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Improving effectiveness of parallel machine scheduling with earliness and tardiness costs: A case study

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This paper assesses the effectiveness in scheduling independent jobs with earliness/tardiness costs and variable setup times applying the Overall Equipment Effectiveness (OEE). The OEE is a common metric for measuring the manufacturing productivity. We defined a mixed-integer linear programming formulation of the parallel machine scheduling problem with four different objective functions in order to compare different scheduling configurations. Real data, from a plastic container manufacturing company located in the Basque Country (Spain), were used to validate this approach. A sensitivity analysis was performed with different production capacities and earliness/tardiness costs in order to evaluate the trade-offs between economic performance (i.e., costs) and the partial rates of OEE (i.e., quality, performance and availability). The objective of this study is to propose a guideline to help management make decisions regarding the measurement and improvement of scheduling effectiveness through contemplating earliness, tardiness and variable setup times.

1. Introduction

Manufacturing companies are aware of the importance of effectively managing equipment efficiency in order to continuously improve the production process. Most losses in productivity derive from a lack of proper equipment efficiency management (Santos et al., 2011). If equipment efficiency is not correctly measured and controlled, it will be difficult for companies to be competitive. Key performance indicators (KPI), such as the Overall Equipment Effectiveness (OEE) (Andersson & Bellgran, 2015), help control and improve this efficiency (Gibbons, 2006). Several manufacturing companies base their improvement activities on optimizing this productivity metric. Although this metric has adjusted to optimize several operational activities, it was initially designed for the maintenance area (Muñoz-Villamizar et al., 2018).

At the operational level, the scheduling of jobs in manufacturing systems is a form of decision-making that plays a crucial role in real industrial contexts where limited resources are allocated to

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the execution tasks over given time periods, with the goal of optimizing one or more objective functions (Pinedo, 2012). Although the complexity of scheduling models depends on the characteristics of the system under study and the assumptions considered in the model (e.g., Msakni et al., 2016; Kiatmanaroj et al., 2016; Sama et al., 2017), the majority of problems are classified as NP-hard, which means that optimal solutions are hard to obtain in reasonable computational time.

Therefore, some characteristics can be included as conditions in real-life production systems such as earliness/tardiness constraints and costs and set-up times. In many real applications of the scheduling problem, for example, optimizing earliness and tardiness is one of the most important criteria (Cheng & Huang, 2017; Yazdani et al., 2017) and are receiving increasing attention (Hung et al., 2017). Furthermore, and as Allahverdi (2015) clearly explained, scheduling involving setup times/costs plays an important role in today's modern manufacturing in terms of delivering reliable products on time. Ignoring setup times/costs may be valid for some applications, but it has a strong adverse effect on the quality of solutions of some other scheduling applications. Indeed, since the setup process is not a value-added activity, setup times/costs need to be explicitly considered when scheduling decisions are made in order to increase productivity, eliminate waste, improve resource utilization, and meet deadlines. The work of Allahverdi and Soroush (2008) presented about 50 different applications in industries where scheduling with explicit consideration of separate setup times/costs is essential. The objective of this paper is to assess the effectiveness of job scheduling with earliness/tardiness costs and variable setup times using the OEE metric. The scheduling problem is solved using a mixed-integer linear programming (MILP) model. In order to compare different scheduling configurations, four different objective functions are separately evaluated using this model. Real-life data from a plastic container manufacturing company located in the Basque Country (Spain) is used to run numerical tests. Insights and highlights, of applying the proposed approach in the problem under study, are obtained through a sensitivity analysis carried out with different production capacities and earliness/tardiness costs. The three key contributions of this paper are as follows: (1) adapting the OEE as a KPI for scheduling problems; (2) using a optimization-based methodology, a MILP scheme is proposed for improving effectiveness of the parallel machine scheduling problem with independent jobs, earliness/tardiness costs and variable setup times; and (3) numerical results obtained after implementing the approach in a case study are presented in order to offer insights into the tradeoffs of different scheduling configurations regarding its effectiveness and their total cost.

The organization of the paper is as follows. The related research is reviewed in Section 2. The problem under study is described in Section 3. The proposed methodology, including the MILP model, is presented in Section 4. Application and analysis of results are reported in Section 5. Finally, conclusions and opportunities for further research are presented in Section 6.

2. Related research

2.1. Scheduling problem

A large body of academic literature has been published about the study of scheduling problems since the first rigorous approach was under taken in the mid-1950s. Furthermore, a large number of survey articles have looked at the substantial amount of research on this subject (Sterna, 2011; Yenisey & Yagmahan, 2014; Rossit et al., 2018; Lee & Loong, 2019; Shen, 2006). A classification and analysis of such survey papers is presented in the work of Abedinnia et al. (2017). The literature distinguishes between different problem variants, and for many problem variants, one or even several surveys have been published, most of them studying the problems through a theoretical lens. Indeed, the literature review carried out by Fuchigami and Rangel (2018), the publication real-life cases on scheduling problems have been scarce, with their frequency only increasing very recently. In addition, according to Allahverdi (2015), more than 90% of the literature on scheduling problems ignores setup times/costs. Kopanos et al. (2009) states that setup times/costs appear in a plethora of industrial and service applications. The interest in scheduling problems where setup times/costs are explicitly considered began in the mid-1960s. To date, three comprehensive literature reviews have been published regarding the research on scheduling problems with setup times/costs. The work of Allahverdi et al. (1999) covered about 200 papers from the mid-1960s to mid-1988. Allahverdi et al. (2008) surveyed the research on scheduling problems with setup times/costs from mid-1988 to mid-2006, covering about 300 papers. The third review paper was published by Allahverdi (2015) and covered about 500 papers published from mid-2006 to the end of 2014.

