufacturing systems (RMS) have been introduced by Koren et al. (1999) to answer to this need. RMS are usually composed of several serial workstations, connected by a conveyor and a gantry to transport the parts. Each workstation is composed of multiple identical machines in parallel, which can be Computer Numerical Control (CNC) machines, Reconfigurable Machine Tools or other types of resources (e.g. workers with cobot).

RMS also offers a lever to deal with variable energy pricing (TOU for instance) or availability, making it possible to adapt the system to better fit to energy requirements. A low consuming configuration can be implemented during expensive periods, at the price of a reduction of productivity that can be compensated, to fulfil the demand, by implementing highly productive, but more energy-consuming, configurations during periods with lower energy cost. This paper proposes an approach to balance and plan a set of configurations on a RMS to simultanously optimise three objectives, namely the energy cost with respect to an energy cost profile, the installation cost and the service level. It has been modeled in Cerqueus et al. (2020) as a Bilevel Optimization problem. The authors have proposed a two-phases decomposition approach to tackle it, for a given demand. In this work, we aim to generalize this approach by considering an uncertain demand, throught demand scenarios. We propose a three-phase matheuristic.

The remainder of the paper is organized as follows: Section 2 briefly reviews similar works in the literature. Section 3 outlines the considered problem, while Section 4 delves into the details of the matheuristic and Section 5 describes the computational experiments. Finally, Section 6 shows the conclusions and perspectives of this work.

2. Literature Review

RMS have been introduced in the late 90s (Koren et al., 1999). They aim at balancing productivity and flexibility to bridge the gap between flexible manufacturing systems and dedicated lines, and rely on physical components such as CNC machines and Reconfigurable Machine Tools. These production systems are designed, rather than on machines, around six specific features, namely: modularity, integrability, convertibility, diagnosability, customization and scalability (Koren et al., 2017).

The concept of scalability is made possible by integrating or removing parallel resources on workstations and is motivated by the need to adapt the production level to possible fluctuations. These fluctuations can be related to evolutions on product demand, but can also originate from changes on energy prices, and be linked to sustainable concerns. As stated in Putnik et al. (2013), 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. If scalability is one of the most studied topics on RMS, research on planning and sustainability of RMS are still scarce (Yelles-Chaouche et al., 2021), and the consideration of both scalability and energy expenditure is even scarcer.

Considering scalability, Deif and ElMaraghy (2007) investigates a model for assessing the performance of different policies (scaling rate, Work In Process level, inventory level and backlog level) in the context of a make-to-order RMS, according to different demand scenarios. In Wang and Koren (2012) a scalability planning methodology for RMS 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 obtain a new throughput value. In Hees et al. (2017), the authors investigate a production planning system that integrates characteristics of RMS, with a focus given to scalability of production capacities and adaptation of functionalities. In Moghaddam et al. (2020), multi-product and scalable RMS are considered. The objective is to minimize design and reconfiguration costs while respecting a given demand, spread over multiple production periods. In their work, it is possible to (i) up- or downgrade the RMS depending on forecasted demands for each period, or (ii) select and reconfigure the Reconfigurable Manufacturing Tools for all periods based on longer-term estimates.

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. In Khezri et al. (2021), three objectives are considered, being the sustainability metric (i.e. liquid hazardous wastes and greenhouse gas (GHG) emissions), the total production time, and total production cost. If energy costs are considered (related to GHG), they are not time-dependent as in Time-Of-Use tarifications.

Although some research projects have considered energy efficiency in RMS, their operational control subject to TOU has been given little attention in the literature. Moreover, this topic is more prevalent in production planning and scheduling. For instance, in Shrouf et al. (2014), the objective is to minimize energy consumption costs in the context of a single-machine production scheduling problem subject to different production modes (switch on/off, stand-by) while considering variable energy prices. In Che et al. (2017) several insights are given on the proper management of an unrelated parallel machine scheduling problem under TOU pricings with the objective of minimizing the total electricity cost. Recently, Masmoudi et al. (2019), a Job-shop scheduling problem is investigated in order to optimize production and economic criteria such as the total production time (makespan) and energy costs subject to a TOU pricing scheme, while respecting a power limitation.

