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EVALUATING PROCESS FLEXIBILITY IN LOT SIZING PROBLEMS: AN APPROACH BASED ON MULTICRITERIA DECISION MAKING

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Abstract. This paper presents a multicriteria analysis of the process flexibility in the context of the lot sizing problem with parallel machines. In the standard design for lot sizing problems, each machine can manufacture all products (total or complete flexibility). However, installing machines with complete flexibility for several practical applications can be costly. Therefore, it becomes interesting to implement only a limited amount of machine flexibility, where each machine can produce only a small number of different products. Recently, some works presented analyses of process flexibility by considering only the production cost as a criterion. However, the literature lacks a more comprehensive analysis that considers other essential criteria regarding the problem to compute the value of a flexibility configuration. Thus, we provide a detailed multicriteria analysis based on the TOPSIS method that produces a ranking of alternatives for the flexibility configurations. Extensive computational experiments and sensitivity analyses for different scenarios of the lot sizing problem compare individual flexibility configurations and evaluate its advantages in manufacturing planning. The computational results showed that limited flexibility configurations outperform the total flexibility in all scenarios. Moreover, different from the studies considering only the total cost as the criterion, investing in flexibility for all capacity levels has advantages.

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1. Introduction

The intense competition for consumer markets has been placing increasing pressure on the manufacturing process of companies to produce quickly and customized products. Therefore, optimizing the process becomes paramount to facing a more complex and volatile environment, including a more diversified product portfolio, shorter product life cycles, and higher demand volatility [50]. Indeed, the company can increase its competitiveness by implementing the operation strategy known as process flexibility to better match supply with uncertain demand.

In general, the process flexibility results from a company's ability to build different types of products in the same manufacturing plant or production facility simultaneously [26]. This adapted manufacturing process appears in several practical production planning problems. We consider the case of a deterministic multiperiod

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production planning where the products can be manufactured on different resources (plants or machines). In this situation, the problems are treated as deterministic lot sizing models.

The lot sizing problem with parallel machines involves determining the number of products to be manufactured from each machine in each period of a planning horizon. There are several practical applications where parallel machines need to be taken into account, for example, the tire industry [25], bottling of liquids [7] and pharmaceutical industry [14]. In the standard design for lot sizing problems, each machine can manufacture all products, meaning the total or complete flexibility [17,47]. However, it can be expensive to implement machines with total flexibility for several practical applications. Thus, it becomes interesting to implement only a limited amount of machine flexibility so that each machine can produce a reduced part of products [18].

Multiple authors addressed some approaches to analyze the effects of flexibility in the lot sizing problem by considering only the production total cost (or profit) as a criterion. These works are mainly separated by stochastic and deterministic approaches. When considering a stochastic environment, the authors assume that the demand of the items is unknown and present some insights about the value of the process flexibility [11, 19, 26, 35]. On the other hand, in a deterministic planning environment, the flexibility configuration decision becomes an operational decision that is taken at the start of the horizon when the demand for the planning horizon is known [18,42,52]. Although several papers analyze the effect of flexibility, the literature still lacks a more consistent analysis that considers other essential criteria of the lot sizing problem to determine whether a flexibility configuration is suitable to be implemented. A flexibility configuration can be defined as a distribution of links in a bipartite graph between machines/plants and products (see Fig. 1). Some of the flexibility configurations, such as the long-chain configuration, present successful results in terms of the production cost [26].

Note that although the production costs are a fundamental operational criterion, in real practical production operational manufacturing systems, other criteria can be important to be taken into account to implement an obtained solution (production planning). For example, considering the studied problem (lot sizing problem with parallel machines), besides the production costs, one should be analyzed the backlog, the number of setups, and the capacity utilization before implementing a solution. More precisely, a solution with the lowest production costs but with significant levels of backlog, especially for the largest/more critical customers, may not be suitable as there is a risk of losing these customers. In the same sense, a solution with many setups that consumes a significant level of the total capacity or with a very high capacity utilization may make it impossible to meet unexpected demands. Therefore, it is important to study the performance of different flexibility configurations from a multicriteria perspective.

We observe that there are some papers in the literature applying multicriteria approaches to analyze flexible manufacturing systems (see, *e.g.*, [1, 2, 27, 32, 39, 41]). These studies are generally related to reconfigurable manufacturing systems in which the organizations have many options and hence face the problem of evaluating the feasible alternative configurations before choosing the best one. Our paper differs from these literature studies by considering a production environment constituted by a planning horizon in which the decisions are related to the machines that products can/should be produced to obtain the best production planning considering the criteria used. Therefore, the decisions are related to the amount of machine flexibility. More specifically, this paper extends the results of Fiorotto *et al.* [18] by analyzing the process flexibility for the lot sizing problem based on a ranking of alternatives. The technique for order preference by similarity to ideal solution (TOPSIS) produces a ranking for the different alternatives of flexibility configurations, allowing to examine the process flexibility. Note that the TOPSIS method has been successfully used in several studies on industrial sectors [54].

This paper aims to provide a detailed multicriteria analysis for flexibility configurations in different scenarios of the lot sizing problem with parallel machines. The main contributions include: (i) the use of the TOPSIS method and the proposition of a multicriteria analysis on the process flexibility; (ii) the examination of different flexibility configurations to determine the most suitable configuration in a multicriteria perspective; (iii) the investigation of the ranking of alternatives by performing a sensitivity analysis by varying different parameters of the model; and (iv) the performing of an extensive computational study to determine the advantages of different flexibility configurations.

The remainder of this paper is organized as follows. Section 2 presents a brief literature review on the process flexibility in lot sizing problems considering a deterministic context. Moreover, it explains some aspects of multicriteria decision analysis and the TOPSIS method. Section 3 provides a formal description of the steps to obtain the ranking in the TOPSIS method. Section 4 gives the mathematical formulations for the lot sizing problem containing a set of constraints that allows setting the different flexibility configurations. Section 5 presents the proposed multicriteria analysis for the process flexibility through computational experiments for different scenarios and flexibility configurations. The last section summarizes our findings and some clues for future research.

2. Literature review

2.1. Capacited lot-sizing with multiple resources

There has been a broad effort to expand decision methods and procedures for the lot sizing problems in the literature. Recently, particular attention has been given to the decision aspects involving the lot sizing with multiple resources and process flexibility. The class of relevant problems with multiple resources for this investigation is the lot sizing problems with multiple machines or plants.

Several studies on the lot sizing problem with multiple machines considering total flexibility are found in the literature. Carreno [7] proposed a heuristic for a lot sizing problem with identical machines, setup times, and constant demand. Jans [24] developed a reformulation based on the shortest path for the same problem and proposed new symmetry-breaking constraints. Considering the problem with unrelated parallel resources, Toledo and Armentano [47] relaxed the capacity constraints and proposed a Lagrangian heuristic to solve the problem. Mateus *et al.* [37] proposed an iterative process to generate production plans considering scheduling constraints. Fiorotto and de Araujo [16] applied a Lagrangian heuristic based on the relaxation of the demand constraints in order to find good feasible solutions. Fiorotto *et al.* [17] proposed hybrid methods using Lagrangian relaxation and Dantzig-Wolfe decomposition and found better lower and upper bounds compared to Toledo and Armentano [47] and Fiorotto and de Araujo [16]. Recently, Vincent *et al.* [49] developed a meta-heuristic based on the relaxation of the capacity constraints to explore the set of solutions and obtain more feasible solutions.

Other relevant studies examine multiple plants with total flexibility. Generally, each plant has its demand, and there is a possibility of transferring production among the plants, with a due cost [45]. Bhatnagar *et al.* [6] presented one of the first studies on a production environment composed of multiple plants. The objective was to coordinate the production plans in all plants to improve the company's performance. Matta and Miller [15] integrated the lot sizing decisions with the transport of the items among the plants of an industry so that some plants produce intermediate products and others the final products. Guimaraes *et al.* [21] presented a formulation for multiple plants in the beverage industry. The authors studied the planning operations that define the scheduling and size of the production, in which the objective is to satisfy the demand by minimizing production, overtime, and transfer costs. Carvalho and Nascimento [8] addressed this problem considering that all plants produce the same items (each one with a single machine) and that the demands must be satisfied without backlog. Regarding the problem with multiple plants and setup carryover, Carvalho and Nascimento [9] applied a meta-heuristic approach to finding feasible solutions. The authors pointed out that the set of feasible solutions becomes significantly bigger considering the possibility of setup carryover.

Jordan and Graves [26] was the first paper considering the efficiency of a limited amount of flexibility for a manufacturing system with stochastic demand for the automotive industry. After the studies presented by Jordan and Graves [26], several works were proposed to analyze the value of resource flexibility in the context of stochastic demand. Koste and Malhotra [30] developed theoretical principles to build measures to quantify the concept of flexibility. Graves and Tomlin [19] extended the work of Jordan and Graves [26] and proposed new strategies to implement the notions of flexibility. Bertrand [5] presented a literature review on the concepts of flexibility and discussed three characteristics of flexibility for the supply chain. Muriel *et al.* [38] showed that can be found almost all the benefits of an increase in sales with the chain principle. Moreover, the inventory level is significantly reduced as more flexibility is added to the system. Mak and Shen [35] pointed out that the long

TABLE 1. Literature classification.

	Data	Problem	Method solution	KPI analysis	Observations
Jordan and Graves [26]	Stochastic	Production planning	Simulation tool	No	Single-criterion
Graves and Tomlin [19]	Stochastic	Production planning	Simulation tool	Yes	Single-criterion
Gurumurthi and Benjaafar [22]	Stochastic	Queuing	Simulation tool	No	Single-criterion
Jans and Degraeve [25]	Stochastic	Parallel lot-sizing and scheduling	Dynamic programming Lagrange relaxation	No	Single-criterion applied problem
Muriel *et al.* [38]	Stochastic	Production planning	Simulation tool	Yes	Single-criterion
Mak and Shen [35]	Stochastic	Production planning	Lagrange relaxation simulation tool	No	Single-criterion
Andradóttir *et al.* [3]	Stochastic	Queuing	Analytic insights	No	Single-criterion
Xiao *et al.* [52]	Stochastic	Parallel lot-sizing and scheduling	Metaheuristic Lagrange relaxation	No	Single-criterion applied problem
Wu *et al.* [51]	Deterministic	Parallel lot-sizing	Dantzig–Wolfe decompositions	No	Single-criterion
Fiorotto *et al.* [18]	Deterministic	Parallel lot-sizing	Solver	Yes	Single-criterion

chain configuration does not present good results for non-homogeneous scenarios. Gurumurthi and Benjaafar [22] presented computational results considering a problem with queuing systems. The results showed that a non-chained configuration performed better than the long chain in asymmetric systems. Andradóttir *et al.* [3] also confirmed that although the long chain configuration is desirable in homogeneous scenarios, it does not perform well when the data are heterogeneous.

Although the lot sizing problem with multiple machines with a limited amount of flexibility considering a deterministic environment is a natural and more realistic extension of the standard assumption (each machine can produce all items), there are few studies on this topic. Jans and Degraeve [25] considered in the tire industry a problem where not all types of heaters can produce every type of tire. Xiao *et al.* [52] studied the capacity lot sizing problem with parallel resources in the semiconductor industry, where not all resources are eligible to produce all items. A proposed hybrid heuristic based on Lagrangian relaxation and simulated annealing outperformed the numerical results obtained by the standalone Lagrangian relaxation algorithm and the standalone simulated annealing algorithm most of the time. Wu *et al.* [51] proposed different mathematical formulations for this problem and analyzed the decomposition of items and periods for these formulations. Moreover, the authors obtained insights into which setup variables assumed value one and used this information to develop a branching strategy.

Recently, Fiorotto *et al.* [18] addressed the process flexibility and the chaining principle in lot sizing problems by analyzing the value of the resource flexibility in balanced systems (the number of items and resources is equal). The comparison of different limited flexibility configurations concluded that the benefits of the best long-chain and the total flexibility configurations are practically the same. Finally, they also pointed out that the importance of flexibility value increases when the data are heterogeneous.

Table 1 presents a classification of the papers cited in this literature review that involve the study of machine flexibility. Note that the studies considering machine flexibility applied to the lot sizing problems with a deterministic context started in 2018. Furthermore, few studies have analyzed the effect of flexibility on some key performance indicators (KPI). Finally, no paper performed a multicriteria analysis of the different flexibility configurations. Therefore, this research adds to the literature on lot sizing problems with multiple machines and limited flexibility by considering a multicriteria perspective.

2.2. Brief review of the TOPSIS method

The field of multiple criteria decision analysis (MCDA) or multiple criteria decision making (MCDM) is a full-grown segment of operations research that explicitly evaluates multiple criteria in decision making (both in everyday life and in particular settings such as business, industrial engineering, and medicine). MCDA is a generic term for all methods that can assist the decision-maker according to its preferences in problems with more than one conflicting criterion. Researches in MCDA have produced many applied and theoretical papers and books consisting of several approaches (see Mardani *et al.* [36], Roy [44], and the references therein). Köksalan *et al.* [29] described the early history of initial conceptions for MCDA that separately tracked the origins of decision utility theory and mathematical programming with multiple objectives.

The MCDA approaches, methods, and techniques are diverse and based on the following straightforward essential ingredients: a finite or an infinite set of actions (alternatives, solutions), at least two criteria, and at least one decision-maker. Given these essential elements, it regards the designing of mathematical and computational tools for solving problems regarding the choice of preferred alternatives, the classification of alternatives in a small number of categories, and the ranking of alternatives in a subjective judgment order [34]. These methods can also be viewed as a way of dealing with intractable problems by splitting them into smaller parts. After weighing some criteria and making previous judgments about the smaller parts, these are regrouped to present a broad overview to assist the decision-maker.