Studies on parallel machine scheduling can be categorized into three types: identical, uniform and unrelated parallel machine scheduling problems (Cheng & Sin, 1990). Among these categories, the parallel unrelated machine problems have been much less studied (Edis & Ozkarahan, 2012). In addition, sequence-dependent processing times between jobs have not been taken into account until recently (Vallada & Ruiz, 2011; Sereshti & Bijari, 2013). Furthermore, research papers related to the problem of parallel machine scheduling with setup times/costs have mainly focused on makespan minimization (Vélez-Gallego et al. 2016; Xanthopoulos et al., 2016). When addressing due-date related objective functions, the majority of research articles have approached the minimization of tardiness. Dinh and Bae (2012) proposed a MILP model, as did Li et al. (2012), who also proposed a Genetic Algorithm. Kang et al. (2007), Armentano and de Franca Filho (2007), Chen (2009), de Paula et al. (2010), Lin and Hsieh (2014) also presented meta-heuristic procedures, such as GRASP (Greedy Randomized Adaptive Search Procedure), Ant Colony Optimization, Iterated hybrid algorithms, and simulated annealing, among others. Exact approaches based on branch-and-bound was presented by Aramon Bajestani and Tavakkoli-Moghaddam (2009). Logendran et al. (2007) and Pfund (2008) proposed the application of various heuristic dispatching rules to deal with the total weighted tardiness problem with the dynamic arrivals of production orders, while Driessel and Mönch (2009, 2011) proposed a variable neighborhood search procedure and some of its variants to solve the parallel machine problem with total weighted tardiness, precedence constraints and order release times. Some multi-objective approaches evaluating tardiness and flow time or makespan are also available in the studies by Gupta and Sivakumar (2005) Chyu and Chang (2010), Torabi et al. (2013), Caniyilmaz et al. (2015).

Minimizing earliness on its own has not been of interest since evaluating both tardiness and earliness together constitutes the main optimization criterion of just-in-time production systems. Akyol and Bayhan (2008) and Anderson et al. (2013) proposed MILP models to minimize the (weighted) sum of earliness and tardiness; the first authors did this for the case of unrelated parallel machines, while the second authors considered the case of identical parallel machines. The same objective function was studied in Behnamian et al. (2009), who proposed three metaheuristics based on simulated annealing, ant colony and variable neighborhood search. Cheng and Huang (2017) formulate the problem of unrelated parallel machines as a MILP model and develop a modified genetic algorithm (GA). Hung et al. (2017) also included machine- and job-dependent processing rates, in addition to sequence-dependent processing times. Behnamian et al. (2010) and Behnamian et al. (2011) respectively proposed a multi-phase Pareto-optimal front method and various meta-heuristics procedures to deal with the multiple optimization of the makespan and the sum of unweighted earliness and tardiness functions. More recently, Afzalirad and Rezaeian (2017) studied a bi-objective problem with the simultaneous minimization of mean weighted flow time and mean weighted tardiness in a real-life unrelated parallel machine environment where sequence-dependent setup times, different release dates, machine eligibility and precedence constraints are included.

2.2. OEE as a Key Performance Indicator

Effectiveness could be defined as a process KPI that indicates the degree to which the process output conforms to the requirements (Muchiri & Pintelon, 2008). This is in agreement with the definition in the literature, which states that OEE measures the degree to which the equipment is doing what it is supposed to do (Williamson, 2006), based on the combined effects of availability, performance and quality (Gibbons, 2006). Therefore, OEE is a well-known hierarchy of partial rates for measuring manufacturing effectiveness (Dunn, 2014). This metric has achieved so many and such good results that scores of consultants and books are available to help managers implement it (Dunn, 2014). Furthermore, this metric has been adjusted to optimize several operational activities as transportation, environmental performance, safety, etc. (Muñoz-Villamizar et al., 2018). As shown in Fig. 1, the OEE includes six big losses and divides them into three categories Q, P and A: Q means quality (i.e., to produce only good parts), P means performance (i.e., to produce as fast as possible) and A means availability (i.e., to produce without stop-times) (Nakajima, 1988). Effectiveness can be correctly measured and improved by the availability, performance and quality partial rates provided by this metric (Santos et al., 2011). However, OEE concepts definition can be adjusted for application in specific contexts (Muñoz-Villamizar et al. 2018). For example, Table 1 shows a comparison between the original author definition (i.e., Nakajima, 1988) and one of the authors who re-defined this rate (i.e., De Groote, 1995). Similarly, our approach re-defines partial rates of OEE in order to evaluate scheduling jobs with earliness and tardiness costs (see Tables 2 and 3).

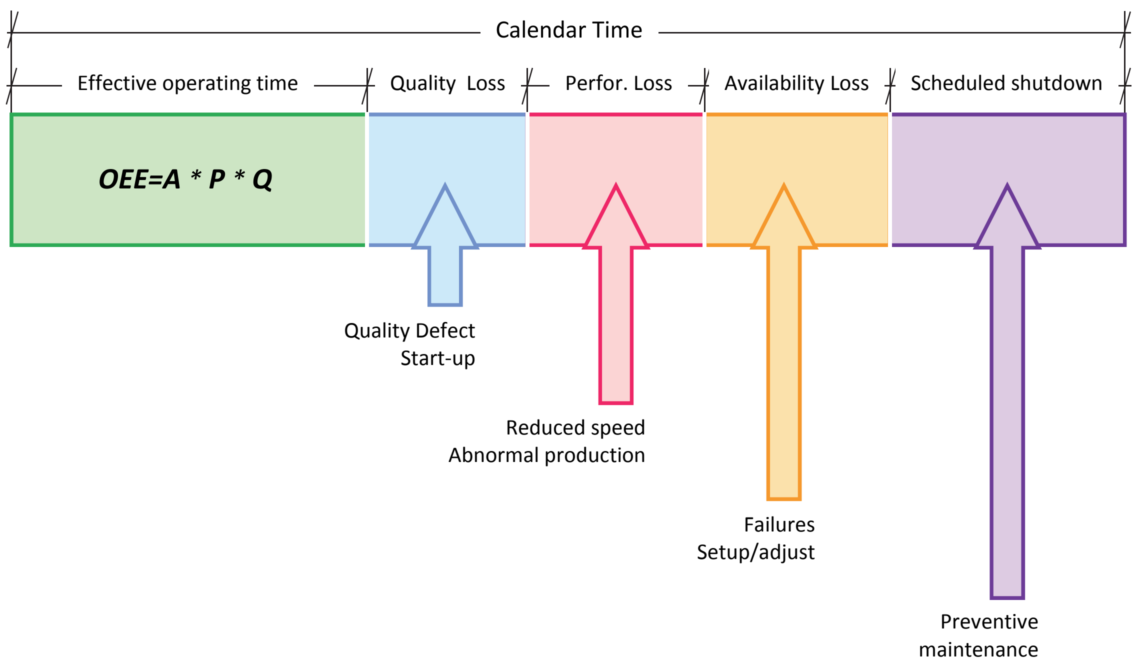

Fig. 1. OEE Timeline. Source: Muñoz-Villamizar et al., (2018).