Even though recent works include sustainable objective and/or constraints, the survey of Battaïa et al. (2020) shows that there is still little research on the ability of RMS to improve energy efficiency and sustainability in production.

To the best of our knowledge, the first studies that have considered scalability as a lever to adjust energy costs and consumption in the context of RMS are Cerqueus et al. (2020) and Gianessi et al. (2021). In this last research, a Bilevel Optimization problem is investigated in order to balance a RMS and obtain a set of configurations that can be used to obtain a production plan. The goal is to fulfill a given demand while minimizing the total energy cost, based on a TOU pricing scheme.

3. Description of the Problem

We consider the optimization problem of designing an RMS, i.e. finding a set of configurations of an RMS at the design stage. The configurations must be designed so as to allow the RMS to fulfill a production demand Δ over a timespan T, while minimizing some production-related costs.

This is a difficult task, since the production planning of the to-be-designed configurations (i.e. the selection of which configuration should be used at each moment of the time horizon T) must be evaluated in terms of the chosen cost criteria, and this evaluation comes into play in the design procedure. With a dedicated line, the design phase is usually based on some arbitrary case of demand scenario or some average value of demand. This allows to consider the balancing and planning problems as independent, and to tackle them in distinct moments. With RMS, one wants to design the production system by taking into consideration since its earliest stages the possibility of reconfiguring it, and exploit it as much as possible w.r.t. to a given objective. As a consequence, and regardless of the specific objective, the two decision problems are not independent anymore: the performance of a set of configurations cannot be assessed without evaluating the production planning over the period T, but at the same time the planning problem cannot be solved as long as the configuration set is unknown. It becomes therefore convenient to tackle them jointly.

Incidentally, this difficulty adds to the fact that designing an RMS is more complex w.r.t. a dedicated MS. Not only the n production tasks must be assigned to the m available workstations while complying with technological constraints and optimizing the chosen criteria, which is already NP-hard in its simplest form (the Simple Assembly Line Balancing Problem (SALBP), see e.g. (Scholl and Becker, 2006)): with RMS, one wants to find a most-fitting *set* of such line configurations that differ in the assignment of tasks to workstations and number of identical resources of each workstation.

This problem is actually a *Bilevel Optimization problem*, in which the design problem represents the upper level, and the planning problem, the lower level (we refer the reader to e.g. Colson et al. (2005), Moore (1988) for a deeper understanding of Bilevel Optimization and its applications to production systems). The work that first investigated it is Cerqueus et al. (2020). The authors stated the Bilevel problem in its most general form, then considered the particular case in which the RMS configurations share the same balancing and only differ in the number of resources of each workstation, in which case system reconfigurations can then be seen as switching on/off resources and reconfiguration times can be neglected.

In this work, we consider, for the first time as far as we are aware of, demand uncertainty in this problem. To do so, we adopt a scenario-based optimization (see e.g. Goerigk, 2013), based on a finite set $\mathscr{D}$ of demand scenarios. Then we propose a multi-objective upper-level problem that considers, for a given balancing x and descending set $\mathscr{C}(x)$ of configurations:

- the expected value $E[\mathscr{S}_d(x)]$ of the service level $\mathscr{S}_d(x)$, defined for a demand $d \in \mathscr{D}$ as the percentage of d that can be fulfilled, i.e. 1 if d is less than or equal to the maximum attainable demand by the most productive configuration in $\mathscr{C}(x)$, or $\widetilde{d}(x)/d$ otherwise;
- the expected value $E[\mathscr{E}(x, y^\star_d)]$ of the per-produced-unit energy cost $\mathscr{E}(x, y^\star_d)$, defined as the energy-related cost of the optimal planning $y^\star_d$ obtained by using the configuration set $\mathscr{C}(x)$ to fulfill demand $d \in \mathscr{D}$;
- the number $m(x)$ of workstations, shared by all the configurations of $\mathscr{C}(x)$ as we adopt the same assumption of Cerqueus et al. (2020) in order to neglect reconfiguration times.

