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Benefits of robust multiobjective optimization for flexible automotive assembly line balancing

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Abstract Changing conditions and variations in the demand are frequent in real industrial environments. Decision makers have to take into account this uncertainty and manage it properly. One clear example is the automotive industry where manufacturers have to assume an uncertain and heterogeneous demand. For instance, automotive manufacturers must adapt their decisions when balancing the assembly line by considering different flexible solutions. Our proposal is using robust multiobjective optimization and simulation techniques to provide managers with a set of robust and equally-preferred solutions for assembly line balancing. We study a Nissan case where the demand of each product family is uncertain. The problem is addressed by considering a robust multiobjective model for assembly line balancing based on a high number of production plans. After the selection of six different assembly line configurations, we study the implications of robustness metrics based on workstations' overload. We show that the adverse managerial effects of not having flexible line configuration when demand changes are alleviated. For the real Nissan automotive case, our analysis and conclusions show the

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managerial and industrial benefits of using robust assembly lines. We also encourage decision makers to use robust multiobjective optimization methods for selecting the most flexible decisions.

Keywords Flexibility · Assembly line balancing · Uncertain demand · Robust optimization

1 Introduction

Most advanced manufacturing industries normally use the same assembly line for assembling different product types. There is a product-oriented production system, able to assemble similar products but with different characteristics. One example is the automotive industry, where major auto assemblers such as Ford, General Motors, and Chrysler have begun to overhaul some of their previously specialized car-assembly plants into "flexible factories" to produce several models on the same production line (Eynan and Dong 2012; Moreno and Terwiesch 2015). The proliferation of product varieties is mandated by competition and customer demands and is clearly evident in the automotive industry (AlGeddawy and ElMaraghy 2010). As also shown by AlGeddawy and ElMaraghy (2010), this is well demonstrated in the example of car engine accessories where families of products that exhibit wide variety exist; yet they have many common functions, components, and assembly processes.

The assembly of these different products is based on similar processing tasks with common features but require, for each product type, different components, specific work, and tools. But within this industrial context, even small variations in the demand of the products' type could lead to unstable assembly line balancing and therefore, a need of constant re-balancing operations (Chica et al. 2016). An a posteriori adaptation to the latter variations corresponds to the reaction of an already existing manufacturing system to changes in the product (ElMaraghy and AlGeddawy 2012). Building flexible manufacturing systems a priori can better manage these production changes. In general, flexibility has to be an important asset to manufacturing firms (Moreno and Terwiesch 2015) and specifically, setting a flexible and proper assembly line configuration is increasing in importance nowadays.

The tasks of an assembly line divide the manufacturing of a production item. A well-known and difficult problem in operations research is to determine how these tasks can be assigned to the stations fulfilling certain restrictions, and it is called assembly line balancing (ALB) (Boysen et al. 2007, 2008; Battaïa and Dolgui 2013). ALB problems optimally partition tasks to stations with respect to some objective (such as the cycle time of the assembly line) in such a way that all the precedence constraints are satisfied. Within the set of available ALB problems, one realistic variant is the time and space assembly line balancing problem (TSALBP) (Bautista and Pereira 2007). TSALBP considers the linear space of tasks and line's workstations and makes use of a multiobjective problem definition (Miettinen 1999; Greco et al. 2005) to search for a set of optimal solutions to three optimization criteria: m (number of stations), c (cycle time), and A (linear area of the stations).

However, the majority of the existing ALB models assume a fixed balance of the assembly lines when producing mixed products. This assumption is not appropriate, especially when managing high-variant mixed-model assembly lines (Dörmer et al. 2015). One example in the automotive industry is assembling engines. This is because of fluctuations caused by clients' calendars and the rise in the variety of final engines in the last decades (e.g., producing 40 variants in the same week) (Garcia-Sabater et al. 2012). These engines' demands are not usually fixed and certain, and when the assembly line produces mixed products in a given sequence (Boysen et al. 2010), the model cannot only consider the operation time of the tasks as the averaged times of the different products and their demand. If the demand changes, the operation time also changes and the assembly line configuration may need a re-balancing. This re-balancing may cause production losses because those workers assigned to workstations will have to comply with new tasks and increase their learning curve to work in the assembly line.