Table 1
OEE definition. Source: Jonsson and Lesshammar (1999)

	Nakajima (1988)	**De Groote (1995)**
Quality (Q)	$\frac{Input - volume\ of\ quality\ defects}{Loading\ time}$	$\frac{Actual\ amount\ of\ production - non\ accepted\ amount}{Actual\ amount\ of\ production}$
Performance (P)	$\frac{Ideal\ cycle\ time * output}{Operating\ time}$	$\frac{Actual\ amount\ of\ production}{Planned\ amount\ of\ production}$
Availability (A)	$\frac{Loading\ time - downtime}{Loading\ time}$	$\frac{Planned\ production\ time - unplanned\ downtime}{Planned\ production\ time}$
OEE	$A * P * Q$	$A * P * Q$

3. Problem description

The major concern of scheduling is how to provide a perfect match or near perfect match between machines and jobs and subsequently determine the processing sequence of the jobs on each machine to achieve certain classic objectives such as minimize makespan (Hung et al., 2017). Finding a feasible schedule is sufficient for most manufacturers (Hung et al., 2017) who mostly prefer the use of simple heuristic algorithms, such as dispatching policies (Montoya-Torres et al., 2016).

In this context, research on scheduling has tried to model real manufacturing environments by incorporating the characteristics of real environments into the scheduling problem as constraints (Romero-Silva et al., 2016). On the one hand, scheduling problems related to the minimization of earliness/tardiness are receiving increasing attention (Hung et al., 2017). Earliness and tardiness can be defined as $E_i = \max(0, d_i - C_i)$ and $T_i = \max(0, C_i - di)$, respectively, where d_i is the due date of job i and Ci is the completion time of job i. Early job completion may increase inventory storage costs, whereas delayed delivery may negatively influence customer satisfaction and company reputation and generate penalties (Cheng & Huang, 2017). On the other hand, as setup is not a value added process, this activity needs to be explicitly considered in scheduling problems in order to increase productivity, eliminate waste, improve resource utilization, and meet deadlines (Allahverdi, 2015). Setup times are sequence-dependent when the time to setup for a given job on a given machine depends on the job that just preceded it on that machine.

In addition to the above considerations, the problem addressed in this study has the following characteristics. A set of n independent jobs are to be processed on a set of m parallel machines. According to availability W, each job i ($i = 1, \ldots, n$) must be processed on one machine k ($k = 1, \ldots, m$) and a machine can only execute one job at a given time. These parallel machines can be identical (i.e., of equal capacity and processing speed) or not. The processing time of job i on each machine k is denoted as p_{ik}. Preemption is not allowed, which means that the execution of a job on a machine cannot be interrupted. As mentioned before, job i has a given due date, denoted as d_i. In addition, to evaluate sequence-dependent setup times, each machine requires an adjustment time a_{ij}, which is the time required to setup the machine from job i to job j ($j = 1, \ldots, n$) before starting the execution of job j. Finally, as companies need to minimize the earliness and tardiness of job completion while achieving their goals and maximizing benefits (Man et al., 2000), our approach defines sc_i as the unitary storage cost per unit of time for job i and pc_i as the penalty cost of late order delivery per unit of time. Parameter pc_i could be a penalization cost defined (or negotiated) with the costumer of job i while sc_i is the internal cost of storing job i. Without loss of generality, processing times for jobs and due dates are supposed to be non-negative integers.

4. Proposed methodology

This section discusses the methodology employed to improve effectiveness of solutions in the described scheduling problem. Four different approaches are proposed in order to compare different scheduling configurations (see Fig. 2). The first is the classic minimization of makespan. The second approach minimizes the sum of earliness and tardiness. The third approach pursues the minimization of storage costs (earliness) and penalty costs per delayed jobs (tardiness). The fourth approach, which is based on the OEE metric, seeks to optimize the effectiveness of scheduling jobs. This last approach is an original contribution of this paper. Finally, results (i.e., costs, effectiveness, makespan, earliness and tardiness) for the four different configurations are compared.

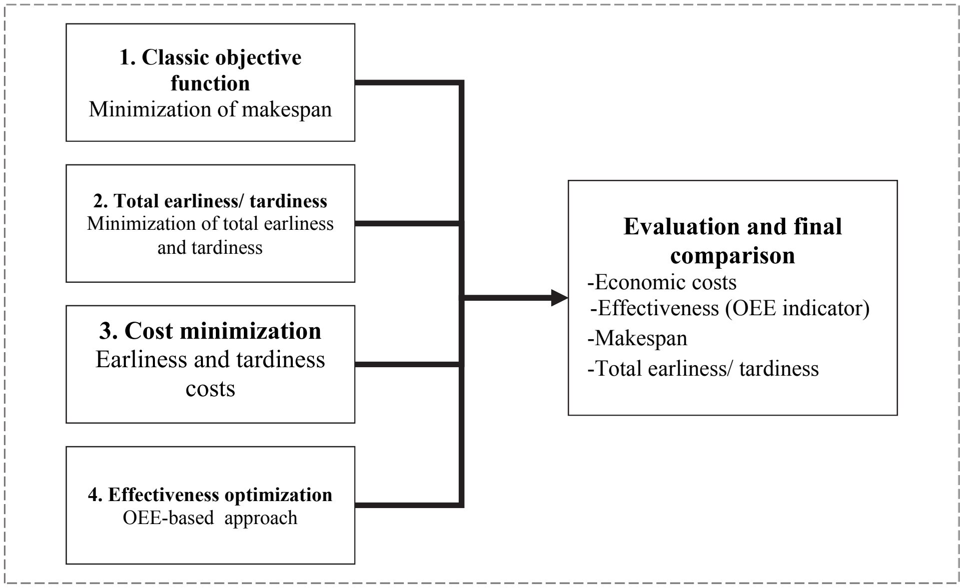

Fig. 2. General schematic of the methodology.