Pomerol and Barba-Romero [40] stated that an aggregation method is compensatory when the increase in the value of one alternative, relative to one criterion, can compensate for the decrease relative to another criterion. In contrast, in the non-compensatory methods, the performance of one specific criterion does not influence the performance of another criterion [20,23]. Some of the compensatory methods are based on referent points that evaluate a relative distance from an "ideal" alternative. Note that the decision-maker would choose the ideal alternative without hesitation. However, in general, this fictitious "ideal" does not figure among the possible choices, and the decision-maker must look for an alternative that is as close as possible to the ideal alternative [40]. Indeed, one of the most popular procedures among those based-referent points is the TOPSIS method.

Hwang and Yoon [23] and Yoon and Hwang [53] proposed and improved the TOPSIS method to assist in choosing the most desirable alternative with a finite number of criteria that makes full use of attribute information and provides a ranking of alternatives. As a popular MCDA method, TOPSIS has received much interest from researchers, and practitioners. Behzadian *et al.* [4] performed a state-of-the-art literature survey to categorize and interpret the studies on TOPSIS applications and methodologies. The classification scheme for this review contains a set of scholarly papers from 2000 to 2012 distributed into nine application areas, which revealed successful applications for the TOPSIS method in a wide range of areas and industrial sectors with varying terms and subjects. These studies make the TOPSIS method workable in handling practical and theoretical problems, such as supply chain management and logistics; design, engineering, and manufacturing systems; business and marketing management; health, safety, and environment management. And other fields such as agriculture, education, and sports.

Zavadskas *et al.* [54] reviewed the developments of TOPSIS techniques from 2000 to 2015 and observed that some key advantages of TOPSIS are its ability to deal with different types of values and address rank reversal issues. Lima-Junior and Carpinetti [33] presented an approach that uses the performance metrics of the supply chain operations reference (SCOR) model to evaluate the suppliers regarding cost and delivery performance. The proposed method combined two fuzzy-TOPSIS models to indicate the need for improvements for the suppliers. From an illustrative application based on a manufacturing environment, the authors described the advantages of the combination between the SCOR and fuzzy-TOPSIS.

Chen [10] analyzed the effects of a series of data normalization approaches on the integrated Entropy and TOPSIS method. It found that normalization can impact the decision result by strongly influencing the diversity of attribute data (DAD). DAD affects the contribution of attributes to each alternative's distance from the positive ideal and negative ideal alternative. Lima Silva and Almeida Filho [13] proposed variants of the TOPSIS method for sorting problems that prevent ranking reversal. The named TOPSIS-Sort-B improved the previous version of TOPSIS-Sort for sorting problems, including a step for determining a domain for each criterion and a normalized interval addressed to problems with boundary profiles. A numerical application for the proposed methods estimated the degree of economic freedom of 180 countries and assigned them to five pre-defined ordered classes.

These reported successful applications are examples that justify the choice of the TOPSIS method as a helpful tool to assist in the interpretation of diverse conflicting objectives of lot sizing problems in terms of the process flexibility.

3. Formulation for TOPSIS method

TOPSIS is a ranking method whose standard approach searches for alternatives that should have the shortest distance from the positive ideal alternative and the farthest distance from the negative ideal alternative [23]. The ideal alternative maximizes the benefit criteria and minimizes the cost criteria, whereas the negative-ideal alternative maximizes the cost criteria and minimizes the benefit criteria [4]. To apply the TOPSIS method each attribute value takes either monotonically increasing or monotonically decreasing utility.

Let $D = (x_{ij})$ be the standard decision matrix, where each row i of D is part of the set of alternatives, $i = 1, \ldots, \bar{m}$, each column j of D belongs to the set of criteria, $j = 1, \ldots, \bar{n}$, and x_{ij} registers the rating of the alternative A_i according to criterion C_j. And let w_j be the individual weight for each criterion C_j, $j = 1, \ldots, \bar{n}$, satisfying $\sum_{j=1}^{\bar{n}} w_j = 1$.

The criteria are generally classified into *benefit* and *cost*, where the benefit criterion indicates that a higher value is better while the cost criterion is valid the reverse. Since, in general, the entries of the decision matrix D originate from different sources, creating the normalized decision matrix is necessary. This procedure attempts to transform the various attribute dimensions into nondimensional attributes, allowing comparison across the attributes. One approach is to take the rating of each criterion divided by the norm ℓ_2 of the total rating vector of this criterion. The approach used takes the rating of each criterion divided by the Euclidean norm (ℓ_2) of the total rating vector of this criterion (the Euclidean norm associates a real number for each vector $x \in R^n$, and can be interpreted geometrically as the length vector x).

Let $R = (r_{ij})$ be the normalized decision matrix, where $r_{ij} = x_{ij}/\sqrt{\sum_{i=1}^{\bar{m}} x_{ij}^2}$ for each $i = 1, \ldots, \bar{m}$, and $j = 1, \ldots, \bar{n}$. The matrix R represents the relative rating of the alternatives. And, let $P = (p_{ij})$ be the weighted normalized decision matrix, where $p_{ij} = w_j r_{ij}$ for each $i = 1, \ldots, \bar{m}$, and $j = 1, \ldots, \bar{n}$. Similarly with Hwang and Yoon [23] and Krohling *et al.* [31], the TOPSIS method is described in the following steps.

Step 1. Identify the positive ideal alternative A^+ (benefits) and the negative ideal alternative A^- (costs) as follows.

$$A^+ = \left(p_1^+, \ldots, p_{\bar{n}}^+\right)^T, \text{ where } p_j^+ = \left(\max_{i=1,\ldots,\bar{m}} \{p_{ij}\}, \text{ if } j \in \bar{J}_1\right) \vee \left(\min_{i=1,\ldots,\bar{m}} \{p_{ij}\}, \text{ if } j \in \bar{J}_2\right); \quad (3.1)$$

$$A^- = \left(p_1^-, \ldots, p_{\bar{n}}^-\right)^T, \text{ where } p_j^- = \left(\min_{i=1,\ldots,\bar{m}} \{p_{ij}\}, \text{ if } j \in \bar{J}_1\right) \vee \left(\max_{i=1,\ldots,\bar{m}} \{p_{ij}\}, \text{ if } j \in \bar{J}_2\right), \quad (3.2)$$

where $\bar{J}_1 \subseteq \{1, \ldots, \bar{n}\}$ and $\bar{J}_2 \subseteq \{1, \ldots, \bar{n}\}$ represent benefit and cost criteria, respectively, and $\bar{J}_1 \cap \bar{J}_2 = \emptyset$.

Step 2. Calculate the separation measures from the positive ideal alternative A^+ and the negative ideal alternative A^- for each alternative A_i, respectively as follows.

$$d_i^+ = \sqrt{\sum_{j=1}^{\bar{n}} \left(p_{ij} - p_j^+\right)^2}, \quad i = 1, \ldots, \bar{m}; \quad (3.3)$$

$$d_i^- = \sqrt{\sum_{j=1}^{\bar{n}} \left(p_{ij} - p_j^-\right)^2}, \quad i = 1, \ldots, \bar{m}. \quad (3.4)$$

Step 3. Calculate the relative closeness coefficient ε_i of each alternative A_i with respect to the positive ideal alternative as follows.

$$\varepsilon_i = \frac{d_i^-}{d_i^+ + d_i^-}. \tag{3.5}$$

Step 4. Rank the alternatives according to the relative closeness coefficients.

Note that $\varepsilon_i = 1$ if $A_i = A^+$, and $\varepsilon_i = 0$ if $A_i = A^-$. The best alternatives are those that have higher value ε_i, and therefore should be chosen.

4. Mathematical formulations for the lot sizing problem with process flexibility

Fiorotto *et al.* [18] proposed some formulations for the lot-sizing problem with process flexibility in which multiple resources have a limited amount of flexibility to be used. In this section, we first present a formulation of the lot sizing problem with unrelated parallel machines considering a limited amount of flexibility where a specific machine can produce only a small number of types of products. This formulation allows us to find the optimal total cost given a specific flexibility configuration. Next, we present a formulation that considers the possibility of investing in flexibility and determines the optimal flexibility configuration for a given number of links or a limited budget.

For the first mathematical formulation of the problem, consider the following parameters and variables:

$I = \{1, ..., n\}$: set of items;
$J = \{1, ..., r\}$: set of machines;
$T = \{1, ..., m\}$: set of periods;
I_j: set of items i that can be produced on machine j;
J_i: set of machines j that can produce item i;
d_{it}: demand of item i in period t;
sd_{i1m}: sum of the demand for item i from period 1 until period m;
hc_{it}: unit inventory cost of item i in period t;
bc_{it}: unit backlog cost of item i in period t;
sc_{ijt}: setup cost for item i on machine j in period t;
vc_{ijt}: production cost of item i on machine j in period t;
st_{ijt}: setup time for item i on machine j in period t;
vt_{ijt}: production time of item i on machine j in period t;
Cap_{jt}: capacity (in units of time) of machine j in period t.

The decision variables are then defined as follows:

x_{ijt}: quantity (lot-size) of item i to be produced on machine j in period t;
y_{ijt}: binary setup variable, indicating if machine j is configured for production or not of item i in period t;
s_{it}: inventory of item i at the end of period t;
b_{it}: backlog of item i at the end of period t.

The mathematical formulation of the problem is then as follows:

$$\text{Min} \sum_{t\in T}\sum_{j\in J}\sum_{i\in I_j}(sc_{ijt}y_{ijt} + vc_{ijt}x_{ijt}) + \sum_{t\in T}\sum_{i\in I}(hc_{it}s_{it} + bc_{it}b_{it}) \tag{4.1}$$

$$\text{s.t. } s_{i(t-1)} - b_{i(t-1)} + \sum_{j\in J_i} x_{ijt} = d_{it} + s_{it} - b_{it}, \qquad i\in I, \quad t\in T; \tag{4.2}$$

$$x_{ijt} \le \min\{(Cap_{jt} - st_{ijt})/vt_{ijt},\ sd_{i1m}\}y_{ijt}, \qquad i\in I_j, \quad j\in J, \quad t\in T; \tag{4.3}$$

$$\sum_{i \in I_j} (st_{ijt} y_{ijt} + vt_{ijt} x_{ijt}) \leq Cap_{jt}, \qquad j \in J, \quad t \in T; \tag{4.4}$$

$$y_{ijt} \in \{0,1\}, \quad x_{ijt} \geq 0, \qquad i \in I_j, \quad j \in J, \quad t \in T; \tag{4.5}$$

$$s_{it} \geq 0, \quad s_{i0} = s_{im} = 0, \; b_{it} \geq 0, \; b_{i0} = 0, \qquad i \in I, \quad t \in T. \tag{4.6}$$

The objective function (4.1) minimizes the total costs, which consists of production, setup, inventory, and backlog costs. Constraints (4.2) ensure that demand is met for each period. Demand that cannot be satisfied on time can be backlogged. The setup constraints (4.3) do not allow any production unless a setup is done. The capacity constraints (4.4) limit the sum of the total setup and production times. Finally, constraints (4.5) and (4.6) define the variable domains.

The first formulation finds the optimal cost from a fixed flexibility configuration. However, the next formulation also gives the flexibility configuration. Therefore, it includes the chance to invest in different flexibilities by upgrading a machine for a specific product. The structure of a flexibility configuration derives from various links (levels of the global budget), each choice is a binary variable, and there is a global budget on the investment decisions.

For the second mathematical formulation, consider the following additional parameters and variables:

fc_{ij}: flexibility investment cost for producing item i on machine j;
$F_{\max}$: global budget (number of links) to invest in flexibility.

The additional decision variables are then defined as follows:

z_{ij}: binary variable, indicating that machine j can produce item i or not.

The mathematical formulation consists of the objective function (4.1) and the constraints (4.2)–(4.6) of the previous formulation replacing the sets I_j and J_i by I and J, respectively. In addition, we have the following constraints:

$$y_{ijt} \leq z_{ij}, \qquad i \in I, \quad j \in J, \quad t \in T; \tag{4.7}$$

$$\sum_{j \in J} \sum_{i \in I} fc_{ij} z_{ij} \leq F_{\max}; \tag{4.8}$$

$$z_{ij} \in \{0,1\}, \qquad i \in I, \quad j \in J. \tag{4.9}$$

Constraints (4.7) ensure that a machine can be set up to produce a specific item in a specific period only if this machine has the flexibility to produce this item. Constraint (4.8) limits the budget (number of links) available for investing in flexibility. Note that in this formulation, the flexibility investment is modeled as part of a budget constraint instead of putting it in the objective function. Remark that companies can put restrictions on the number of machine-product combinations, which is modeled as a special case of our global budget constraint. Observe that if $F_{\max} = n^2$, then we have the total flexibility configuration. We emphasize that we chose the budget constraint approach instead of considering the flexibility investment as part of the objective function because it is the way found to analyze the effect of varying the amount of flexibility and develop the multicriteria study of the flexibility configurations.

5. Multicriteria analysis of flexibility configurations

We analyze the concept of process flexibility in a deterministic lot sizing context considering a multicriteria perspective. The objective of the experiments presented in this section is to analyze the effect of considering several criteria when analyzing the value of different flexibility configurations compared to the study proposed by Fiorotto *et al.* [18] in which only one criterion (total cost) is used to determine the value of the flexibility configurations. All chosen criteria are computed directly from the structure of each solution (number of setups, backlog, etc.) presented by Fiorotto *et al.* [18] to make this comparison.

5.1. Setup of the computational tests

Using the ideas proposed by Fiorotto *et al.* [18], we adapted a standard synthetic data set proposed by Trigeiro *et al.* [48]. We used the problem sets $F1-F20$ and $G51-G60$. The $F1-F20$ set contains 20 instances with 6 items and 15 periods. The $G51-G55$ set consists of 5 instances with 12 items and 15 periods, and $G56-G60$ set consists of 5 instances with 24 items and 15 periods. For each of the 30 problem instances, we created identical parallel machine problems, *i.e.*, the capacities are the same for each machine, and for a given item, the setup time, unit production time, and setup cost are the same on each machine. The backlog cost for each item is equal to 300, which is 100 times the average inventory holding cost, and the setup times are equal to zero. For $F1-F20$, $G51-G55$ and $G56-G60$, the original capacity level was set at 728, 1456 and 2912, respectively. In this paper, the capacity levels for the parallel machine case were based on preliminary tests and varied from 40 to 140 to have a broad range of problems so that the solutions have different levels of backlog. By changing the capacity level, each original single-machine test problem resulted in 12 different parallel machine test problems. As a result, 360 different test problems were created. The generated instances are available on `https://www.github.com/gsamaro/trigeiro_fdata`.