The goal of the design stage is then to find x s.t. the descending set $\mathscr{C}(x)$ is the most fitting w.r.t. the three objectives $E[\mathscr{S}_d(x)]$, $E[\mathscr{E}(x, y^\star_d)]$ and $m(x)$. While the first two objectives serve to take into account the future performances of the system usage, the third relates to investment costs.
The Bilevel Optimization problem at hand can then be expressed as:

$$\min\ m(x) \tag{1}$$
$$\min\ E[\mathscr{E}(x, y^\star_d)] \tag{2}$$
$$\max\ E[\mathscr{S}_d(x)] \tag{3}$$
$$\text{s.t.} \qquad \mathscr{B}(x) \le 0 \tag{4}$$
$$y^\star_d = \underset{y_d}{\operatorname{argmin}}\ \mathscr{E}(x, y_d) \qquad \forall d \in \mathscr{D} \tag{5}$$
$$\text{s.t.} \qquad \mathscr{P}(y) \le 0 \tag{6}$$

In the *upper-level problem* (1)-(5), relations (1)-(3) seek to optimize the aforementioned criteria. *Upper-level variables* x_{jk} represent whether workstation $k \in \{1 \dots m\}$ is assigned task $j \in \{1 \dots n\}$, and determine the balancing x. Relations (4) introduce the balancing constraints $\mathscr{B}(x)$, namely the precedence constraints among production tasks and the assignment constraints. In the *lower-level* (5)-(6), *Lower-level variables* y_{ip} represent the planning decisions, i.e. how the configurations $i \in \mathscr{C}(x)$ are used w.r.t. the periods p of the considered pricing scheme. Consequently, (5) ensures that the planning $y^\star_d$ minimizes, when the considered demand is $d \in \mathscr{D}$, the energy-related, per-unit production cost $\mathscr{E}$, provided the balancing x; finally, (6) introduce the planning constraints $\mathscr{P}(y)$, that enforce planning feasibility and the fulfillment of the demand, known in advance. It is worth highlighting that while the lower-level is composed of as many independent deterministic planning problems as the demand scenarios $d \in \mathscr{D}$, the uncertainty over the demand, which resides entirely at upper level, introduces a further level of separation between the two levels of decision, other than the difference in the decisions and the temporality.

As for energy consumption, we assume that during idle time $I_k = c - c_k$, workstations have a residual energy consumption which is proportional by a factor α to I_k, the number of resources r_k and the energy consumption (per resource and time unit) of tasks assigned $\frac{\eta_k}{W_k}$, with $\eta_k = \sum_j e_j x_{jk}$, and e_j the total energy consumption of task j. This allows to compute the energy consumption of workstation k during a takt, E_k, and therefore E^i and Q^i, the energy consumption values (per-produced-unit and per-time-unit) of each configuration $i \in \mathscr{C}(x)$:

$$E^i = \sum_k E_k^i \quad ; \quad Q^i = \frac{1}{c^i} E^i = \frac{1}{c^i} \sum_k \eta_k \left(1 + \alpha \frac{r_k^i I_k^i}{W_k}\right) \tag{7}$$

in which η_k and W_k only depend on the configuration i, whereas c^i, r_k^i, I_k^i and thus E_k^i depend on i. The values of E^i, Q^i, $i \in \mathscr{C}(x)$, computed this way allow to determine the energy consumption, thus the cost, of a planning in the lower-level problem.

4. Matheuristic Approach

We developed a three-phase matheuristic for this problem. The First Phase of the method adresses the balancing problem by executing a metaheuristics, which returns a set of balancings x considered the best ones and their derived configurations. The Second Phase solves the planning problem via Linear Programming for all balancings returned by the First Phase. The Third and last Phase ranks the solutions to keep only the best one.