As mentioned above, and given our aim to optimize the effectiveness of scheduling jobs with earliness and tardiness using the OEE metric, it is necessary to adjust the original author definition (i.e., Nakajima, 1988). Table 2 compares original definition of OEE (see Fig. 1 and Table 1) and the concepts used here. Generally speaking, in the original OEE approach, Q means that there are no defects in operation, P means that the operation is running as fast as possible, and A means that the operation is always running during planned production time (no stop time) (Muñoz-Villamizar et al., 2018). Consequently, in our approach the Q rate measures the orders are delivered before their due date (i.e., non-tardiness). However, and for this particular problem, producing as fast as possible could not be a good indicator because the increasing of storage cost and the only stop time. Therefore, our P rate measures storage waste (i.e., earliness). Finally, the A rate measures downtimes (i.e., setup/adjust times). Accordingly, , Table 3 presents the definition of OEE variables in our approach. For example, *Loading time* is equivalent to *Makespan* (i.e., total length of the schedule). presented in Table 1

Table 2
Definitions of OEE concepts

	Our Approach	Classic OEE
Quality losses	Delayed jobs	Defects Start-up
Performance losses	Storage	Reduced speed Abnormal production
Availability losses	Setup/adjust	Process failures Setup/adjust

Table 3
Definition of OEE variables

	Our Approach
Quality (Q)	$\frac{Delivered\ jobs\ before\ due\ time}{Total\ delivered\ orders}$
Performance (P)	$\frac{Sum\ of\ jobs'\ completion\ time}{Sum\ of\ jobs'\ delivery\ time}$
Availability (A)	$\frac{Makespan - Total\ adjustment\ time}{Makespan}$
OEE	$A * P * Q$

The base MILP model employed to solve the scheduling problem with earliness and tardiness costs is presented below. Differences between each of the four approaches are explained in the next sub-sections. This model was inspired by the methodology proposed by Muñoz-Villamizar et al. (2018) where authors implemented the OEE in transportation systems. Parameters and decision variables used in formulating this new version of the model are defined as follows. Note that a fictitious node i (or j) = 0 is used to evaluate the first processed job in each machine.

Set:

k	set of machines $\{1, 2,\ldots, m\}$
i, j	set of jobs $\{0, \ldots, n\}$

Parameters:

dd_i	due date of job i
a_{ijk}	setup time for job j after processing job i on machine k
L	a large number
pt_{ik}	processing time of job i on machine k
pc_i	late order penalty cost per unit of time
sc_i	unitary storage cost per unit of time

Decision Variables:

$Cmax$	total makespan (i.e. loading time of Figure 1)
C_i	is the completion time of job i
E_i	earliness of job i
T_i	tardiness of job i
DT_i	delivery time of job i
TC	cost of earliness/tardiness in the scheduling process
U_i	subtours auxiliary variables

Binary Variables:

$$X_{ijk} = \begin{Bmatrix} 1, \text{if job } j \text{ is preceded by job } i \text{ on machine } k \\ 0, \text{otherwise} \end{Bmatrix}$$

$$D_i = \begin{Bmatrix} 1, \text{if job } i \text{ is delivered after its due date (i.e., delayed)} \\ 0, \text{otherwise} \end{Bmatrix}$$

The mathematical model of the problem can be formulated as follows:

$$\sum_{j} X_{0jk} \leq 1, \qquad \forall k \tag{1}$$

$$\sum_{i}\sum_{k} X_{ijk} = 1, \qquad \forall j > 0 \tag{2}$$

$$\sum_{i} X_{ijk} = \sum_{i} X_{jik}, \qquad \forall k, \forall j > 0 \tag{3}$$

$$\sum_{j}\sum_{k} X_{0jk} = \sum_{j}\sum_{k} X_{j0k} \tag{4}$$

$$C_j + (1 - X_{0jk}) * L \geq pt_{jk}, \qquad \forall k, j > 0 \tag{5}$$

$$C_j + (1 - X_{ijk}) * L \geq C_i + pt_{jk} + a_{ijk}, \qquad \forall k, \forall i > 0, \forall j > 0 \tag{6}$$

$$Cmax \geq C_i, \qquad \forall i > 0 \tag{7}$$

$$E_i \geq dd_i - C_i, \qquad \forall i > 0 \tag{8}$$

$$T_i \geq C_i - dd_i, \qquad \forall i > 0 \tag{9}$$

$$T_i \leq L * D_i, \qquad \forall i > 0 \tag{10}$$

$$DT_i = C_i + E_i, \qquad \forall i > 0 \tag{11}$$

$$TC = \sum_{i} (E_i * sc_i + T_i * pc_i) \tag{12}$$

$$U_i - U_j + n * X_{ijk} \leq n - 1, \qquad \forall k, \forall i > 0, \forall j > 0 \tag{13}$$

Constraint (1) sets a limit of one job per machine at most. Constraint (2) forces all jobs to be processed exactly once. Schedule continuity is represented by Constraints (3) and (4). Constraint (5) calculates the completion time for the job scheduled in the first position of each machine, while constraint (6) computes the completion for the rest of the jobs. Constraint (7) computes the value of the makespan (i.e. *Cmax*). Constraints (8) and (9) define a job's delivery time as early or late, respectively. Constraint (10) is the activation constraint of variable D_i for delayed jobs. Constraint (11) computes the delivery time of each job. Constraint (12) computes the earliness/tardiness costs of the scheduling process. Constraint (13) forces the elimination of sub-sequences (i.e. subtours) using the easy-implementation formula of Miller et al. (1960). Finally, the four objective functions, which leads to four different scheduling of jobs, are presented next. It is important to note that each objective function is evaluated separately in the model presented above.