In order to apply the TOPSIS method, we consider eight alternatives and five criteria. More specifically, for each instance, we ranked eight alternatives of flexibility configurations named Dedicated, Cluster, Random, Long chain, Best chain, $F_{\max 1}$, $F_{\max 2}$, and Total flexibility (Fig. 1 illustrates these alternatives). The criteria are the total cost, capacity utilization, total backlog, the total number of setups, and the amount of flexibility considered on each of the eight alternatives of flexibility configurations. The criteria were chosen to take into account different aspects of the analyzed flexibility configurations. Note that other operational criteria could be used, for example, inventory level, percentage of demand satisfied on time, etc. However, we have limited our choice according to the criteria most considered in practice for operational decision-making, *i.e.*, amount of setup, total backlog, level of flexibility, total production costs, and capacity utilization. Observe that these criteria are the indicators used by most papers proposed in the literature in order to analyze the solution of the production plan problems [18, 38, 46, 47].

Observe that when solving a specific instance with the mathematical formulation (4.1)–(4.6), the general solution given by the objective function is only the total cost of the production planning (which is the criterion used by Fiorotto *et al.* [18] and only one of the five criteria that are considered in this study). However, the other considered criteria are related to operational issues of the production planning and can be calculated with the generated solution of the mathematical formulation. The values of the other criteria are calculated as follows: let $\mathrm{CU}_{ij} = \left(\left(\sum_{i\in I_j}(st_{ijt}y_{ijt} + vt_{ijt}x_{ijt})\right)/Cap_{jt}\right) \times 100$, therefore, the capacity utilization is given by $\mathrm{CU} = \left(\sum_{j\in J}\sum_{t\in T}\mathrm{CU}_{ij}\right)/|J||T|$; the total backlog is calculated by $\mathrm{Back} = \left(\sum_{i\in I}\sum_{t\in T} b_{it}\right)$; the total number of setups is given by $\mathrm{NS} = \left(\sum_{t\in T}\sum_{j\in J}\sum_{i\in I_j} y_{ijt}\right)$; and finally, the level of flexibility directly computed by amount of links of the considered alternative (flexibility configuration).

According to Roy [43] a set of criteria must be exhaustive, *i.e.*, none of the attributes that discriminate the alternatives can be forgotten. In order to analyze whether the criteria used are appropriate, we have compared the results of the paper (considering all the five criteria) with the results of TOPSIS considering four criteria (amount of setup, total backlog, level of flexibility, and capacity utilization) and with only two criteria (total production costs and level of flexibility) using the well-known Kendall–Tau distance [28]. From the results, we conclude that the five criteria, although not independent, are discriminant of the alternatives. They can be considered together without generating distortion in the analysis to represent different possibilities of the decision maker's choice.

It is also important to see that, in general, the capacity utilization should be at an intermediate level because when the capacity utilization is very low, there is a considered amount of idle fixed assets, which is not desirable (since it represents idle money). On the other hand, when the capacity utilization is very high, there is no time to deal with any unforeseen events (such as a machine breakdown). However, in the studied problem, it is considered that there is not enough capacity to meet the demand on time, *i.e.*, it is known in advance that

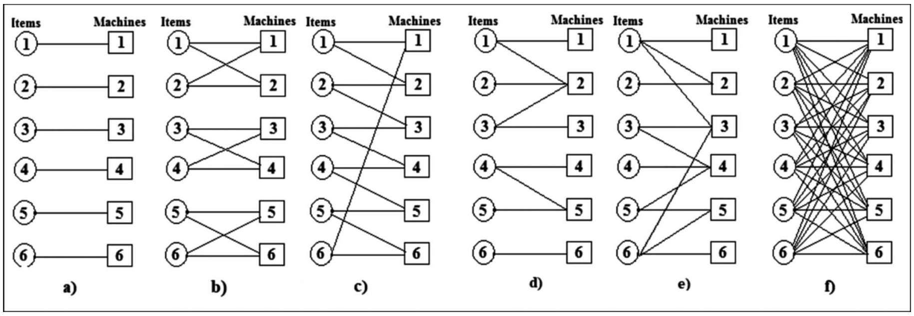

FIGURE 1. Flexibility configurations for an example with 6 items and 6 machines. (a) Dedicated. (b) Cluster 6 links added. (c) Long chain 6 links added. (d) $F_{\max 1}$ 3 links added. (e) $F_{\max 2}$ 6 links added. (f) Total 30 links added.

the solutions present some amount of backlog. Therefore, in this specific scenario, we would like to maximize capacity utilization to reduce the number of backlogged items.

Figure 1 illustrates the flexibility configurations analyzed from the TOPSIS method in this section. The figure refers to an instance containing six items and six machines. The Dedicated configuration is a pattern as Figure 1a, where each machine can produce only one item (the number of links of this configuration is equal to the number of items). The Cluster configuration appears in Figure 1b, where the pattern contains 3 clusters of 2 machines (the number of additional links on the Dedicated configuration is equal to the number of items). The pattern in Figure 1c is the Long chain configuration, for which excepting Machine 1 that produces Item 1 and $n = 6$, each Machine i produces Items i and $i - 1$ (the number of additional links of this configuration is equal to the Cluster configuration in Fig. 1b). The Total flexibility configuration is as Figure 1f, where all the flexibility links inform that each machine can produce all items. The configurations in Figures 1d and 1e do not follow a typical pattern. Instead, they are the configurations the solver obtains at the optimal solution when the total number of allowed links (parameter $F_{\max}$) is $n + n/2$ and $2n$, respectively. The parameter $F_{\max}$ will lend its name to these configurations, *i.e.*, Configuration $F_{\max 1}$ refers to $F_{\max} = n + n/2$, and Configuration $F_{\max 2}$ refers to $F_{\max} = 2n$. Here, the solver gives the optimal flexibility configurations related to the fixed total number of links. This figure is extended in a straightforward way in the case of 12 and 24 machines.

We also consider the Random flexibility configuration in which there is no pattern, and the links are added randomly. In the Random flexibility configuration, the number of additional links on the Dedicated configuration is again equal to the number of items. We also observe that there are many possible Long chain configurations by changing the sequence of the items. Therefore, the performance of the best of them is also analyzed, *i.e.*, the Best chain configuration.

We observe that the formulation (4.1)–(4.6) with the appropriate configuration of the links is used to analyze the following cases: Dedicated, Cluster, Random, Long chain, Best chain, and Total flexibility. And, equations (4.1)–(4.6) and (4.7)–(4.9) form the formulation used to analyze the case where process flexibility is a decision variable (configurations $F_{\max 1}$ and $F_{\max 2}$). Note that in constraints (4.8) the set fc_{ij} is fixed to one, and $F_{\max}$ is equal to the number of links that are allowed to add. It limits the total number of links that can be used, *i.e.*, imposing a limit on the number of machine-product combinations that are allowed. To run the computational tests, the weights of the criteria were considered equal for all criteria for most analyzed experiments. However, in order to analyze different types of solutions, a section with different variations for the weights of the criteria is considered. Finally, The tests were done on a computer with 2 Intel(R) Xeon(R) X5675 processors, 3.07 GHz with 96 GB of RAM and the Linux operating system. Moreover, when solving the formulations, we have limited the computational time for each instance to 3 h (10 800 s).

5.2. Computational results

A set of the decision matrices provides the input data for the TOPSIS method. Each decision matrix $D = (x_{ij})$ used in the computational experiments is presented in Tables 2 and B.1–B.14. Table 2 is showed in this section to give the details of the experiments, and the other tables appear in Appendix B. Each table gives six decision matrices according to the considered capacity levels, *i.e.*, 40, 60, 80, 100, 120, and 140. Table 2 illustrates the six decision matrices for the instances with 12 items and machines for the base case experiments, and the decision matrices for 6 and 24 items and machines are presented in Tables B.1 and B.2 of Appendix B, respectively. For each capacity level, the table contains five columns of criteria. Each column gives the average of the relative upper bounds (columns UB), capacity utilization (columns CU), the total backlog (columns Back), the total number of setups (columns NS), and the total number of links allowed (columns NL) found for the instances and flexibility configurations. Note that we set the total cost of the Dedicated configuration as the referential value (equal to 100%) and calculate the upper bounds of the other flexibility configurations related to these values. The symbols Min and Max indicate the cost criterion and benefit criterion in the TOPSIS method, respectively. Moreover, the table also gives the standard deviation (S.E.) and the coefficient of variation (C.V.) of each criterion.

We use as an example the decision matrix $D = (x_{ij})$ for the capacity level 100 in Table 2 to illustrate how to calculate the positive ideal alternative A^+ and the negative ideal alternative A^- along with the simulation experiments. The range for the criterion UB (cost criterion) in the first column of the decision matrix is $[30.7, 100.0]$, then the range for the first column of the normalized decision matrix $R = (r_{ij})$ is $[0.09, 0.30]$, where $r_{i1} = x_{i1}/\sqrt{\sum_{i=1}^{\bar{m}} x_{i1}^2}$. Considering the same weight for the five criteria, then $w_1 = 0.2$ and we obtain the range $[p_1^+, p_1^-] = [0.018, 0.060]$ for the first column of the weighted normalized decision matrix $P = (p_{ij})$. Hence, the last range is used to select the first component of A^+ and A^-.

Table 2 shows that some criteria present the same value (are tied) for all flexibility configurations and the amount of ties varies according to the capacity levels. More specifically, for low capacity levels, only one criterion presents equal values (CU). However, for high capacity levels (equal to 140), three of the five criteria have the same values for all flexibility configurations. It is also important to note that, as expected, in terms of the total cost (column UB), the Total flexibility presents the best values (lowest values) for all capacity levels. And the Total and Dedicated configurations are opposite each other in the total number of links. The overall average of the optimality gap is 2.7% (see all information about the value of the gap in Table A.1 of Appendix A).

Table 3 presents the position obtained for each flexibility configuration applying the TOPSIS method for all instances and capacity levels. Besides to presenting the numerical position, a color system was used to facilitate the visualization of the positions obtained for each flexibility configuration, i.e., it starts with dark green for the first position and goes to dark pink for the last position. Note that for the instances with 6 items and machines and the capacity level equal to 140, the Dedicated configuration is ranked in the first position, followed by $F_{\max 1}$ and $F_{\max 2}$ configurations.

The results show that the Total flexibility stayed in the last positions for all sizes of instances and capacity levels. It occurs mainly due to the large number of links (n^2) presented in this flexibility configuration compared to the total number of links given by the other flexibility configuration, which is smaller than $2n$. We observe that it is in line with practice applications since it can be costly and/or usually impossible to install machines with Total flexibility. Moreover, although the Total flexibility obtained the best upper bounds for all instances, other flexibility configurations such as the Long chain, $F_{\max 1}$ and $F_{\max 2}$ presented values in the decision matrix very similar to the Total flexibility for this criterion. Therefore, the upper bound is not a criterion that highlights the Total flexibility. Considering the Cluster and Random flexibility, we see that they ranked between the 5th and 7th positions for almost all instances with 6 and 12 items and machines. We observe that the instances with 24 items and machines are challenging to solve. The results presented large optimality gaps (see Tab. A.1) for most flexibility configurations. These gaps have a significant influence on the conclusions for these instances. It is also interesting to note that the Dedicated configuration ranked first for very low (40 and 60) and high capacity levels (140). Note that for very low and high capacity levels, the benefits of investing in flexibility are almost 0 (the upper bounds presented by all flexibility configurations are close to 100%). Finally, Table 3 shows that $F_{\max 1}$ ranked in the first positions for almost all sizes of instances and capacity levels.

Table 2. Decision matrix for the instances with 12 items and machines for different configurations for the base case experiments.

	40					60					80				
	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL
Dedicated	100	100	73 349	180.0	12	100	100	44 851	180.0	12	100	100	17 526	180.0	12
Cluster	99.7	100	73 214	180.9	24	99.2	100	44 535	190.8	24	95.0	100	16 668	190.3	24
Random	99.7	100	73 219	181.1	24	99.0	100	44 462	194.1	24	92.1	100	16 182	198.1	24
Long	99.7	100	73 209	181.2	24	98.9	100	44 431	194.3	24	91.0	100	16 001	201.4	24
Best	99.6	100	73 212	180.4	24	98.8	100	44 402	188.4	24	90.8	100	15 965	197.6	24
$F_{\max 1}$	99.6	100	73 222	181.4	18	98.8	100	44 409	186.6	18	92.0	100	16 169	189.6	18
$F_{\max 2}$	99.6	100	73 227	180.4	24	98.8	100	44 407	188.2	24	90.9	100	15 975	199.4	24
Total	99.6	100	73 195	200.4	144	98.8	100	44 395	203.0	144	90.7	100	15 964	201.2	144
S.E.	0.1	0	48.7	7.0	43.6	0.4	0	154.3	6.7	43.6	3.2	0	546.3	7.5	43.6
C.V. (%)	0.1	0	0.1	3.8	118.5	0.4	0	0.3	3.5	118.5	3.5	0	3.4	3.8	118.5
	100					120					140				
Dedicated	100	94.1	980	176.4	12	100	78.9	5	161.0	12	100	67.6	0	144.8	12
Cluster	47.4	94.5	255	184.1	24	99.1	78.9	1	161.3	24	100	67.6	0	144.6	24
Random	33.3	94.7	31	184.9	24	98.9	78.9	0	161.0	24	100	67.6	0	144.7	24
Long	31.0	94.7	0	184.5	24	98.9	78.9	0	160.9	24	100	67.6	0	144.7	24
Best	31.0	94.7	0	184.4	24	98.8	78.9	0	160.8	24	100	67.6	0	144.6	24
$F_{\max 1}$	33.0	94.7	25	181.4	18	98.8	78.9	0	160.8	18	100	67.6	0	144.8	18
$F_{\max 2}$	31.3	94.7	0	185.0	24	98.9	78.9	0	160.8	24	100	67.6	0	144.6	24
Total	30.7	94.7	0	184.0	144	98.8	78.9	0	160.8	144	100	67.6	0	144.6	144
S.E.	24.0	0.2	342.0	2.9	43.6	0.4	0	1.8	0.2	43.6	0	0	0	0.1	43.6
C.V. (%)	56.9	0	211.9	1.6	118.5	0.4	0	233.7	0.1	118.5	0	0	–	0.1	118.5

Table 3. Position obtained for the flexibility configurations using TOPSIS method.