4.1. First Phase: a metaheuristic for the upper-level problem

The metaheuristic of the First Phase is a *Simulated Annealing* (SA) algorithm. A SA algorithm (see e.g. Aarts et al., 2005) is based on local search and an "annealing" process inspired by the termal process of condensed matter physics.

The method is initialized with a random balancing x, obtained from a constructive method which only concern is to respect the precedence constraints between tasks, the maximum number of stations $r_{\max}$, and the maximum number of tasks per workstation $n_{\max}$. A first configuration is derived from this balancing by assigning one resource to each workstations and the other configurations are derived by incrementally add resources to the bottleneck workstation by the processus explained in the previous section.

The neighborhood defined for the local search consists in moving one task j from its current workstation to another one of the $r_{\max}$ workstations respecting the precedence constraints and the maximum number of operations per workstation. A new workstation can be opened as long as there is no more than $R_{\max}$ workstations and the current one can be closed if it becomes empty. At each iteration of the SA, one balancing is randomly chosen in the neighborhood and the derived configurations are generated.

The fitness function used to evaluate the balancings during the SA is a weighted sum of three terms: the hypervolume $\mathscr{H}(x)$ (proxy of the expected per-produced-unit energy cost $E[\mathscr{E}(x, y_d^\star)]$, which cannot be evaluated at the upper-level), the expected service rate $E[\mathscr{S}_d(x)]$ and the number of workstations $m(x)$. These three components are normalized to not bias the weighted sum. For $m(x)$ the normalization is done by dividing by the maximum number of stations allowed in the system ($m_{\max}$).

The hypervolume objective aims to evaluate, at the upper-level, the energy consumption of the derived configurations. It is computed based on the per-time-unit energy consumption $\mathscr{Q}$ and the takt time c of each configuration. Only the non-dominated configurations regarding $\mathscr{Q}$ and c are kept, i.e. the configurations such that there does not exist another configuration for the same balancing with a lower $\mathscr{Q}$ and c (with one strictly lower). The values of c and Q are normalized by an upper bound (c_U, Q_U) and a lower bound (c_L, Q_L): $\tilde{c} = \frac{c-c_L}{c_U-c_L}$ and $\tilde{Q} = \frac{Q-Q_L}{Q_U-Q_L}$. The formula of the hypervolume associated to a balancing x, for which we ordered the configurations by decreasing c values, is

$$\mathscr{H}(x) = (1-\tilde{c}^1)(1-\tilde{Q}^1) + \sum_{i\geq 2}(\tilde{c}^{i-1}-\tilde{c}^i)\cdot(1-\tilde{Q}^i) \tag{8}$$

The maximization of $\mathscr{H}$ is meant to hopefully lead to configurations with diversified values for $\mathscr{Q}$ and c and as low as possible. These configurations are of particular interest for RMS since they offer both highly producing configurations and energy efficient configurations. Figure 1 illustrates the calculation of $\mathscr{H}$ for an example configuration set.

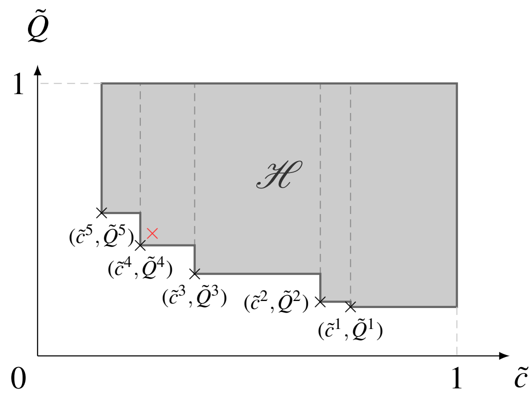

Figure 1: Hypervolume calculation for a set of 6 configurations (1 dominated, in red).