4.1. Classic scheduling optimization

The classic optimization in scheduling problems (i.e., minimization of makespan) is achieved by objective function (14).

$$\min Cmax \tag{14}$$

4.2. Total earliness and tardiness minimization

Another commonly used performance measure in scheduling problems include maximum tardiness, mean tardiness, total weighted tardiness and earliness, and the number of delayed job penalties (Cheng and Huang, 2017). Given the acceptance of just-in-time systems in practice, in recent decades there has been a growing interest in analyzing scheduling problems where both earliness and tardiness are penalized (Fernandez-Viagas et al., 2016). In this case, the optimization of earliness and tardiness is achieved by objective function (15).

$$\min \sum_i E_i + T_i \tag{15}$$

4.3. Cost minimization

This objective function uses economic costs to avoid quality and performance losses. Quality losses are penalized using the cost for late order delivery (pc_i), while availability losses are penalized using the storage cost (sc_i). Consequently, the minimization of costs is achieved by objective function (16).

$$\min TC \tag{16}$$

4.4. Effectiveness optimization

As the OEE computation is not linear (i.e., $OEE = A \times P \times Q$), its equation must be linearized. To do so, a hierarchical multi-objective procedure is used to employ the OEE metric in the proposed MILP model. The procedure used for this linearization consider three objectives functions (i.e., $Z_1, Z_2\ and\ Z_3$) and optimize them sequentially. The idea of this hierarchical multi-objective procedure is to sequentially optimize one objective function and then to optimize the next objective by using the last solution as a constraint. After several experiments, and in order to find non-dominated solutions (Samà et al., 2017) the best hierarchical sequence is: first, maximize the result of processed orders minus delayed orders (i.e. Q) using objective function (17); second, minimize total storage time (i.e., P) using objective function and constrain (18); and third, minimize makespan (i.e., A) using objective function and constraints in (19). It is important to note that for this procedure the three partial rates of OEE (i.e., Q, P and A) have the same weight (Muñoz Villamizar et al., 2017; Muchiri & Pintelon, 2008). Thus, conceptually speaking, our approach achieves the highest number of deliveries on time with the minimum storage time and the minimum adjustment time.

$$Z_1 = \min \sum_i D_i \tag{17}$$

$$Z_2 = \min \sum_i E_i\,, \qquad \sum_i D_i \le Z_1 \tag{18}$$

$$Z_3 = \min Cmax\,, \qquad \sum_i D_i \le Z_1\ and \sum_i E_i \le Z_2 \tag{19}$$

5. Application and analysis of results

Our study is based on a real-world problem originating from a plastic container manufacturing company that has more than 30 years of experience in the sector. The company is located in the Basque Country (Spain) and supplies containers made via different technologies for the food and non-food industries. The plastic containers are manufactured both by extrusion-blowing and by stretch-blowing. The company was interested in improving the effectiveness of its extrusion-blown production process. The company's primary need was to reduce penalization costs for late order delivery and costs related to storage. The company selected its sole blowing machine as is the most complex piece of equipment and has the most limited production capacity. Therefore, we focused on this processing stage to define production scheduling for three months' worth of orders. The objective of this methodology is to provide the company with a decision-making tool that allows it to optimize the effectiveness of its job scheduling and to determine the actual capacity of its production line in order to re-negotiate new delivery dates with clients. The characteristics and data of the case studied are summarized in Table 4. Note that the job processing time is equivalent to the job size divided by the production rate. Other important parameters are the storage cost per unit (0.001 €/day) and the set-up times (4 or 6 hours). Sequence-dependent setup times are defined by the color of the containers (see Table 4). There are three different colors (orange, black, white) in addition to a transparent version. Sequential orders with the same color have shorter setup times (4 hours) than sequential orders with different colors (6 hours). This is also asymmetry in setup times for sequential orders that use different colors, including transparent. When jobs that use color are scheduled before jobs that do not (i.e. transparent), setup time is 6 hours, but for jobs that use no color (i.e. transparent) are scheduled before jobs that do use color, the setup time is only 4 hours. Finally, to carry out statistical analyses, 10 different instances for 15 jobs were generated using the historical data of the company. In order to replicate the experiments, full data sets are available upon request to the corresponding author of this paper.

Table 4
Parameters for the jobs in the case study

Job	Job Size (units)	Production rate (units/h)	Due Date (days)	Delay penalty (€/ day)	Order Color
1	100,000	800	24	2,000	Orange
2	50,000	800	15	3,000	Black
3	200,000	1,000	15	500	White
4	250,000	1,200	25	500	Transparent
5	250,000	1,200	30	500	Transparent
6	180,000	800	46	2,000	Orange
7	70,000	800	47	3,000	Black
8	100,000	1,000	48	500	White
9	200,000	2,000	52	500	Transparent
10	90,000	1,200	77	500	Transparent
11	280,000	800	85	2,000	Orange
12	150,000	800	80	3,000	Black
13	250,000	1,000	84	500	White
14	50,000	1,200	76	500	Transparent
15	300,000	1,200	86	500	Transparent

The MILP model was implemented using GAMS commercial software version 24.1.3, with a time limit of 1000 seconds in a personal computer Intel(R) Core(TM) i5 with 1.4 GHz and 4 GB RAM. Furthermore, in order to carry out the sensitivity analyses, two different variations were evaluated. Subsection 5.2 proposes a scenario to evaluate the effectiveness and costs of the company's current jobs demand with different production capacity. Subsection 5.3 evaluates the impact of effectiveness and different storage and penalty costs. The first scenario allows the company to evaluate the convenience of increasing its current capacity, while the second one could be used as a guideline that helps the company determine new policies on penalization cost and/or investment in reducing the storage cost, in order to improve cost-effectiveness of manufacturing operation. The full sensitivity analysis data are available upon request to the corresponding author of this paper.

5.1. Current situation

Table 5 presents the average results of using the model with the four objective functions in the ten generated instances, including current situation of the company. These initial results provide several insights. First, the classic minimization of makespan is the most expensive approach. That is, minimizing the total time in scheduling jobs is not the most beneficial solution, as implies the highest storage and delay time. Second, minimizing total earliness and tardiness implies the greatest number of delays. As the storage time and the delay time have the same value in this objective function, this solution causes 59% of orders to be delivered late. These delays are equivalent to a Q of 41%. Consequently, this approach has the worst OEE rate. Third, minimizing costs obviously leads to the best economic results.

However, this approach has a Q rate of only 67%. Finally, the OEE optimization leads to the best results on effectiveness. This approach has an OEE of 77%, which is obtained mainly by a high quality rate (Q = 83%), although it does entail significantly high total costs. For this last objective function, the average obtained cost (141,933 €) is almost four times higher than the cost obtained in the objective function of minimizing costs (42,093 €). It is evident, that for the current company situation, having a higher service level (i.e., a higher Q) is way too expensive. Therefore, an analysis of different cost proportions (i.e., storage costs vs. delay costs) could be interesting.