		Dedicated	Cluster	Random	Long	Best	$F_{\max 1}$	$F_{\max 2}$	Total
6	140	1	7	6	5	4	2	3	8
	120	8	6	5	2	4	1	3	7
	100	8	6	5	4	3	1	2	7
	80	1	7	5	6	4	2	3	8
	60	1	5	6	7	3	2	4	8
	40	1	4	6	5	3	2	7	8
12	140	1	5	7	6	4	2	3	8
	120	8	6	5	4	2	1	3	7
	100	8	6	5	3	2	1	4	7
	80	2	3	5	7	4	1	6	8
	60	1	5	6	7	4	2	3	8
	40	1	5	6	7	3	2	4	8
24	140	1	4	3	2	6	5	8	7
	120	1	4	2	3	8	5	6	7
	100	8	5	3	1	2	4	6	7
	80	3	2	4	5	6	1	7	8
	60	1	5	6	7	3	2	4	8
	40	1	4	5	6	3	2	7	8
1st–2nd		13	2	3	5	9	15	7	0
7th–8th		5	6	7	8	3	0	7	18

Table 3 also summarizes the frequency that a flexibility configuration appears in the top positions (1st or 2nd position) and bottom positions (7th or 8th position). $F_{\max 1}$ is in the top positions for most instances and is the only one that does not appear in the last positions. On the other hand, Total flexibility appears in the bottom positions for all experiments. Moreover, Dedicated configuration is the second that appears most in the top positions. Note also that the frequency of the Long chain configuration in the bottom positions is higher than the Best chain configuration, but they have the same frequency in the top positions.

Finally, these results show some significant differences compared to the conclusions presented by Fiorotto *et al.* [18] that considered only the total cost as a criterion. More specifically, Fiorotto *et al.* [18] showed that the Total flexibility and Long chain configurations are very similar and outperform the other flexibility configurations. However, our multicriteria study shows that the Total flexibility configuration frequently ranked in the bottom positions, and the Long chain configuration regularly ranked in intermediate positions.

5.3. Sensitivity analysis for the process flexibility

It is well known from the literature on lot sizing problems that the process flexibility performs better for homogeneous cases. This section analyzes different cases with heterogeneity data to verify the behavior of the process flexibility in a deterministic context considering a multicriteria approach. More specifically, we analyze the backlog cost and demand heterogeneity separately using the ideas proposed by Fiorotto *et al.* [18]. Additionally, we analyze the case where setup times are present. Finally, we also address the case considering all these three factors together.

5.3.1. Backlog cost heterogeneity

In order to create a case with backlog heterogeneity, the same data sets considered in the previous section are used, and the backlog cost for each item is 100 times the inventory holding cost. In all instances, each item has a different inventory holding cost, taken from a discrete uniform distribution between 1 and 5. As such, items will have different backlog costs in the adapted instances. This allows us to check the influence of the level of the backlog cost.

In Table 4 we present the position obtained for each flexibility configuration applying the TOPSIS method for all instances and capacity levels considering the backlog cost heterogeneity. The tables with the decision matrices considering the backlog cost heterogeneity used to build Table 4 are presented in Appendix B (Tabs. B.3–B.5). The global analysis shows that the Total flexibility is ranked again in the last positions for all sizes of instances and capacity levels. However, different from the results with backlog homogeneity, the Dedicated configuration ranked in the last positions for many sizes of instances and capacity levels. It occurs in this scenario because there are items with backlog costs more expensive than others (what is common in practice), and the Dedicated configuration does not allow readjustment capacity among the machines (each machine produces only one item). It is interesting to observe that, just like in the backlog homogeneity, the configuration $F_{\max 1}$ ranked first and second for 15 from 18 sizes of instances and capacity levels (see Tabs. 3 and 4). Considering the configurations Long chain, Best chain, and $F_{\max 2}$, we see a small improvement compared to the previous scenario, specially for the instances with medium and high capacity levels, due to the better performance of these alternatives considering the upper bound criterion. On the other hand, the Cluster configuration performed worse. It makes sense that since the Long and Best chain configurations are well-connected, they perform better in heterogeneous scenarios, while the Dedicated and Cluster configurations should perform worse.

In Table 4 we also present the results summarized by the top and bottom positions considering the backlog cost heterogeneity. While the flexibility configuration $F_{\max 1}$ is in the top positions for most instances and does not appear in the bottom positions, the Total flexibility is in the bottom positions for all sizes of instances and levels of flexibility. Moreover, different from Table 3, the Dedicated configuration ranked seventh or eighth for 12 from 18 sizes of instances and levels of capacity. Finally, note that the Long and Best chain configurations are in the top positions for some instances.

Table 4. Position obtained for the flexibility configurations using TOPSIS method with backlog heterogeneity.

		Dedicated	Cluster	Random	Long	Best	$F_{\max 1}$	$F_{\max 2}$	Total
6	140	1	7	6	5	4	2	3	8
	120	8	6	5	4	3	1	2	7
	100	8	6	5	4	3	1	2	7
	80	7	6	5	4	2	1	3	8
	60	2	7	6	5	4	1	3	8
	40	2	6	5	4	3	1	7	8
12	140	1	6	5	4	3	2	7	8
	120	8	6	5	4	3	1	2	7
	100	8	6	5	3	2	1	4	7
	80	7	6	4	2	5	1	3	8
	60	7	6	5	4	2	1	3	8
	40	7	5	6	4	2	1	3	8
24	140	1	4	3	2	7	5	6	8
	120	1	5	4	3	8	2	6	7
	100	8	5	2	1	3	6	4	7
	80	7	6	4	1	3	5	2	8
	60	7	6	5	4	2	1	3	8
	40	7	6	5	4	1	2	3	8
1st–2nd		6	0	1	4	6	15	4	0
7th–8th		12	2	0	0	2	0	2	18

5.3.2. Setup times heterogeneity

This section considers the setup times, which have a uniform distribution between 10 and 50. Note that the backlog costs for all items are fixed to 300 as in the base setting. Table 5 shows the position obtained for each flexibility configuration applying the TOPSIS method for all instances and capacity levels considering setup times. The tables with the decision matrices considering setup times used to build the Table 5 are presented in Appendix B (Tabs. B.6–B.8). A global analysis of the results (Tab. 5) indicates that the configuration $F_{\max 1}$ performed very well as in the previous scenarios. However, although the Dedicated configuration ranked first for the instances with 6 items and machines, and medium and high capacity levels, it ranked in the last positions for all other sizes of instances and capacity levels. Moreover, the configuration $F_{\max 2}$ presents a small ascent in the ranking compared to the base case and the backlog heterogeneity scenarios (note that in the base case, considering 24 items, $F_{\max 2}$ ranked in the last positions due to the high optimality gaps).

Table 5 also provides information on the other flexibility configurations. Comparing the performance of the Cluster and Random configurations, we see that the Random ranked best for all sizes of instances and capacity levels. Moreover, the long chain ranked first for some instances with 24 items and machines (instances in which the optimality gap found for configurations $F_{\max 1}$ is high), and it does not rank in the last positions for any instance. Comparing the Long and Best chain configurations, we see that, in general, the Long chain appears in intermediate positions while the Best chain is at the top of the ranking, which is expected since the Best chain configuration is the best long chain in terms of the total cost. Finally, the Total flexibility ranked in the last positions as in the previous scenarios.

Table 5 also summarizes the results for the top and bottom positions. Compared to the base case in Table 3, we observe some differences concerning the ranking of some flexibility configurations. Considering setup times, the Dedicated and Cluster configurations ranked considerably more times in the bottom positions than the base case. Moreover, the number of times that the Random and $F_{\max 2}$ appear in the top positions increases significantly. Moreover, the Dedicated configuration ranked in the bottom positions for 11 from 18 sizes of

TABLE 5. Position obtained for the flexibility configurations using TOPSIS method with setup times heterogeneity.

		Dedicated	Cluster	Random	Long	Best	$F_{\max 1}$	$F_{\max 2}$	Total
6	140	8	6	5	4	3	1	2	7
	120	7	6	5	4	2	1	3	8
	100	1	7	6	5	4	2	3	8
	80	1	7	6	5	4	2	3	8
	60	1	7	5	6	4	2	3	8
	40	1	5	3	4	6	2	7	8
12	140	8	6	5	4	3	1	2	7
	120	7	6	5	2	3	1	4	8
	100	4	7	6	5	2	1	3	8
	80	6	7	5	4	3	1	2	8
	60	7	6	5	4	3	1	2	8
	40	5	3	2	4	7	1	6	8
24	140	8	6	3	1	2	5	4	7
	120	7	5	2	1	3	6	4	8
	100	7	6	1	4	3	2	5	8
	80	7	6	5	4	2	1	3	8
	60	7	6	5	4	3	1	2	8
	40	7	2	3	1	6	4	5	8
1st–2nd		4	1	3	4	4	15	5	0
7th–8th		11	5	0	0	1	0	1	18

instances and capacity levels (this configuration ranked in the first position for 12 sizes of instances in the base case (Tab. 3)).

5.3.3. Demand heterogeneity

In order to create a demand heterogeneity case, the demand distribution of the items has been changed. In the base setting, each item had the same average demand. In this new case, the demand of the first half of the items is increased by 50%, and the other half is decreased by 50%. Note that the backlog costs for all items are fixed to 300 as in the base setting and there is no setup time in this scenario.

Table 6 presents the position obtained for each flexibility configuration applying the TOPSIS method for all instances and capacity levels considering demand heterogeneity. The tables with the decision matrices considering demand heterogeneity used to build the Table 6 are presented in Appendix B (Tabs. B.9–B.11).

The results show that the Total flexibility remains in the last positions as in the previous scenarios. Moreover, although the Cluster configuration ranked between 5th and 7th positions as in the base setting, the Random configuration ranked between 3rd and 5th positions. Considering the Dedicated configuration, it still ranked first for low capacity levels. However, different from the base setting, the Dedicated configuration ranked in the last positions for medium and high capacity levels. This occurs in this scenario because the Dedicated configuration presents substantial backlog levels for these capacity levels because of the very high demand of the first half of the items. It is also interesting to see that the Best chain performed much better than the Long chain configuration for this scenario. The reason is that the Best long chain can always combine one item with high and one with low demand distribution on one machine, and it does not always happen for a fixed long chain. Finally, Table 6 shows that $F_{\max 1}$ remain ranked in the first positions for almost all size of instances and capacity levels.

Table 6 also presents the results summarized by the top and bottom positions considering demand heterogeneity. We observe that, different from the base setting, the Cluster and Random configurations do not rank in the top positions for any instance. Moreover, the Cluster configuration ranked in the bottom positions more

Table 6. Position obtained for the flexibility configurations using TOPSIS method with demand heterogeneity.

		Dedicated	Cluster	Random	Long	Best	$F_{\max 1}$	$F_{\max 2}$	Total
6	140	8	6	5	4	3	1	2	7
	120	8	6	5	4	3	1	2	7
	100	8	6	5	4	2	1	3	7
	80	7	6	5	4	2	1	3	8
	60	2	7	5	6	3	1	4	8
	40	1	7	6	5	3	2	4	8
12	140	8	6	5	3	4	1	2	7
	120	8	6	5	4	2	1	3	7
	100	8	6	5	4	2	1	3	7
	80	7	6	5	4	2	1	3	8
	60	7	6	5	4	3	1	2	8
	40	1	7	6	5	3	2	4	8
24	140	8	6	3	1	2	4	5	7
	120	8	6	4	1	2	5	3	7
	100	7	6	3	2	5	1	4	8
	80	1	5	6	7	3	2	4	8
	60	1	7	5	4	3	2	6	8
	40	1	5	4	6	3	2	7	8
1st–2nd		6	0	0	3	7	16	4	0
7th–8th		12	4	0	1	0	0	1	18

times. It shows that these configurations had a bad performance for this scenario. We also see that the Best chain is in the top positions for many instances, while the Long chain configuration presents a similar trend to the base setting.

5.3.4. *Backlog and demand heterogeneity considering setup times*

In order to create a case with a very high level of heterogeneity, the three factors that have been analyzed (backlog and demand heterogeneity and setup times) are considered together. Table 7 presents the position obtained for each flexibility configuration. The tables with the decision matrices considering used to build the Table 7 are presented in Appendix B (Tabs. B.12–B.14). The results show that the Total flexibility and Dedicated configuration ranked in 8th and 7th position for most instances, respectively. It is interesting to see that the configuration $F_{\max 2}$, different from the other scenarios, ranked better than the Long and Best chain configuration for most instances. Finally, the configuration $F_{\max 1}$ remains in the first positions for most instances.