4.2. *Second Phase: optimally solving the lower-level problem*

The planning problem of the Second Phase consists in optimally planning the usage configurations of $\mathscr{C}(x)$ over a period T to fulfill each of the considered demands $d \in \mathscr{D}$. However, the cases represented by the $|\mathscr{D}|$ different demand scenarios are completely independent, therefore they can be solved separately, giving rise to as many Linear Programs (LP), which we illustrate in the following. Demands are all considered to be associated with a time horizon T, over which they must be fulfilled.

Since a balancing x has a maximum attainable demand $\widetilde{d}(x)$, the demand that the Linear Problem aims to fulfill for scenario $d \in \mathscr{D}$ is $\Delta = \min\{d, \widetilde{d}(x)\}$. We suppose a TOU pricing scheme, featuring a set P of time periods, each with a energy unit cost U_p and a duration D_p s.t. $T = \sum_{p\in P} D_p$. Lower-level variables y_{ip} are then $[0,1]$ real variables representing the percentage of period p during which production uses configuration $i \in \mathscr{C}(x)$. The LP model is:

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

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

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

$D_p y_{ip}$ is the time of usage of $i \in \mathscr{C}(x)$ during TOU period p. Hence:

- (9) is the overall energy cost to minimize, $Q^i D_p y_{ip}$ being the associated energy consumption;
- (10) enforces satisfaction of demand Δ, since $\frac{1}{c^i} D_p y_{ip}$ is the corresponding produced quantity, derived from the takt c^i.

Finally, (11) forbids production in period p to exceed D_p; the case $\sum_i y_{ip} < 1$ means that production is suspended for a time $(1 - \sum_i y_{ip}) D_p$.

It is worth noting that since some demand value $d \in \mathscr{D}$ could not be accomplished by the configurations of set $\mathscr{C}(x)$, the assessment of the suitability of a balancing x could not be done based on the overall energy cost of objective function (9). This is why the energy-related term of the upper-level problem (1)-(5) concerns the per-produced-unit energy cost.

4.3. Third Phase: final ranking of configurations

Once all the balancings retained at the end of the First Phase have been evaluated in terms of per-unit energy cost, and the criterion $E[\mathscr{E}(x, y_d^\star)]$ of (2) can be computed for each of them, a new ranking can be performed that considers $E[\mathscr{E}(x, y_d^\star)]$ instead of the hypervolume $\mathscr{H}$. The weighted sum considers the same weight factors of the First Phase, and $E[\mathscr{E}(x, y_d^\star)]$ is normalized w.r.t. the sum of the energy consumption of all the production tasks, multiplied by $\max_{p \in P} U_p$, i.e. the highest unit cost among those of the TOU scheme.

5. Experimental results

We tested our approach on instances derived from Scholl (1995). In this article, and for sake of conciseness, we only present result for 5 instances, diversified in terms of number of operations: Mansoor, Sawyer30, Hahn, Mukherje and Barthold. For each instance, we consider ten demand scenarios, associating a demand value and a probability. The demand values are centered on the median of the demands considered in Scholl (1995), bounded to an increase and decrease of demand of 25%. The probabilities associated to these demands form a discretized gaussian distribution.

To fit to the problem, we generated an energy consumption e_j for each task j as the product of its processing time t_j and a power consumption randomly generated according to the uniform distribution in [5;50].

The TOU profile use in the experiment is composed of 4 periods on a timespan T of 24 hours:

- period $p = 1$, with cost $U_p = 25$ and duration $D_p = 13$ hours;
- period $p = 2$, with cost $U_p = 50$ and duration $D_p = 6$ hours;

- period $p = 3$, with cost $U_p = 60$ and duration $D_p = 3$ hours;
- period $p = 4$, with cost $U_p = 250$ and duration $D_p = 2$ hours.

We fixed an upper limit on the number of stations to the number of operations for each instance. The maximum number of resources on a workstation is $r_{\max} = 3$.