Table 5
Average results per objective function

Metrics	Objective Function			
	Min Cmax	**Min Total E/T**	**Min Costs**	**OEE Optimization**
# of delayed jobs	7.2	8.8	5	2.6
Total E/T time (h)	11,207	**2,257**	3,056	4,966
Makespan (h)	**2,436**	2,615	2,526	2,825
Costs	416,827 €	125,687 €	**42,093 €**	141,933 €
Total setup time (h)	62.8	69.2	68.4	70
Q	52%	41%	67%	83%
P	81%	97%	93%	96%
A	97%	97%	97%	98%
OEE	**40%**	**39%**	**60%**	**77%**

Fig. 3 compares time and costs for storage (earliness) and delay (tardiness) for the current situation. Setup times can be omitted given their relatively low participation in makespan. The maximum difference in total setup times is only 6 hours, when all makespan are greater than 2500 hours. With the exception of OEE optimization, storage and delay time is almost the same in every objective function. Furthermore, it can be seen that tardiness generates the highest proportion of costs in every objective function. However, although the costs of tardiness are the highest, the cost-minimization objective function only met eight of the due dates. That is, the approach of minimizing costs is not concerned with fulfilling or not fulfilling client orders; instead it seeks the lowest penalty (cost). In an extreme case, this objective function could lead to the non-fulfillment of every due date because the cheapest solution is to having a very little delay time for every job.

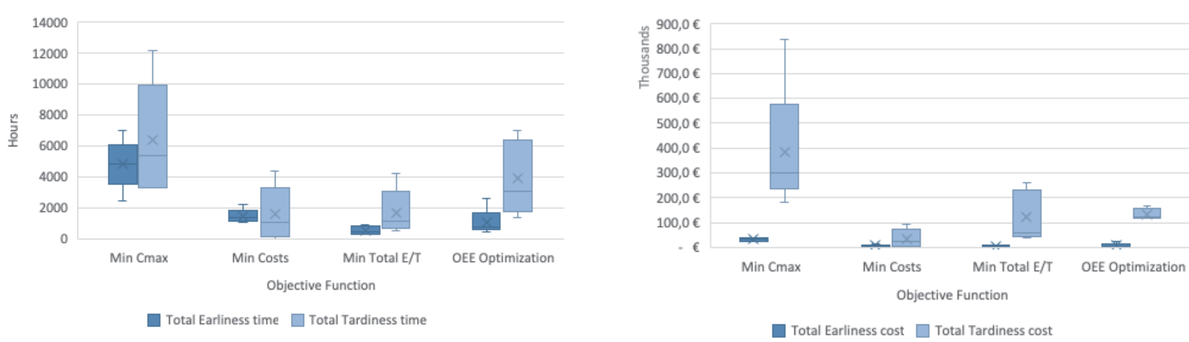

Fig. 3. Earliness vs. Tardiness boxplots

From these results, it is apparent that the company has some capacity problems since it cannot meet 100% of its due dates. In fact, the lowest total cost is obtained (using objective function 3) by meeting only 50.3% of these dates. However, trying to meet the maximum possible dates (i.e. the results obtained by using objective function 4) can be quite expensive compared with the minimum possible cost. Therefore, it is interesting to evaluate other scenarios with different capabilities and costs in order to see the changes in both the profitability of the process and its effectiveness. Finally, it is important to mention than the last two objective functions (i.e. cost minimization and OEE optimization) can be considered the most influential and important for decision makers since the first optimizes the economic benefit and the second optimizes the overall effectiveness of the process.

5.2. Sensitivity analysis 1: variation of production capacity

Variations in the capacity of the plant can be achieved by obtaining new machines with the same or different capacity. However, in addition to evaluating the impact of increased capacity, it may also be interesting to analyze a scenario where capacity is lower than the current one. In this way, decision makers can have a broader picture of the effects that production capacity have on the profitability and efficiency of their scheduling process. Thus, for this sensitivity analysis, five different scenarios are proposed. Scenario 1.1 considers a machine with half the production capacity (i.e., processing times for each job are doubled). Scenario 1.2 is the current situation. Scenario 1.3 contemplates a machine with twice the production capacity (i.e., the processing times for each job are reduced by half). In reality, this scenario can occur through a replacement of the current machine with a new one. Scenario 1.4 contemplates a scenario in which the purchase of an additional machine results in two parallel machines with the current capacity. Finally, Scenario 1.5 considers three parallel machines.

The effectiveness and cost results for the five proposed scenarios are presented in Table 6 and Figure 4. Only the last two objective functions (i.e. cost minimization and OEE optimization) were used in order to simplify the data. As mentioned before, these two objective functions could be the most interesting for decisions makers. It is important to note that the scenarios have an ascending capacity. That is, scenario 1.1 is the scenario with the least capacity. Scenario 1.2 has greater capacity, and so on. In this context, scenarios where the company's capacity does not allow it to fulfill the jobs' due dates are the most ineffective and the most expensive. As capacity increases, effectiveness begins to increase and costs start to reduce considerably. These results allow decision-makers to consider the possible savings by increasing process capacity, either by replacing the machine with a new one with twice the speed (Scenario 1.3), or by buying an additional one with the same speed (Scenario 1.4).

Table 6
Effectiveness and cost for sensitivity analysis 1

	Effectiveness (OEE)		**Total Cost**	
	Objective Function		**Objective Function**	
	Min. Cost	**OEE Optimization**	**Min. Cost**	**OEE Optimization**
Scenario 1.1	37.7%	47.6%	375,121 €	816,355 €
Scenario 1.2 (current)	48.3%	75.4%	31,155 €	121,378 €
Scenario 1.3	86.1%	91.6%	7,164 €	8,989 €
Scenario 1.4	92.8%	92.9%	5,617 €	5,820 €
Scenario 1.5	95.3%	95.9%	1,310 €	1,344 €

In Scenario 1.1. and Scenario 1.2 (the scenarios with the lowest production capacity), the objective function of optimizing OEE allows high levels of effectiveness but at a very high cost (see Table 6). As capacity increases (scenarios 1.3, 1.4 and 1.5), both objective functions yield similar results in cost and in effectiveness. A more detailed comparison of both objective functions can be seen in Figs. 4-6. The procedure proposed for effectiveness optimization (i.e., OEE optimization) leads to the best OEE in every scenario. The greater penalty on OEE is given by the orders delivered late (see Fig. 4). The objective function of minimizing costs is not good for meeting due dates because it is not useful to minimize late deliveries. If not fulfilling any delivery dates was the most economical option, in using this objective function the company would have a 0% service level. In order to avoid delayed jobs, the OEE optimization leads to long storage times (See Fig. 5). This earliness generates higher storage costs in order to achieve the greatest number of deliveries on time. Finally, since the setup times are so short compared to the processing time, both objective functions (i.e., minimizing costs and OEE optimization) generate a similar performance in availability metric (A) (see Fig. 6).