Table 7 also summarizes the results for the top and bottom positions, considering the backlog and demand heterogeneity with setup times. We see that while the flexibility configuration $F_{\max 1}$ is in the top positions for most instances, followed by the configuration $F_{\max 2}$, the Total flexibility and Dedicated configurations have the bottom positions for almost all instances. Therefore, the flexibility configurations with a very limited amount of links ($F_{\max 1}$ and $F_{\max 2}$) are the most efficient for the most heterogeneity scenarios. It is also interesting to observe that the well-known chain configurations present an intermediate performance from a multicriteria point of view.

Concerning managerial insights, the decisions about process flexibility can be related to different planning decision areas. It can be first considered strategic decisions, in which it is necessary to define which plants can produce each product. Since it involves high investments, the decision maker is usually the company steering committee. On the other hand, the process flexibility can also be considered a tactical decision, for example, the decision to purchase a set of machines for a specific production line. In this case, the decision makers are usually

TABLE 7. Position obtained for the flexibility configurations using TOPSIS method with backlog and demand heterogeneity considering setup times.

		Dedicated	Cluster	Random	Long	Best	$F_{\max 1}$	$F_{\max 2}$	Total
6	140	8	6	5	4	3	1	2	7
	120	8	6	5	4	2	1	3	7
	100	7	6	4	5	3	1	2	8
	80	7	6	5	4	3	1	2	8
	60	2	7	6	5	4	1	3	8
	40	1	5	3	4	7	2	6	8
12	140	8	6	5	4	2	1	3	7
	120	8	6	5	4	2	1	3	7
	100	7	6	5	4	3	1	2	8
	80	7	6	5	4	3	1	2	8
	60	7	6	5	4	3	1	2	8
	40	7	5	1	4	6	2	3	8
24	140	7	6	3	1	2	5	4	8
	120	7	6	5	3	2	4	1	8
	100	7	6	5	4	3	1	2	8
	80	7	6	5	4	3	1	2	8
	60	7	6	5	4	3	1	2	8
	40	7	1	3	2	6	4	5	8
1st–2nd		2	1	1	2	5	15	10	0
7th–8th		16	1	0	0	1	0	0	18

the industrial direction and/or the production supervisor. Regardless of the decision maker, the methodology remains the same. First, it is necessary to understand the alternatives, *i.e.*, the different possible flexibility configurations. Next, it is needed to define/choose and prioritize which criteria will be taken into account. The considered criteria are related to different aspects of production planning. In practice, the decision maker must evaluate the different possibilities/consequences for the manufacturing system when prioritizing one or more criteria according to the company's reality. More specifically, for example, prioritizing production costs affects the criterion related to the amount of flexibility, which significantly impacts the investments needed to deploy the production plant. Another example is when large production batches are necessary. In this situation, priority should be given to minimizing the setup (another operational criterion), often leading to production planning with very high inventory levels. Finally, maximizing capacity utilization impacts the level of service the industry offers and is usually disadvantaged in dealing with unforeseen events (such as a machine breakdown or unexpected demands).

5.4. Sensitivity analysis for the weights of the criteria

The previous sections analyzed the ranking position of each flexibility configuration, considering an equal weight for each criterion. In order to make a more consistent analysis, this section studies the behavior of the process flexibility for the lot sizing problem considering a multicriteria approach by varying the weight of the criteria for the homogeneous case and the instances of 6, 12, and 24 products. More specifically, each weight obtains a value from a uniform distribution $U(0,1)$. The size of the weight vector normalizes the weights. After weighting each criterion, the TOPSIS method ranks the studied flexibility configurations (alternatives). Moreover, in order to have a wide range of results, we have generated 50 000 experiments.

Figure 2 shows the proportion that each flexibility configuration ranked in a specific position. Note that the configuration $F_{\max 1}$ ranked 50% in the first position. Moreover, $F_{\max 1}$ has the highest proportion in top positions. It means that even varying the weights, configuration $F_{\max 1}$ is robust and can be appropriated to

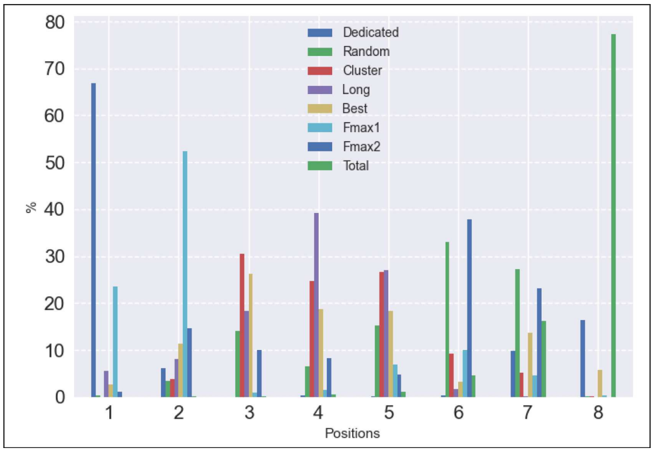

FIGURE 2. Proportion that each flexibility configuration ranked in a specific position.

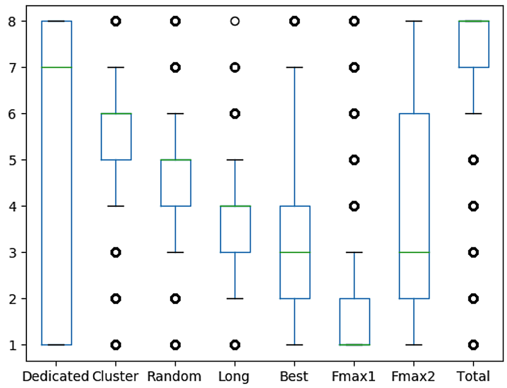

FIGURE 3. Variability of the positions for each flexibility configuration.

the decision-maker. We also observe that the Best and Long chain configurations are most ranked in the third and fourth positions, respectively. Finally, the Total flexibility ranked around 70% in the last position, and the Dedicated configuration is the second most appearing both in the first and last positions.

Figures 3 and 4 present a series of the box plot charts to compare the variability of the positions for each flexibility configuration in the ranking. The bullet points of the charts are outliers in the data. Thus, Figure 3 shows that each configuration ranked at least once in each such position. Note that the Cluster, Random, and Long chain configurations ranked mainly in the intermediate positions, while the Total flexibility ranked mostly in the 7th or 8th positions. Moreover, although the Dedicated configuration ranked around 30% in the 1st position (see Fig. 2), it ranked 50% in the bottom position. Furthermore, $F_{\max 1}$ configuration highlighted by ranking 75% from 1st to 3rd positions.

Figure 4 aims to examine the sensibility of ranking alternatives by varying capacity levels (40, 80, and 140). Note that the spreading of the Dedicated configuration from 1st to 8th positions in the ranking (Fig. 3) mainly occurs because of the results for low capacity level (Fig. 4a). We also observe that it regularly ranked in the 7th and 1st positions for medium and high capacity levels, respectively (Figs. 4b and 4c). This last observation is in line with the literature, considering that there is no (or only a little) benefit of investing in flexibility for systems with very high capacity levels. Moreover, Figure 4 provides two significant insights of this research. Figure 4a

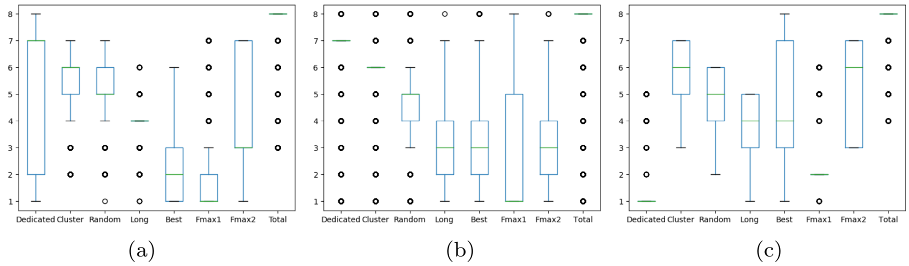

FIGURE 4. Variability of the positions for each flexibility configuration separated by capacity levels. (a) Boxplot cap 40. (b) Boxplot cap 80. (c) Boxplot cap 140.

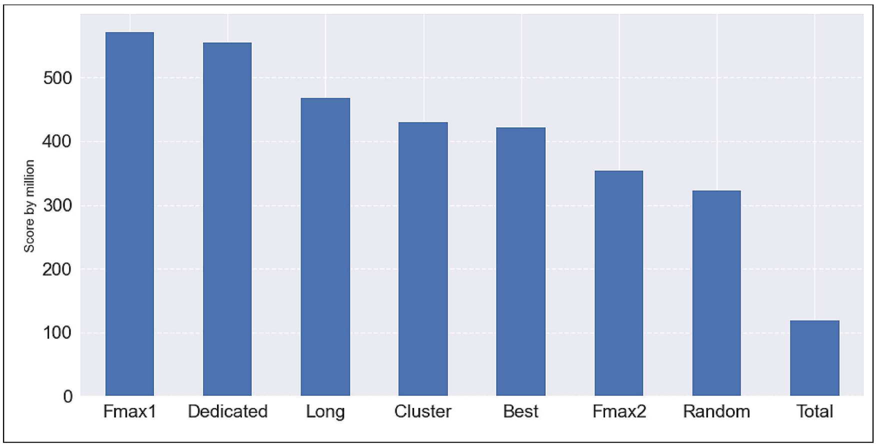

FIGURE 5. Performance of the flexibility configurations aggregated by scored points.

(low capacity levels) shows that the Dedicated configuration is spread between the second and seventh positions. At the same time, $F_{\max 1}$ is predominantly in the first or second positions, and the Best chain configuration is between the first and third positions. It shows that different from the insights obtained by Fiorotto *et al.* [18] in which the Dedicated configuration has the same benefits compared to all flexibility configurations, for the case with only one criterion, considering a multicriteria approach, to implement a limited flexibility configuration has advantages even for low capacity levels. Finally, although the Total flexibility configuration is known for having the best values for total production cost, Figure 4 shows that concerning the multicriteria approach, the Total flexibility configuration is mostly ranked in the last position for all capacity levels and should not be chosen.

As a final remark, we apply Borda's method [12] as an aggregated method to verify where each flexibility configuration stands out in the ranking of alternatives. We score each flexibility configuration according to its position in the ranking as follows. If the flexibility configuration ranked in the first position, it scores 8 points; in the second position, it scores 7 points; and so on, in the eighth position, it scores 1 point. Figure 5 presents the total scored points by each flexibility configuration, in which the $F_{\max 1}$ and Total flexibility configurations presented the best and worst performance, respectively. Moreover, except for the $F_{\max 1}$ configuration, the Best chain and Long chain configurations score better than other configurations. Furthermore, the Dedicated configuration outperforms only the Cluster and Total flexibility configurations.

6. Conclusions

In this paper, the process flexibility was studied in the context of a deterministic lot sizing problem. Different from the standard lot sizing problem with parallel machines, the studied problem considers a limited amount of machine flexibility so that each machine can produce only certain types of products. In order to fill a gap in the literature, a multicriteria analysis is proposed to analyze the efficiency of several flexibility configurations. Our computational experiments showed that the Total flexibility configuration ranked in the last positions for all proposed scenarios. Moreover, the well-known Long chain configuration had, in general, an intermediate behavior for most instances. The configuration $F_{\max 1}$ (configuration with $n + n/2$ links) showed that only a small amount of flexibility obtains the best results for all scenarios analyzed. The computational experiments also indicate that the Dedicated configuration ranked in the first positions for very high capacity levels. However, it ranked in the last positions for medium capacity levels. Finally, different from the studies considering only the total cost as the criterion, investing in flexibility for all capacity levels has advantages. The limitations of this study are related to the fixed flexibility configurations and complexity of the mathematical formulation. Although the used flexibility configurations are the most used in the literature, they are not necessarily the most appropriate for all practical applications. Moreover, we need the optimal or very close to the optimal solutions to calculate good values for the criteria. Then, it is complicated to analyze very large instances because of the difficulty of the mathematical formulation.

Several interesting issues can be explored as further research, for example, to extend the study to unbalanced systems where the number of products and machines is not the same. It would also be interesting to focus on developing specific heuristics to add flexibility, *i.e.*, given a level of flexibility (links between products and machines), the heuristic would determine a good way to distribute these links. Furthermore, it would be interesting to analyze the differences between the formulation considered in this work, which uses a flexibility budget as a constraint, with an approach that penalizes the amount of flexibility in the objective function of the problem.

Another possibility that can be explored is to study the two levels of flexibility with different plants and customers. In this case, each plant can deliver its products to only a certain number of customers. The objective would be to analyze the value of flexibility and develop solution methods for this case. A final extension could be to study this problem considering a multicriteria context. In such a case, there is not enough capacity to satisfy the demand of all customers, and different criteria can be used to determine the preferred customers and what proportion of the demands will be satisfied.

Appendix A. Optimality gap

Table A.1. Average of optimality gap.

		Dedicated	Cluster	Random	Long	Best	$F_{\max 1}$	$F_{\max 2}$	Total
Section 5.2 Base case	6	0	0	0	0	0.1	0.2	0.4	0
	12	0	0	0.1	0.1	0.8	1.7	1	0.1
	24	0	0	0.2	0.3	7.8	14.7	14	0.4
	Av.	0	0	0.1	0.1	2.9	5.5	5.1	0.2
Section 5.3.1 Backlog cost heterogeneity	6	0	0	0	0	0.1	0.2	0.5	0.1
	12	0	0	0.1	0.1	1.4	4.7	1.3	0.3
	24	0	0	0.2	0.3	11.1	16.1	8.5	0.6
	Av.	0	0	0.1	0.1	4.2	7	3.4	0.3
Section 5.3.2 Setup times heterogeneity	6	0	0	0.1	0.2	0.5	0	1	0.4
	12	0	0	0.6	1.1	3.1	6.4	3.9	1.6
	24	0	0.1	0.9	1.1	7.7	17.4	11.7	2.1
	Av.	0	0	0.5	0.8	3.8	7.9	5.5	1.4
Section 5.3.3 Demand heterogeneity	6	0	0	0	0	0.1	0.1	0.5	0.1
	12	0	0	0	0	1.1	4.5	1.3	0.3
	24	0	0	0.1	0.2	2.8	13.3	7.9	0.4
	Av.	0	0	0	0.1	1.3	6.0	3.2	0.3
Section 5.3.4 Backlog and demand heterogeneity considering setup times	6	0	0	0	0	0.2	0.1	1.7	0.6
	12	0	0	0	0	3.9	9.2	4.4	1.9
	24	0	0	0.4	0.7	7.9	14.9	11.5	2.6
	Av.	0	0	0.1	0.2	4	8.1	5.9	1.7
Av.		0	0	0.2	0.3	3.2	6.9	4.6	0.8

Appendix B. Matrix decisions for all instances and scenarios

Table B.1. Decision matrix for the instances with 6 items and machines for different configurations for the base case experiments.