Since the approach contains a random component in the Simulated Annealing part, the indicators are averaged over 10 independent runs in the results we give in this section. In the Simulated Annealing, the descent factor for the temperature is 0.98 and the initial temperature is set to 10. The weights used in the weighted sum for the objective function are 0.5 for the hypervolume, 0.25 for the expected service level and 0.25 for the number of workstations, giving the hypervolume twice the importance of the two other objectives. The total number of iterations and the length of the steps are proportional to the number of tasks n in the instance (resp. $1250n$ and $5n$). The set of solutions returned by the SA contains 5 solutions.

We compare the system obtained by our approach with dedicated lines with one resource on each workstation, by solving the corresponding SALBP-1 problem by the commercial solver IBM CPLEX. Since the demand is uncertain, we compare with 5 different paradigms that could be encountered in industry: designing a system to answer to the demand of the quantiles 50%, 75%, 90%, 95%, 100%. The last one considers the worst-case scenario, designing a productive system at the cost of a large number of workstations; the first one, on the other hand, aims to satisfy the median demand, which might be the most often used in industry to keep a relatively high service level and a relatively low number of workstations. For all the instances and the 5 quantiles considered, the solving by IBM CPLEX is given a time limit of 3 hours. The LP-based algorithm of the Second Phase of the matheuristic is run to plan the usage of the unique configuration and compute the values of the different objective functions associated with the different demand scenarios.

Table 1 presents a comparison of the RMS obtained by our approach (RMS) and the five dedicated lines (denoted DL q%, where q is the quantile considered). Since 10 replications have been done for the matheuristics, the results presented for the RMS are the average over the replications. The systems are compared according to the three objectives m, $E[\mathscr{E}]$ and $E[\mathscr{S}]$; and an additional indicator: the expected value $E[\mathscr{U}]$ of the time usage rate $\mathscr{U}$, i.e. the effective production time over the time horizon. In this table, instead of writing the absolute values for the expected value of energy consumption per piece, which is difficult to interpret, we choose to express the increase in percentage according to a reference energy consumption value. We took the DL 50% as reference, since it might be the most usual paradigm used in industry.

In Table 1, it is not surprising to see that the expected value of service level tends to increase for the dedicated lines as the quantile increases. We can however note that the values are all very high. We also remark that the RMS is the only system, along with DL 100%, to give an expected service level of 100%. This means that there is highly productive configurations among the set of configurations of the RMS.

Regarding the expected value of the energy cost per piece $E[\mathscr{E}]$, an important point that this table reveals is that the lower the quantile is for the dedicated line, the higher is the energy cost.

		m	$E[\mathscr{E}]$ (in %)	$E[\mathscr{S}]$ (in %)	$E[\mathscr{U}]$ (in %)
Mansoor	RMS	3.8	-38.24	100.0	33.66
	DL 50 %	4	-	99.7	89.94
	DL 75 %	4	7.72	99.2	92.64
	DL 90 %	4	-12.32	100.0	83.82
	DL 95 %	4	-19.68	100.0	77.39
	DL 100 %	4	-19.68	100.0	77.39
Sawyer	RMS	7.5	-41.70	100.0	57.15
	DL 50 %	10	-	98.1	95.19
	DL 75 %	11	-9.48	99.5	91.15
	DL 90 %	11	-14.80	99.8	88.68
	DL 95 %	11	-19.55	99.9	86.04
	DL 100 %	12	-28.15	100.0	77.78
Hahn	RMS	6	-45.99	100.0	37.14
	DL 50 %	5	-	96.9	96.18
	DL 75 %	6	-9.70	99.0	91.67
	DL 90 %	6	-14.46	99.5	89.44
	DL 95 %	6	-18.72	99.8	87.26
	DL 100 %	8	-28.31	100.0	76.74
Mukherje	RMS	21	-39.00	100.0	60.90
	DL 50 %	19	-	97.6	96.04
	DL 75 %	21	-7.81	99.2	92.64
	DL 90 %	21	-16.07	99.8	89.02
	DL 95 %	22	-19.52	99.9	87.02
	DL 100 %	24	-27.88	100.0	79.86
Barthold	RMS	13	-45.83	100.0	43.33
	DL 50 %	12	-	97.5	96.06
	DL 75 %	12	-8.52	99.1	92.78
	DL 90 %	13	-15.66	99.7	89.36
	DL 95 %	13	-19.45	99.9	87.38
	DL 100 %	14	-28.60	100.0	79.71