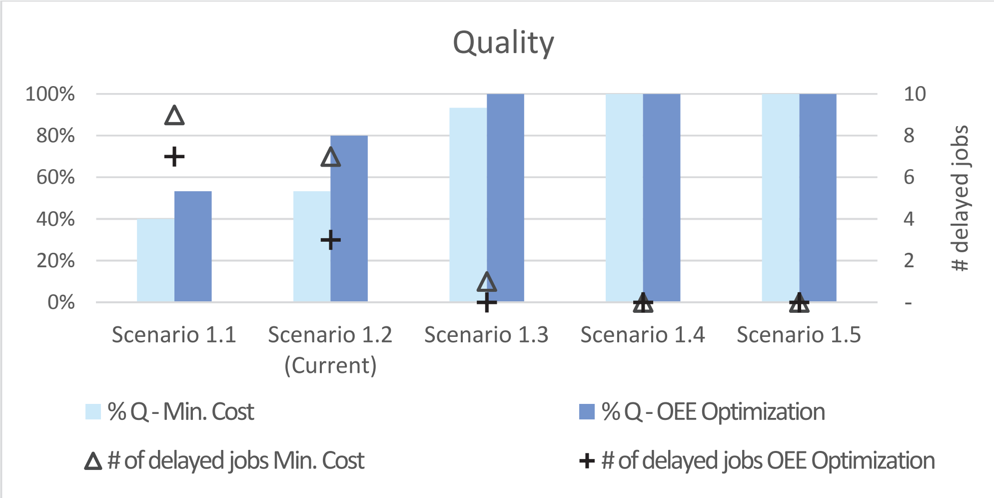

Fig. 4. Quality rate comparison per scenario

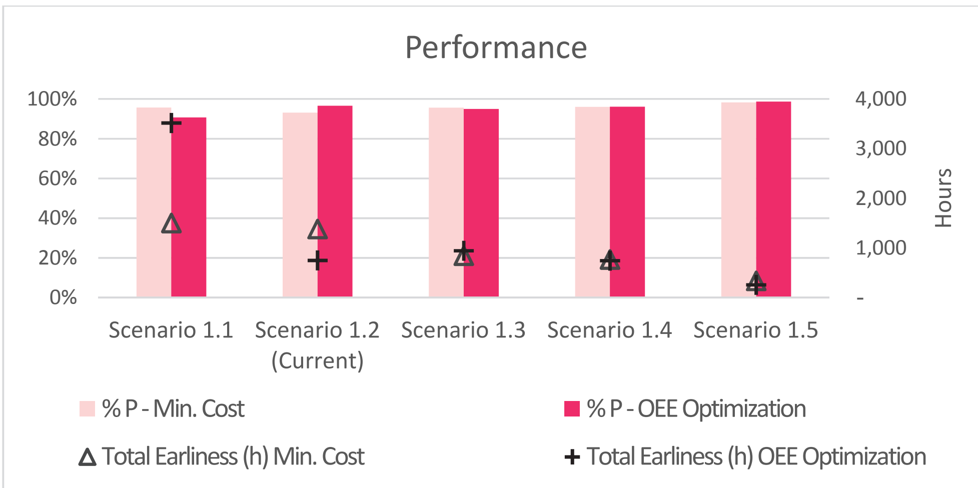

Fig. 5. Performance rate comparison per scenario

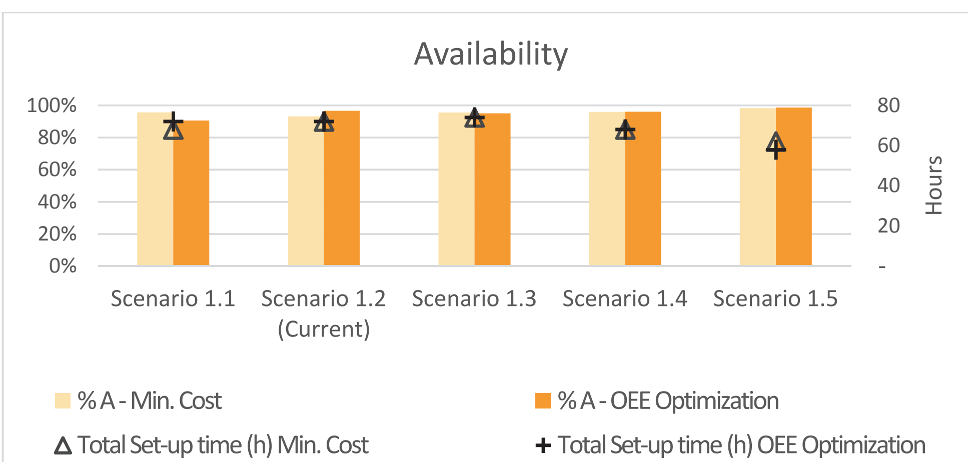

Fig. 6. Availability rate comparison per scenario

5.3. Sensitivity analysis 2: costs variations

Each company has a different proportion of storage and delay costs (i.e., average of storage cost over delay cost per job). For example, for this case the average ratio is 0.13 per job and per hour. That is, the delay cost per job is 7.7 times greater than the storage cost. In this context, analyzing several scenarios with different cost proportions can be used to see the effects of the proposed approach in other companies. Furthermore, this analysis can be used by decision makers to develop or generate alternatives that improve company performance. This is, the company can know whether it is more convenient to focus on renegotiating a job's due date and/or the penalty costs associated with the respective costumers or whether to focus on improving storage conditions (e.g., the lease conditions or the warehouse maintenance). Six different scenarios are evaluated by changing storage costs. Scenario 2.1 presents the average earliness/tardiness cost ratio of the actual situation (i.e., 0.13). Scenario 2.2 and Scenario 2.3 present a cost proportion of 0.25 and 0.5, respectively. That means that the delay cost per job is 4 times and 2 times greater than the storage cost. Scenario 2.4 has an earliness/tardiness cost radio of 1. That is, the storage cost and delay cost are equal per each job. Finally, Scenario 2.5 and Scenario 2.6 present a cost proportion of 1.5 and 2, respectively. In these cases, the storage cost is 1.5 times and 2 times greater than the delay cost per job. Compared with the storage costs of the initial situation, the storage cost of Scenario 2.2 is 1.93 times bigger; Scenario 2.3 is 3.87 times bigger; Scenario 2.4 is 7.74 times bigger; Scenario 2.5 is 11.61 times bigger; and Scenario 2.3 is 15.48 times bigger. The effectiveness and cost results for the six proposals are presented in Table 7. As in the previous section, only two objective functions are used. Note that the value of OEE does not change much in the objective function of minimizing costs. Furthermore, in all scenarios the values for the objective function of optimizing OEE are the same. Thus, it can be stated that the value of OEE is not very sensitive to the variation of costs in both objective functions. This is mainly due to the fact that the number of delayed jobs is almost the same for each scenario (see Fig. 7). In the objective function of minimizing cost, only the last three scenarios (where the costs of storing are very high) have an increase in the number of late jobs. On the other hand, given that OEE optimization does not take into account the costs, the scheduling solution remains the same in every scenario. Therefore, the number of delayed jobs is the same. This objective function meets the highest number of jobs on time with the minimum storage time and the minimum adjustment time regardless of the costs.

Table 7
Effectiveness and cost for sensitivity analysis 2

	Effectiveness (OEE)		Total Cost	
	Objective Function		Objective Function	
	Min. Cost	OEE Optimization	Min. Cost	OEE Optimization