	40					60					80				
	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL
Dedicated	100	100	35 948	90.0	6	100	100	21 786	90.0	6	100	100	8403	90.0	6
Cluster	99.5	100	35 837	90.8	12	98.9	100	21 566	95.4	12	93.4	100	7887	94.8	12
Random	99.5	100	35 824	91.0	12	98.4	100	21 481	97.0	12	89.8	100	7599	97.2	12
Long	99.5	100	35 820	91.0	12	98.2	100	21 447	97.4	12	87.4	100	7408	99.3	12
Best	99.4	100	35 809	90.5	12	98.1	100	21 430	94.8	12	87.3	100	7405	98.3	12
$F_{\max 1}$	99.4	100	35 813	91.1	9	98.2	100	21 441	93.6	9	88.2	100	7471	95.1	9
$F_{\max 2}$	99.4	100	35 812	91.9	12	98.1	100	21 431	94.8	12	87.3	100	7405	97.7	12
Total	99.4	100	35 803	98.2	36	98.1	100	21 425	100.8	36	87.3	100	7405	99.4	36
S.E.	0.2	0	47.5	2.6	9.2	0.7	0	124.3	3.1	9.2	4.5	0	356.7	3.1	9.2
C.V. (%)	0.2	0	0.1	2.9	66.3	0.7	0	0.6	3.3	66.3	5.0	0	4.7	3.2	66.3
	100					120					140				
Dedicated	100	93.5	488	87.5	6	100	78.4	1	80.4	6	100	67.2	0	72.5	6
Cluster	54.5	93.9	146	91.6	12	99.8	78.4	0	80.5	12	100	67.2	0	72.5	12
Random	42.4	94.0	35	92.2	12	99.7	78.4	0	80.4	12	100	67.2	0	72.5	12
Long	38.1	94.1	0	91.9	12	99.7	78.4	0	80.3	12	100	67.2	0	72.5	12
Best	37.9	94.1	0	91.8	12	99.7	78.4	0	80.4	12	100	67.2	0	72.5	12
$F_{\max 1}$	39.5	94.0	13	90.9	9	99.7	78.4	0	80.4	9	100	67.2	0	72.5	9
$F_{\max 2}$	37.9	94.1	0	91.2	12	99.7	78.4	0	80.4	12	100	67.2	0	72.4	12
Total	37.9	94.1	0	91.9	36	99.7	78.4	0	80.4	36	100	67.2	0	72.3	36
S.E.	21.6	0.2	170.2	1.5	9.2	0.1	0	0.4	0.1	9.2	0	0	0	0.1	9.2
C.V. (%)	44.4	0.2	199.6	1.7	66.3	0.1	0	282.8	0.1	66.3	0	0	–	0.1	66.3

Table B.2. Decision matrix for the instances with 24 items and machines for different configurations for the base case experiments.

	40					60					80				
	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL
Dedicated	100	100	146 320	360.0	24	100	100	89 377	360.0	24	100	100	34 641	360.0	24
Cluster	99.7	100	146 030	360.8	48	99.2	100	88 761	383.3	48	94.5	100	32 737	378.4	48
Random	99.7	100	146 028	361.2	48	99.0	100	88 543	389.8	48	91.6	100	31 716	393.6	48
Long	99.7	100	146 001	361.8	48	98.9	100	88 497	390.2	48	91.0	100	31 511	395.3	48
Best	99.6	100	145 978	360.2	48	98.7	100	88 378	374.2	48	90.6	100	31 365	396.6	48
$F_{\max 1}$	99.6	100	145 996	364.4	36	99.2	100	88 780	371.2	36	93.3	100	32 370	375.0	36
$F_{\max 2}$	99.6	100	145 991	365.8	48	98.7	100	88 368	378.8	48	90.8	100	31 417	397.0	48
Total	99.6	100	145 947	417.2	576	98.7	100	88 353	408.2	576	90.3	100	31 279	399.0	576
S.E.	0.1	0	117.6	19.6	188.7	0.4	0	344.7	14.6	188.7	3.3	0	1140.4	14.1	188.7
C.V. (%)	0.1	0	0.1	5.3	172.3	0.4	0	0.4	3.8	172.3	3.5	0	3.5	3.6	172.3
	100					120					140				
Dedicated	100	92.5	2177	346.2	24	100	77.5	3	317.4	24	100	66.4	0	285	24
Cluster	50.0	92.9	635	364.4	48	99.8	77.5	0	317.6	48	100	66.4	0	284.6	48
Random	30.9	93.0	53	363.9	48	99.7	77.5	0	317.2	48	100	66.4	0	284.6	48
Long	29.0	93.0	1	361.7	48	99.7	77.5	0	317.3	48	100	66.4	0	284.6	48
Best	30.8	93.0	5	371.4	48	339.8	77.0	1609	314.6	48	114.1	66.4	37	287.0	48
$F_{\max 1}$	48.7	92.8	570	361.2	36	195.3	77.2	468	315.8	36	107.6	66.4	14	284	36
$F_{\max 2}$	69.3	92.5	1225	363.6	48	214.3	77.3	567	316.0	48	142.7	66.4	224	284.0	48
Total	28.7	93.0	1	360.0	576	99.7	77.5	0	317.2	576	100	66.4	0	284.4	576
S.E.	25.3	0.2	779.0	7.1	188.7	88.3	0.2	567.4	1.1	188.7	14.9	0	77.7	1.0	188.7
C.V. (%)	52.3	0.2	133.5	2.0	172.3	56.6	0.2	171.5	0.3	172.3	13.8	0	226.1	0.3	172.3

Table B.3. Decision matrix for the instances with 6 items and machines for different configurations with backlog heterogeneity.

	40					60					80				
	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL
Dedicated	100	100	35 948	90.0	6	100	100	21 786	90.0	6	100	100	8403	90.0	6
Cluster	79.0	100	36 102	90.6	12	71.8	100	21 570	121.5	12	68.6	100	7894	114.9	12
Random	78.5	100	36 010	90.6	12	61.9	100	21 805	111.0	12	49.7	100	7709	123.5	12
Long	78.5	100	35 977	90.6	12	60.5	100	21 706	111.3	12	39.0	100	7734	121.8	12
Best	73.0	100	36 021	90.6	12	55.3	100	21 770	114.2	12	38.7	100	7711	121.7	12
$F_{\max 1}$	69.7	100	35 877	101.9	9	55.4	100	21 914	114.6	9	45.7	100	8086	115.5	9
$F_{\max 2}$	69.7	100	35 847	103.8	12	54.9	100	21 718	117.3	12	38.6	100	7703	121.9	12
Total	69.7	100	35 839	107.1	36	54.9	100	21 711	117.2	36	38.6	100	7699	120.8	36
S.E.	10.1	0	93.1	7.3	9.2	15.5	0	98.9	9.6	9.2	21.8	0	255.8	11.1	9.2
C.V. (%)	13.1	0	0.3	7.6	66.3	24.1	0	0.5	8.5	66.3	41.6	0	3.3	9.5	66.3
	100					120					140				
Dedicated	100	93.5	488	87.5	6	100	78.4	1	80.4	6	100	67.2	0	72.5	6
Cluster	51.0	93.9	147	93.5	12	99.6	78.4	0	80.5	12	100	67.2	0	72.5	12
Random	42.5	94.0	36	92.9	12	99.6	78.4	0	80.4	12	100	67.2	0	72.5	12
Long	39.4	94.1	0	91.8	12	99.5	78.4	0	80.4	12	100	67.2	0	72.5	12
Best	39.2	94.1	0	91.8	12	99.5	78.4	0	80.4	12	100	67.2	0	72.5	12
$F_{\max 1}$	40.9	94.1	21	90.9	9	99.5	78.4	0	80.4	9	100	67.2	0	72.5	9
$F_{\max 2}$	39.2	94.1	0	91.7	12	99.5	78.4	0	80.4	12	100	67.2	0	72.5	12
Total	39.2	94.1	0	91.8	36	99.5	78.4	0	80.4	36	100	67.2	0	72.5	36
S.E.	21.0	0.2	169.7	1.8	9.2	0.2	0	0.4	0.0	9.2	0	0	0	0.0	9.2
C.V. (%)	43.0	0.2	196.2	2.0	66.3	0.2	0	282.8	0.0	66.3	0	0	–	0.0	66.3

Table B.4. Decision matrix for the instances with 12 items and machines for different configurations with backlog heterogeneity.

	40					60					80				
	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL
Dedicated	100	100	73 349	180.0	12	100	100	44 851	180.0	12	100	100	17 526	180.0	12
Cluster	78.1	100	73 761	181.2	24	71.8	100	44 541	242.9	24	70.4	100	16 680	233.8	24
Random	80.6	100	73 469	181.7	24	64.6	100	44 877	220.6	24	49.9	100	16 560	246.4	24
Long	77.9	100	73 514	181.6	24	59.9	100	44 959	222.2	24	41.4	100	16 550	251.8	24
Best	70.5	100	73 559	180.8	24	48.3	100	45 392	221.4	24	39.6	100	16 207	264.8	24
$F_{\max 1}$	66.8	100	73 394	208.0	18	47.9	100	45 565	220.0	18	45.8	100	17 747	224.8	18
$F_{\max 2}$	66.5	100	73 263	205.8	24	47.3	100	45 291	224.0	24	39.6	100	16 244	263.2	24
Total	66.5	100	73 259	217.4	144	47.3	100	45 153	228.8	144	39.3	100	16 168	260.2	144
S.E.	11.3	0	168.1	15.5	43.6	18.4	0	334.1	17.8	43.6	21.6	0	604.1	28.3	43.6
C.V. (%)	15.0	0	0.2	8.1	118.5	30.2	0	0.7	8.1	118.5	40.5	0	3.6	11.8	118.5
	100					120					140				
Dedicated	100	94.1	980	176.4	12	100	78.9	5	161.0	12	100	67.6	0	144.8	12
Cluster	46.6	94.5	256	187.3	24	99.5	78.9	1	161.2	24	100	67.6	0	144.7	24
Random	37.1	94.7	32	185.1	24	99.3	78.9	0	160.9	24	100	67.6	0	144.7	24
Long	35.4	94.7	1	184.4	24	99.3	78.9	0	160.9	24	100	67.6	0	144.6	24
Best	35.4	94.7	0	184.2	24	99.2	78.9	0	160.8	24	100	67.6	0	144.6	24
$F_{\max 1}$	38.2	94.6	62	183.2	18	99.2	78.9	0	160.8	18	100	67.6	0	144.8	18
$F_{\max 2}$	35.8	94.7	11	184.6	24	99.2	78.9	0	160.8	24	100	67.6	0	144.8	24
Total	35.0	94.7	1	184.2	144	99.2	78.9	0	160.8	144	100	67.6	0	145.0	144
S.E.	22.4	0.2	339.2	3.2	43.6	0.3	0	1.8	0.1	43.6	0	0	0	0.1	43.6
C.V. (%)	49.2	0	202.1	1.7	118.5	0.3	0	233.7	0.1	118.5	0	0	–	0.1	118.5

Table B.5. Decision matrix for the instances with 24 items and machines for different configurations with backlog heterogeneity.

	40					60					80				
	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL
Dedicated	100	100	146 320	360.0	24	100	100	89 377	360.0	24	100	100	34 641	360.0	24
Cluster	78.6	100	146 921	361.6	48	71.1	100	88 776	482.7	48	68.6	100	32 759	467.6	48
Random	78.4	100	146 627	361.4	48	61.8	100	89 378	442.4	48	42.2	100	32 553	496.7	48
Long	78.2	100	146 561	361.7	48	59.9	100	89 406	444.3	48	38.5	100	32 581	498.1	48
Best	67.5	100	146 862	360.8	48	49.9	100	89 349	457.2	48	34.6	100	32 429	512.6	48
$F_{\max 1}$	62.9	100	146 507	410.2	36	49.7	98.9	91 895	439.6	36	55.4	97.0	43 181	403.0	36
$F_{\max 2}$	62.7	100	146 360	415.4	48	47.0	100	89 108	475.8	48	34.2	100	32 442	507.8	48
Total	62.7	100	146 342	431.0	576	46.6	100	88 737	493.4	576	33.3	100	31 848	516.6	576
S.E.	12.8	0	231.1	30.5	188.7	18.0	0.4	1004.1	41.3	188.7	23.4	1.1	3776.8	58.0	188.7
C.V. (%)	17.4	0	0.2	8.0	172.3	29.7	0.4	1.1	9.2	172.3	46.0	1.1	11.1	12.3	172.3
	100					120					140				
Dedicated	100	92.5	2177	346.2	24	100	77.5	3	317.2	24	100	66.4	0	285.0	24
Cluster	44.2	92.9	639	372.2	48	99.8	77.5	1	317.3	48	100	66.4	0	284.6	48
Random	31.3	93.0	54	365.0	48	99.7	77.5	1	317.1	48	100	66.4	0	284.6	48
Long	29.6	93.0	1	361.7	48	99.7	77.5	1	317.1	48	100	66.4	0	284.6	48
Best	32.0	93.0	16	373.4	48	171.9	77.5	509	319.8	48	131.7	66.4	239	282.4	48
$F_{\max 1}$	49.0	92.7	765	360.2	36	103.9	77.5	4	319.2	36	104.2	66.4	15	282.0	36
$F_{\max 2}$	38.8	92.9	270	368.0	48	103.7	77.5	5	320.4	48	116.0	66.4	108	286.6	48
Total	29.4	93.0	0	360.4	576	99.7	77.5	1	317.0	576	100	66.4	0	284.6	576
S.E.	23.6	0.2	745.1	8.6	188.7	25.2	0	179.2	1.4	188.7	12	0	86.7	1.5	188.7
C.V. (%)	53.4	0.2	152.0	2.4	172.3	22.9	0	273.0	0.4	172.3	11	0	191.6	0.5	172.3

Table B.6. Decision matrix for the instances with 6 items and machines for different configurations with setup times heterogeneity.