Table 1: Comparison of the three objectives m, $E[\mathscr{E}]$, $E[\mathscr{S}]$, and the indicator $E[\mathscr{U}]$, on the RMS and the 5 dedicated lines, for the 5 instances.

This is can be explained by the fact that a lower demand leads to a higher takt time and thus to a higher time required to fulfil the demand. Since it seems that the planning phase uses in priority the periods with the lowest energy cost, when a system is used longer its energy cost would be increased. Based on a similar reasoning, it is not surprising to see that the expected value of the time usage $E[\mathscr{U}]$ is largely lower for the RMS than for all other systems.

The RMS is the system with the lowest energy cost per product, with a significant difference with DL 100%, which offers the same expected service level. It represents a gain in energy cost of more than 38% for all instances compared to the reference and 42% on average.

Figure 2 is useful to depict how the RMS reacts to a changing demand, and more specifically how its configurations share the different periods of the TOU energy cost profile. In it, the considered tarifs for energy are the same introduced before: the horizontal dimension accounts for the time horizon, which is divided into four sections, in order of increasing unit cost from left to right and for $p = 1$ to $p = 4$.

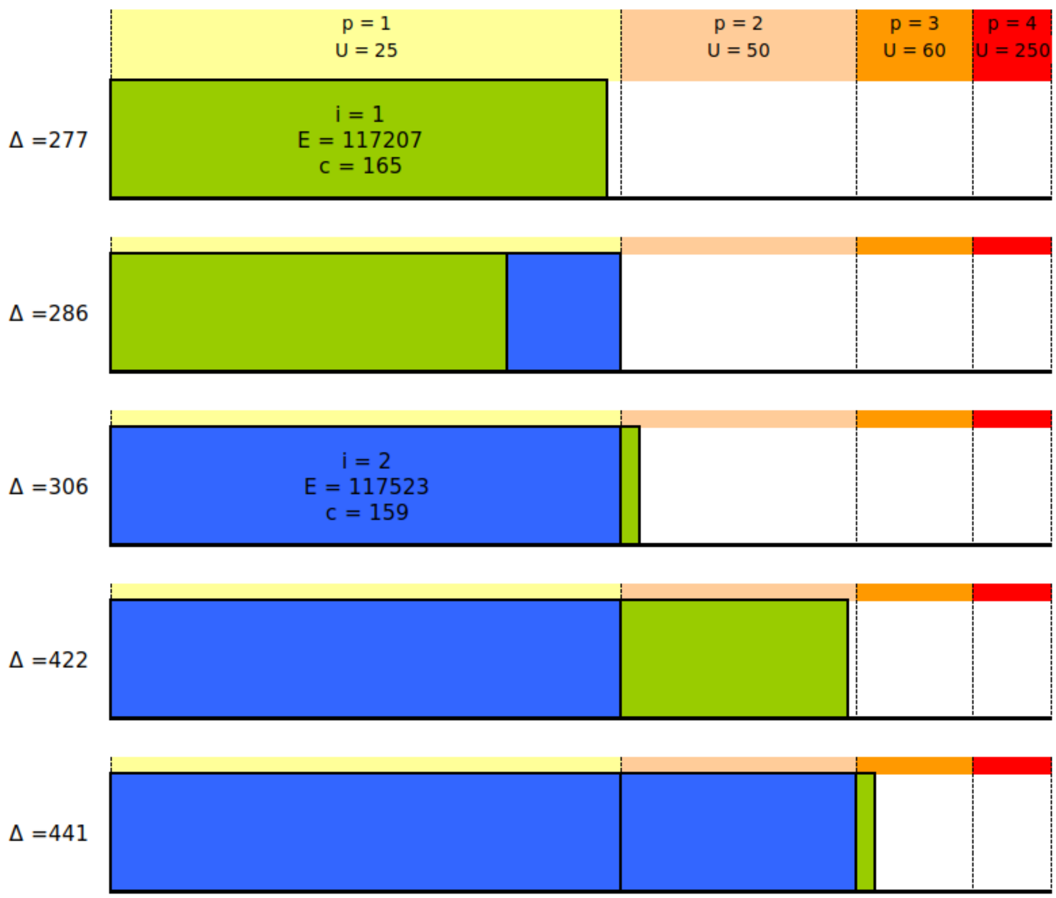

Figure 2: Behavior of the configurations of an RMS for a changing demand.

The RMS is designed based on the instance Mukherje and is an example of a possible RMS, one of the best output by one of the run of SA at the end of First Phase. The RMS accounts for 16 configurations, but here two are used: the configuration depicted in green, $i = 1$, is the one with the least energy consumption per produced unit (see the reported values of E and c), whereas the one depicted in blue, $i = 2$, is the most productive one, i.e. with minimum takt time c.

The uppermost subfigure shows the case of the weakest demand value ($\Delta = 277$), which the RMS can entirely fulfil by using configuration $i = 1$, although not the most productive, in period $p = 1$ alone. When the demand increases ($\Delta = 286$), instead of continuing using $i = 1$ during the second lowest cost period $p = 2$, the RMS prefers to divide the lowest cost period $p = 1$ with configuration $i = 2$, since its augmented energy consumption per produced unit is largely overcompensated by the difference in terms of energy unit cost between periods $p = 1$ and $p = 2$. The second lowest cost period $p = 2$ is only used when the most productive configuration $i = 2$ is not enough to satisfy the demand (see case $\Delta = 306$) during the period with $U = 25$ alone. Then (case $\Delta = 422$), as long as the demand can be completely satisfied by using configuration $i = 1$ during period $p = 2$, so does the RMS; period $p = 3$ will be only used, again, when the most productive configuration $i = 2$ is not enough (as in last case, $\Delta = 441$) to cover the demand during periods $p = 1$ and $p = 2$.

6. Conclusions and Perspectives

In this work we have studied the Bilevel Optimization Problem that consists in designing a Reconfigurable Manufacturing System (RMS) in order to minimize the energy-related production costs w.r.t. a Time-Of-Use electricity pricing scheme. The problem has been introduced recently to study whether the scalability property of RMSs can be beneficial in terms of energy efficiency, and more specifically of economic costs related to energy.

In this work, however, we deal for (as far as we are aware of) the first time with uncertainty in the demand by performing a scenario-based optimization approach. A three-phase matheuristic algorithm is proposed that first finds a set of candidate RMS designs via Simulated Annealing (SA), then computes the energy cost performance of each of them w.r.t. all the considered demand values, and finally determines the overall best design. Experimental results have shown the benefits of RMS, by comparing it to reference dedicated lines dimensioned according to different demand scenarios from median to worst-case. The comparison on 5 instances taken from the literature on a realistic TOU energy cost profile has shown that RMS always yields the best possible results in terms of energy cost and number of workstations, while being always competitive in terms of service level. The fact that the RMS design has been obtained with a matheuristic algorithm, while the dedicated line has been designed with an exact approach, leads to think that these performance gap could be even more important.

These results suggest to further assess the effectiveness of RMS in these respects on a wider instance set, and w.r.t. a larger number of diversified pricing schemes. It would certainly also be interesting to deal with the RMS design problem with a more performing algorithm than the simple SA-based heuristic used here, e.g. with an exact algorithm.

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