Scenario 2.1(Actual)	48%	75%	31,155 €	121,378 €
Scenario 2.2	43%	75%	36,702 €	125,399 €
Scenario 2.3	44%	75%	47,919 €	133,721 €
Scenario 2.4	43%	75%	69,533 €	150,366 €
Scenario 2.5	44%	75%	84,725 €	167,011 €
Scenario 2.6	38%	75%	96,247 €	183,655 €

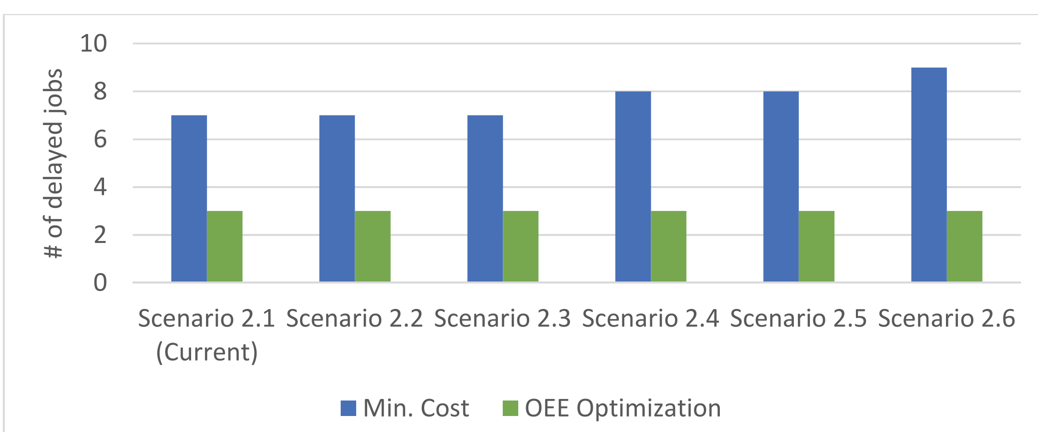

Fig. 7. Number of delayed jobs per scenario of sensitivity analysis 2

6. Conclusions

This article proposed an approach for evaluating effectiveness in scheduling jobs with earliness/tardiness costs and variable setup times by applying the OEE metric. This approach uses four different objectives functions in order to compare different scheduling configurations. Real data, from a plastic container manufacturing company located in the Basque Country (Spain), were used to validate this approach. Several theoretical experiments were performed to analyze the impact of the proposed methodology in the scheduling operation. Our findings suggest that cost optimization does not guarantee the highest effectiveness level in the scheduling operation. This is mainly because of the quality metric (i.e. orders delivered on time). Thus, trying to meet the maximum possible due dates could be quite expensive relative to the minimum possible cost of executing all jobs. However, as the capacity of the company increases, minimizing costs and optimizing effectiveness tend to yield similar results. In addition, we can state that effectiveness is not sensitive to variation in earliness and/or tardiness costs. According to our sensitivity analysis, a 15-fold increase in the cost of storage only generated an 28% increase in late deliveries. To the best of our knowledge, this paper is the first that proposes a clear methodology for measuring effectiveness in scheduling jobs. In addition, the hierarchy approach proposed for optimizing this effectiveness (i.e. OEE optimization) allows for the integration and improvement of late deliveries, storage and setup times. This approach sequentially achieves the highest number of deliveries on time with, the minimum storage time and then the minimum adjustment time and can be used by decision-makers as a guideline regarding measuring and improving scheduling effectiveness. The main contribution of this study is that, depending on the business scenario, decision makers have the flexibility to choose the appropriate solution for the configuration of the scheduling process. Furthermore, the company can know if it is more convenient to focus on renegotiating job due dates and/or the penalty costs or to focus on improving storage conditions. As an opportunity for further research, this optimization approach can be considered compatible with green/environmental initiatives (Duarte & Cruz-Machado, 2017) because of its focus on waste reduction and the effective use of resources. Our approach aims to eliminate waste (i.e., losses in OEE metrics) in scheduling jobs in order to use fewer resources and generate the same (or best) outcome. This is clearly environmentally friendly as fewer materials are used in production and the improvement in effectiveness reduces the wastes, resource consumption and pollution costs associated with the scheduling operation. The results of this combination could help guide managers and practitioners in their efforts towards sustainable development.

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