	40					60					80				
	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL
Dedicated	100	81.7	56 111	73.5	6	100	100	42 434	90.0	6	100	100	28 182	90.0	6
Cluster	94.3	94.7	52 927	85.2	12	92.1	100	39 038	90.0	12	93.6	100	26 370	90.0	12
Random	94.1	95.5	52 783	85.0	12	91.6	100	38 823	90.0	12	91.3	100	25 721	90.2	12
Long	94.4	94.3	52 993	84.8	12	91.9	100	38 983	90.0	12	91.1	100	25 641	90.1	12
Best	92.2	98.2	51 730	88.4	12	89.1	100	37 744	90.0	12	89.8	100	25 295	90.2	12
$F_{\max 1}$	89.7	100	50 340	90.0	9	88.4	100	37 435	90.0	9	89.9	100	25 317	90.5	9
$F_{\max 2}$	89.7	100	50 337	90.0	12	88.4	100	37 424	90.2	12	89.7	100	25 252	90.4	12
Total	89.7	100	50 336	90.0	36	88.4	100	374 27	90.3	36	89.7	100	25 249	90.4	36
S.E.	3.5	6.1	1979.1	5.5	9.2	3.9	0	1686.3	0.1	9.2	3.5	0	1005.2	0.2	9.2
C.V. (%)	3.8	6.4	3.8	6.4	66.3	4.3	0	4.4	0.1	66.3	3.8	0	3.9	0.2	66.3
	100					120					140				
Dedicated	100	99.9	14 371	90.0	6	100	97.3	3818	89.2	6	100	86.3	267	83.3	6
Cluster	95.0	100	13 653	90.0	12	72.9	98.8	2789	90.5	12	71.6	87.0	51	84.2	12
Random	92.0	100	13 228	90.3	12	66.8	99.6	2459	90.8	12	65.4	87.1	14	84.5	12
Long	90.4	100	13 008	90.4	12	45.9	99.9	1836	91.0	12	63.0	87.2	0	84.8	12
Best	90.0	100	12 947	90.8	12	45.3	99.9	1818	91.5	12	62.9	87.2	0	84.8	12
$F_{\max 1}$	91.7	100	13 185	90.4	9	49.0	99.8	1950	90.7	9	63.0	87.2	0	84.7	9
$F_{\max 2}$	90.0	100	12 943	90.7	12	45.4	99.9	1819	91.4	12	62.9	87.2	0	84.8	12
Total	90.0	100	12 942	90.7	36	45.3	99.9	1817	91.6	36	62.9	87.2	0	84.9	36
S.E.	3.5	0	500.5	0.3	9.2	19.9	0.9	717.4	0.8	9.2	13	0.3	93	0.5	9.2
C.V. (%)	3.8	0	3.8	0.3	66.3	33.8	0.9	31.4	0.9	66.3	18.7	0.4	223.7	0.6	66.3

Table B.7. Decision matrix for the instances with 12 items and machines for different configurations with setup times heterogeneity.

	40					60					80				
	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL
Dedicated	100	68.3	110 923.0	123.0	12	100	100	84 367.0	180.0	12	100	100	55 874.0	180.0	12
Cluster	91.1	91.0	101 030.0	163.8	24	88.2	99.9	74 406.0	180.0	24	91.3	99.9	50 952.0	180.0	24
Random	91.8	89.8	101 773.0	161.7	24	88.2	99.9	74 327.0	180.0	24	88.3	99.9	49 293.0	180.3	24
Long	91.1	91.5	101 004.0	164.7	24	87.6	99.9	73 876.0	180.0	24	87.6	99.9	48 901.0	180.1	24
Best	88.3	100	97 841.0	180.0	24	83.9	100	70 671.0	180.0	24	84.5	100	47 090.0	180.4	24
$F_{\max 1}$	82.7	99.8	91 596.0	180.0	18	83.2	100	70 081.0	180.6	18	84.5	99.9	47 073.0	180.2	18
$F_{\max 2}$	82.7	99.9	91 598.0	180.0	24	83.1	99.9	70 040.0	181.2	24	84.2	100	46 947.0	181.2	24
Total	82.7	99.8	91 594.0	180.0	144	83.1	100	70 038.0	181.8	144	84.2	100	46 939.0	182.2	144
S.E.	6.1	10.8	6772.8	19.5	43.6	5.7	0.1	4831.2	0.7	43.6	5.5	0.1	3090.1	0.8	43.6
C.V. (%)	6.8	11.7	6.9	11.7	118.5	6.5	0.1	6.6	0.4	118.5	6.2	0.1	6.3	0.4	118.5
	100					120					140				
Dedicated	100	99.7	28 701	180.0	12	100	95.5	9067	176.8	12	100	86.0	881	166.2	12
Cluster	93.2	99.9	26 769	180.0	24	71.8	97.6	6635	179.7	24	56.3	86.8	214	168.0	24
Random	88.2	99.9	25 349	180.9	24	49.9	99.1	4769	182.8	24	45.3	87.2	33	169.9	24
Long	86.8	99.9	24 923	180.9	24	40.0	99.9	3962	183.9	24	42.9	87.3	3	170.2	24
Best	85.2	100	24 443	181.8	24	40.1	99.9	3969	184.6	24	42.7	87.3	1	170.2	24
$F_{\max 1}$	87.3	100	25 006	180.6	18	46.6	99.4	4458	181.0	18	42.9	87.2	1	169.8	18
$F_{\max 2}$	85.1	99.9	24 410	182.4	24	41.2	99.8	4051	183.8	24	42.7	87.3	0	170.4	24
Total	84.9	100	24 347	183.2	144	38.8	99.9	3842	186.8	144	42.6	87.2	0	169.8	144
S.E.	5.3	0.1	1516.1	1.1	43.6	21.7	1.6	1846.7	3.1	43.6	20.0	0.5	308	1.5	43.6
C.V. (%)	5.9	0.1	5.9	0.6	118.5	40.5	1.6	36.3	1.7	118.5	38.5	0.5	217.2	0.9	118.5

TABLE B.8. Decision matrix for the instances with 24 items and machines for different configurations with setup times heterogeneity.

	40					60					80				
	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL
Dedicated	100	55.0	227 639	198.0	24	100	100	174 795	360.0	24	100	100	117 670	360.0	24
Cluster	91.7	79.5	208 622	286.2	48	88.6	100	154 888	360.0	48	91.3	100	107 440	360.0	48
Random	92.2	78.3	209 724	282.0	48	88.1	100	153 938	360.0	48	88.0	100	103 527	360.5	48
Long	91.4	80.6	207 847	290.1	48	87.6	100	153 044	360.0	48	87.8	100	103 238	360.6	48
Best	86.7	100	197 077	360.0	48	81.9	100	143 106	360.0	48	84.7	100	99 603	361.8	48
$F_{\max 1}$	81.2	100	184 643	360.2	36	80.7	99.9	140 997	360.0	36	86.7	98.8	101 839	359.0	36
$F_{\max 2}$	81.2	100	184 618	360.0	48	80.6	100	140 753	361.2	48	84.8	100	99 663	361.6	48
Total	81.2	100	184 598	360.4	576	80.5	100	140 567	363.4	576	84.0	100	98 758	366.8	576
S.E.	6.8	16.3	15 628.5	58.9	188.7	6.7	0.1	11 747.2	1.2	188.7	5.2	0.4	6208.2	2.4	188.7
C.V. (%)	7.7	18.8	7.8	18.9	172.3	7.8	0.1	7.8	0.3	172.3	5.9	0.4	6.0	0.7	172.3
	100					120					140				
Dedicated	100	99.6	63 107	359.2	24	100	95.5	21 414	350.4	24	100	86.2	2220	332.0	24
Cluster	93.2	99.9	58 760	360.5	48	77.8	97.6	16 634	358.5	48	52.8	87.0	845	336.2	48
Random	88.7	99.9	55 909	326.2	48	51.9	99.7	11 250	364.9	48	29.6	87.4	93	339.5	48
Long	88.3	99.9	55 690	362.1	48	47.0	99.9	10 269	364.4	48	26.9	87.5	6	340.4	48
Best	87.8	99.7	55 243	362.0	48	56.6	99.6	12 199	364.8	48	30.0	87.3	74	336.8	48
$F_{\max 1}$	93.1	99.4	58 589	359.2	36	97.5	95.9	20 194	354.8	36	48.9	87.2	445	337.4	36
$F_{\max 2}$	88.5	99.7	55 725	361.8	48	61.1	98.6	13 349	358.0	48	37.5	87.4	212	340.4	48
Total	85.8	100	54 036	366.4	576	45.2	100	9872	370.4	576	26.6	87.5	0	339.8	576
S.E.	4.6	0.2	2907.7	12.7	188.7	22.0	1.8	4491.2	6.5	188.7	24.7	0.4	756.2	2.9	188.7
C.V. (%)	5.0	0.2	5.1	3.6	172.3	32.7	1.9	31.2	1.8	172.3	56.1	0.5	155.3	0.9	172.3

TABLE B.9. Decision matrix for the instances with 6 items and machines for different configurations with demand heterogeneity.

	40					60					80				
	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL
Dedicated	100	100	36 534	90.0	6	100	89.3	27 272	85.0	6	100	79.4	20 153	79.4	6
Cluster	99.1	100	36 222	96.3	12	85.5	97.2	23 320	94.3	12	56.5	94.5	11 413	92.0	12
Random	98.9	100	36 165	96.0	12	80.3	100	21 901	96.4	12	44.1	99.2	8878	98.7	12
Long	98.9	100	36 158	95.9	12	80.1	100	21 866	98.6	12	44.5	98.4	8986	97.0	12
Best	98.8	100	36 148	91.3	12	79.8	100	21 784	94.1	12	38.3	100	7748	98.5	12
$F_{\max 1}$	98.7	100	36 138	91.4	9	79.7	100	21 777	93.2	9	38.8	100	7843	98.7	9
$F_{\max 2}$	98.7	100	36 137	92.2	12	79.6	100	21 762	94.6	12	38.2	100	7732	99.0	12
Total	98.7	100	36 131	99.3	36	79.6	100	21 757	102.0	36	38.2	100	7732	100.0	36
S.E.	0.4	0	136.4	3.3	9.2	7.1	3.8	1930.2	4.9	9.2	21.2	7.1	4265.3	6.9	9.2
C.V. (%)	0.4	0	0.4	3.5	66.3	8.6	3.8	8.5	5.2	66.3	42.6	7.4	42.4	7.3	66.3
	100					120					140				
Dedicated	100	73.6	13 154	75.1	6	100	69.6	6570	69.6	6	100	65.7	1673	65.9	6
Cluster	28.0	88.7	3557	91.9	12	26.0	76.3	1577	78.0	12	28.4	67.1	234	70.7	12
Random	12.4	91.7	1528	92.1	12	2.9	78.7	4	80.7	12	18.6	67.5	0	71.1	12
Long	7.1	92.7	832	93.2	12	2.8	78.7	1	80.1	12	18.5	67.5	0	70.9	12
Best	1.5	94.4	1	94.3	12	2.8	78.7	0	79.7	12	18.5	67.5	0	70.7	12
$F_{\max 1}$	1.7	94.4	30	95.4	9	2.8	78.7	0	79.7	9	18.5	67.5	0	70.8	9
$F_{\max 2}$	1.5	94.4	1	94.5	12	2.8	78.7	0	79.6	12	18.5	67.5	0	70.7	12
Total	1.5	94.4	1	94.7	36	2.8	78.7	0	79.6	36	18.5	67.5	0	70.7	36
S.E.	33.9	7.1	4521.2	6.7	9.2	34.2	3.2	2309.8	3.6	9.2	29	0.6	585.4	1.7	9.2
C.V. (%)	176.5	7.9	189.3	7.3	66.3	191.3	4.2	226.7	4.6	66.3	95	0.9	245.6	2.5	66.3

TABLE B.10. Decision matrix for the instances with 12 items and machines for different configurations with demand heterogeneity.

	40					60					80				
	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL
Dedicated	100	100	74 713	180.0	12	100	89.2	56 139	167.6	12	100	79.4	41 847	154.2	12
Cluster	99.5	100	74 362	194.0	24	91.1	94.3	51 137	187.8	24	73.0	89.0	30 479	174.3	24
Random	99.3	100	74 224	191.8	24	83.9	98.6	47 043	195.6	24	56.0	95.4	23 304	188.9	24
Long	99.2	100	74 190	190.0	24	82.0	99.8	45 956	196.3	24	51.3	96.9	21 332	194.3	24
Best	99.2	99.9	74 190	181.8	24	80.9	100	45 377	188.0	24	40.9	100	169 65	199.4	24
$F_{\max 1}$	99.1	100	74 182	181.8	18	80.8	100	45 377	186.6	18	41.4	100	17 170	197.8	18
$F_{\max 2}$	99.1	99.9	74 194	182.4	24	80.8	100	45 381	187.2	24	40.8	100	16 929	202.4	24
Total	99.1	100	74 165	197.4	144	80.8	100	45 365	206.4	144	40.7	100	16 902	203.0	144
S.E.	0.3	0	186.6	6.7	43.6	7.0	4.0	3930.1	11.1	43.6	21.2	7.4	8931.2	17.0	43.6
C.V. (%)	0.3	0	0.3	3.6	118.5	8.2	4.1	8.2	5.9	118.5	38.2	7.8	38.6	9.0	118.5
	100					120					140				
Dedicated	100	73.6	27 728	145.4	12	100	69.6	14 193	135.6	12	100	66.0	3316	130.6	12
Cluster	53.9	83.0	14 764	169.9	24	51.8	74.2	7190	149.5	24	38.6	67.2	1151	138.4	24
Random	25.8	89.1	6340	181.3	24	11.7	78.5	1361	160.0	24	15.1	68.0	224	141.2	24
Long	17.6	91.0	4611	184.2	24	3.3	79.3	149	161.6	24	9.2	68.1	0	141.9	24
Best	1.4	95.4	0	191.2	24	2.4	79.5	0	160.2	24	9.2	68.1	0	142.0	24
$F_{\max 1}$	2.2	95.2	207	196.6	18	2.4	79.5	1	160.6	18	9.2	68.1	0	141.4	18
$F_{\max 2}$	1.5	95.4	0	194.8	24	2.4	79.5	0	160.4	24	9.2	68.1	0	141.8	24
Total	1.4	95.4	0	190.0	144	2.4	79.5	0	160.6	144	9.2	68.1	0	141.6	144
S.E.	35.3	7.9	9917.7	17.0	43.6	35.8	3.7	5203.0	9.1	43.6	32.0	0.8	1172	3.9	43.6
C.V. (%)	138.4	8.8	147.9	9.3	118.5	162.3	4.7	181.8	5.9	118.5	128.1	1.1	199.9	2.8	118.5

TABLE B.11. Decision matrix for the instances with 24 items and machines for different configurations with demand heterogeneity.

	40					60					80				
	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL
Dedicated	100	100	193 468	360.0	24	100	100	136 176	360.0	24	100	100	79 701	359.8	24
Cluster	99.7	100	193 137	361.3	48	99.5	100	135 688	375.6	48	98.5	100	78 515	387.1	48
Random	99.7	100	193 137	361.0	48	99.4	100	135 595	372.7	48	98.1	100	78 182	391.8	48
Long	99.7	100	193 108	361.5	48	99.4	100	135 577	372.2	48	98.0	100	78 144	393.2	48
Best	99.7	100	193 070	360.0	48	99.3	100	135 471	366.2	48	97.6	100	77 873	373.8	48
$F_{\max 1}$	99.7	99.8	193 111	360.4	36	99.3	100	135 494	363.8	36	97.9	99.9	78 042	367.6	36
$F_{\max 2}$	99.8	99.5	193 157	360.4	48	99.3	100	135 466	373.0	48	97.6	100	77 863	375.8	48
Total	99.6	100	193 043	396.2	576	99.3	100	135 443	424.8	576	97.6	100	77 843	397.8	576
S.E.	0.1	0.2	132.3	12.6	188.7	0.2	0	241.7	20.4	188.7	0.8	0.1	619.8	13.6	188.7
C.V. (%)	0.1	0.2	0.1	3.4	172.3	0.2	0	0.2	5.4	172.3	0.8	0.1	0.8	3.6	172.3
	100					120					140				
Dedicated	100	92.2	31 758	343.2	24	100	77.5	7815	299.2	24	100	66.5	842	268.4	24
Cluster	88.6	92.8	28 057	363.8	48	61.6	77.5	4592	319.9	48	60.1	66.5	234	279.6	48
Random	81.0	93.0	25 575	379.1	48	27.1	77.5	1633	344.6	48	46.2	66.5	35	280.8	48
Long	79.6	93.0	25 156	376.9	48	16.4	77.5	673	358.3	48	43.5	66.5	1	280.7	48
Best	78.3	93.0	24 697	389.4	48	15.0	77.5	522	372.4	48	46.6	66.5	21	282.4	48
$F_{\max 1}$	84.2	92.8	26 579	359.2	36	53.2	77.5	3785	322.4	36	50.5	66.5	72	283.2	36
$F_{\max 2}$	79.6	93.0	25 119	385.4	48	26.6	77.5	1578	354.8	48	51.6	66.5	93	281.8	48
Total	77.9	93.0	24 611	379.0	576	13.8	77.5	490	350.6	576	43.4	66.5	0	277.2	576
S.E.	7.5	0.3	2433.1	15.4	188.7	30.4	0	2591.8	24.2	188.7	18.9	0	285.0	4.8	188.7
C.V. (%)	9.0	0.3	9.2	4.1	172.3	77.4	0	98.3	7.1	172.3	34.2	0	175.7	1.7	172.3

TABLE B.12. Decision matrix for the instances with 6 items and machines for different configurations with backlog and demand heterogeneity considering setup times.

	40					60					80				
	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL
Dedicated	100	81.4	56 439	73.3	6	100	99.9	42 893	90.0	6	100	96.1	31 032	88.7	6
Cluster	92.9	93.6	543 27	84.6	12	87.7	99.8	41 487	90.1	12	79.2	98.9	28 582	89.6	12
Random	92.5	94.0	53 985	84.8	12	85.7	100	41 076	90.1	12	72.5	100	28 017	90.2	12
Long	92.6	93.9	54 210	84.6	12	85.4	100	41 225	90.1	12	71.9	100	28 066	90.3	12
Best	90.9	97.3	53 590	87.9	12	82.8	100	40 625	90.3	12	68.3	100	27 844	90.4	12
$F_{\max 1}$	84.0	99.1	52 370	89.3	9	74.2	100	39 877	90.3	9	60.9	100	27 876	90.6	9
$F_{\max 2}$	84.0	99.1	52 367	89.5	12	74.1	100	39 911	90.3	12	60.6	100	27 687	90.7	12
Total	84.0	99.1	52 427	89.3	36	74.1	100	39 913	90.4	36	60.5	100	27 642	90.8	36
S.E.	5.7	5.9	1384.3	5.4	9.2	8.9	0	1036.7	0.1	9.2	13.3	1.3	1125.0	0.7	9.2
C.V. (%)	6.4	6.2	2.6	6.3	66.3	10.8	0	2.5	0.2	66.3	18.5	1.3	4.0	0.8	66.3
	100					120					140				
Dedicated	100	86.0	23 169	82.0	6	100	78.4	16 111	76.1	6	100	72.9	9351	70.5	6
Cluster	57.5	95.2	16 830	87.7	12	32.0	92.9	6896	86.6	12	22.0	83.2	2583	80.5	12
Random	45.1	99.8	15 011	90.8	12	19.6	96.7	4598	90.3	12	5.7	86.5	503	83.9	12
Long	45.8	99.5	15 199	90.8	12	17.5	97.3	4058	90.8	12	3.2	87.2	114	85.0	12
Best	39.4	99.8	15 209	90.8	12	10.1	99.8	2643	92.9	12	2.5	87.5	3	85.4	12
$F_{\max 1}$	39.0	99.7	15 631	90.4	9	11.7	99.5	2963	91.3	9	2.7	87.4	32	85.1	9
$F_{\max 2}$	37.7	99.8	15 091	91.5	12	9.7	99.8	2653	93.1	12	2.5	87.5	3	85.2	12
Total	37.6	99.9	15 089	91.7	36	9.6	99.8	2634	93.6	36	2.5	87.5	3	85.2	36
S.E.	21.2	4.9	2798.4	3.3	9.2	30.7	7.3	4599.6	5.8	9.2	33.9	5.1	3263.7	5.2	9.2
C.V. (%)	42.1	5.0	17.1	3.6	66.3	117.0	7.7	86.5	6.5	66.3	192.4	6.0	207.3	6.2	66.3

TABLE B.13. Decision matrix for the instances with 12 items and machines for different configurations with backlog and demand heterogeneity considering setup times.

	40					60					80				
	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL
Dedicated	100	68.3	111 915	123.0	12	100	99.1	86 504	179.6	12	100	93.2	64 582	172.2	12
Cluster	92.0	88.9	105 055	161.4	24	87.8	99.7	83 664	180.1	24	77.1	97.1	59 617	176.5	24
Random	92.0	88.9	81 957	160.5	24	86.6	99.8	81 957	180.3	24	73.4	99.1	57 168	180.0	24
Long	91.6	90.5	104 371	163.5	24	86.1	99.8	82 497	180.3	24	71.5	99.8	57 320	181.3	24
Best	89.0	98.4	101 479	177.8	24	82.1	100	82 025	180.2	24	63.4	100	58 363	181.4	24
$F_{\max 1}$	78.9	100	97 814	180.2	18	70.0	100	78 063	180.8	18	52.7	100	58 107	181.0	18
$F_{\max 2}$	78.9	99.9	97 794	180.0	24	69.9	100	78 082	181.2	24	52.4	100	57 915	182.2	24
Total	78.9	100	97 809	180.0	144	69.9	100	78 065	181.2	144	52.4	100	57 936	182.2	144
S.E.	7.9	10.8	8688.3	19.4	43.6	10.9	0.3	3078.3	0.6	43.6	16.4	2.4	2423.3	3.5	43.6
C.V. (%)	9.0	11.7	8.7	11.7	118.5	13.4	0.3	3.8	0.3	118.5	24.2	2.4	4.1	2.0	118.5
	100					120					140				
Dedicated	100	84.6	48 074	157.8	12	100	77.4	33 902	147.8	12	100	72.4	20 303	140.2	12
Cluster	62.9	91.4	39 819	168.0	24	46.8	86.3	22 468	161.1	24	38.6	79.3	11 079	153.1	24
Random	52.3	96.9	33 597	178.3	24	29.7	92.4	14 976	173.9	24	13.8	85.1	3392	165.4	24
Long	49.0	98.5	32 734	181.3	24	23.2	94.6	12 523	177.3	24	6.7	86.3	1931	167.9	24
Best	36.4	99.8	31 601	183.0	24	9.3	99.8	6448	188.2	24	2.1	88.3	8	171.2	24
$F_{\max 1}$	32.1	99.4	33 112	181.0	18	11.2	99.0	7815	184.4	18	2.4	88.6	62	175.8	18
$F_{\max 2}$	30.7	99.8	32 402	184.4	24	9.0	99.6	6724	189.4	24	2.2	88.7	0	176.0	24
Total	30.5	99.9	32 320	187.0	144	8.6	100	6382	195.6	144	2.1	88.5	0	172.6	144
S.E.	23.7	5.5	5715.0	9.8	43.6	31.4	8.1	9835.2	16.0	43.6	34.3	5.9	7379.0	12.5	43.6
C.V. (%)	48.1	5.7	16.1	5.5	118.5	105.7	8.7	70.7	9.0	118.5	163.3	6.9	160.5	7.6	118.5

TABLE B.14. Decision matrix for the instances with 24 items and machines for different configurations with backlog and demand heterogeneity considering setup times.

	40					60					80				
	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL	Min UB	Max CU	Min Back	Min NS	Min NL
Dedicated	100	55.0	274 743	198.0	24	100	100	221 911	360.0	24	100	100	164 652	360.0	24
Cluster	92.9	79.5	257 402	286.2	48	86.4	100	219 812	360.0	48	78.7	100	161 906	361.4	48
Random	93.2	78.3	258 783	282.0	48	86.6	100	208 647	360.0	48	77.6	100	160 445	360.7	48
Long	92.7	80.6	256 720	290.1	48	86.1	100	208 933	360.1	48	76.9	100	160 759	360.7	48
Best	89.7	100	244 629	360.0	48	81.1	100	206 351	359.8	48	68.5	100	162 433	362.2	48
$F_{\max 1}$	79.3	98.2	239 837	354.8	36	75.2	99.3	207 276	359.4	36	65.3	97.7	165 336	355.2	36
$F_{\max 2}$	79.1	100	239 435	359.8	48	74.9	100	205 035	361.0	48	64.7	98.6	164 613	359.0	48
Total	79.1	100	239 213	360.4	576	74.9	100	205 912	361.2	576	63.9	100	164 104	364.0	576
S.E.	8.1	16.1	12 733.2	58.3	188.7	8.6	0.2	6561.1	0.6	188.7	12.0	0.8	1892.4	2.6	188.7
C.V. (%)	9.1	18.6	5.1	18.7	172.3	10.4	0.2	3.1	0.2	172.3	16.2	0.8	1.2	0.7	172.3
	100					120					140				
Dedicated	100	99.3	108 294	358.4	24	100	95.1	57 818	347.4	24	100	85.7	21 793	320.4	24
Cluster	73.7	99.8	109 736	362.9	48	70.9	97.3	56 521	360.0	48	63.8	86.8	18 377	332.0	48
Random	66.3	99.7	109 007	365.6	48	53.0	98.3	56 893	370.5	48	37.2	87.3	16 181	338.7	48
Long	65.1	99.7	109 495	364.8	48	50.6	98.5	56 748	373.5	48	33.4	87.4	15 636	339.7	48
Best	54.0	99.4	110 850	364.8	48	44.5	98.5	58 324	372.2	48	32.2	87.7	16 492	344.2	48
$F_{\max 1}$	54.4	94.8	114 227	348.2	36	50.6	92.0	64 720	340.4	36	48.4	85.7	20 390	324.6	36
$F_{\max 2}$	52.5	96.9	112 640	356.6	48	44.5	95.7	60 332	358.6	48	38.5	86.6	18 497	334.0	48
Total	50.7	100	110 389	376.4	576	40.0	99.9	57 225	391.4	576	26.4	88.2	15 204	362.4	576
S.E.	16.5	1.8	1972.8	8.2	188.7	19.8	2.5	2769.5	16.2	188.7	24.2	0.9	2367.1	12.9	188.7
C.V. (%)	25.5	1.9	1.8	2.3	172.3	34.9	2.6	4.7	4.4	172.3	50.9	1.0	13.3	3.8	172.3

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