New optimization models such as those considering robust solutions (Beyer and Sendhoff 2007; Ben-Tal et al. 2009; Roy 2010) have emerged, given their possible benefits to managerial decisions in the production system of the plant. In this work, we will focus on a multiobjective robust ALB model (the r-TSALBP) to study a set of flexible ALB solutions to a real automotive case study. We define a "flexible" ALB solution as a solution which is able to easily absorb changes in the input (i.e., demand) without being replaced by another one. The r-TSALBP integrates the concepts of robust optimization and multiobjective optimization to find the most flexible and efficient assembly line configurations (i.e., in terms of a sufficient minimization of number of stations and their area, m and A). The model links robustness with the flexibility of an assembly line configuration when demand changes according to a set of real production plans. One production plan is defined as the demand for each type of product to be assembled. The model identifies and measures how robust a assembly line configuration is for a set of production plans according to both operation time and the linear area (i.e., one dimensional length) needed for workers and tools to perform the tasks of the assembly line.

Three temporal non-robustness metrics, set as optimization constraints, are proposed to measure the robustness of the assembly line configurations. Our proposed metrics provide a way to identify the least flexible workstations when having different production plans. These metrics define when a solution is robust or not (i.e., feasible or unfeasible) taking into account the uncertainty defined by a set of possible demand scenarios (i.e., production plans). These three temporal non-robustness metrics are calculated based on those stations which are overloaded by the production plans. The first one measures how many production plans overload the stations of the assembly line (g_1^c). The second one, g_2^c, is a ratio of the overloaded stations by any production plan. Finally, the third metric, g_3^c, measures the averaged exceeding processing time of the stations with respect to the set of production plans.

Additionally, we propose a novel methodology for robust ALB by making use of a Monte Carlo simulation technique to better evaluate the risk of deploying the assembly line configurations under changing conditions. To the best of our knowledge, this is the first attempt of using simulation techniques to extend the evaluation of the robustness of assembly line configurations. In general, simulation modeling is the best approach for dealing with the optimization of systems under uncertainty (Borshchev and Filippov 2004) because a simulation model can capture the system variation in a realistic way while still producing results that can be made as accurate as desired. The hybridization of simulation techniques with the EMO algorithms will provide automotive decision makers with a flexible and rich tool when dealing with optimization problems in uncertain domains (Juan et al. 2016).

Finding a flexible configuration will also have a positive impact on the management of the plant as different departments will obtains benefits (from planning to production departments). In order to empirically show this, we apply the methods to a real engine assembly line of the Nissan automotive industrial plant in Barcelona (Spain). The results of the case study are evaluated in terms of the managerial and industrial advantages for the company and how the lack of using a robust approach can generate difficulties in several departments of the organization. To do this we first solve the assembly line balancing problem of the Nissan case study by using two evolutionary multiobjective optimization (EMO) algorithms (Talbi 2009; Coello et al. 2007), with and without robustness mechanisms. The first algorithm is the standard non-robust NSGA-II (Deb et al. 2002). The second one is our adaptive IDEA which is applied to the robust r-TSALBP model. The adaptive IDEA is an extension of the original IDEA version (Singh et al. 2008) to search for robust solutions by making IDEA adaptive. This behavior is achieved by dividing the population of the algorithm in robust and non-robust subpopulations of solutions and by adapting the size of both populations depending on the robustness of the Pareto archive in every generation.

During the experimentation of the study we start by selecting three pairs of Pareto-optimal assembly line configurations with 18, 21, and 23 workstations. These configurations are non-dominated solutions obtained by the two EMO algorithms with and without a specific robust search. They are evaluated for the Nissan case study by the non-robustness metrics and, by using the Monte Carlo simulation approach, the set of demand scenarios is increased up to 1000 different demand plans. The use of the latter simulation method allows us to better measure the reliability of the robustness of the configuration solutions and to compare the results against the non-robust approaches.

Next Sect. 2 presents some background information and our research methodology (i.e., multiobjective robust optimization, the use of simulation for uncertainty, and the r-TSALBP model). Then, Sect. 3 explains the case study used in our work and the methods' details. Section 4 describes the experimental results. Finally, Sect. 5 discusses the implications and benefits of our proposal for making managerial decisions and presents some concluding remarks.

2 Background and research methodology

We first describe the mathematical ALB problem (Sect. 2.1). Later, multiobjective and robust optimization are described in Sects. 2.2 and 2.3, respectively. How simulation can be used as a tool in optimization under uncertainty is presented in Sect. 2.4. Finally, a multiobjective model for ALB that considers uncertainty in its formulation is described in Sect. 2.5.

2.1 Assembly line balancing description

Mathematically, a general ALB problem is defined as follows. We divide the manufacturing of a production item into a set J of n tasks. ALB problems focus on grouping the latter set of tasks J in workstations by an efficient and coherent way (Baybars 1986; Scholl and Becker 2006; Dolgui and Kovalev 2012). A subset of tasks S_k ($S_k \subseteq J$) is assigned to each station $k = \{1, 2, \ldots, m\}$, called the workload of the station. Each task j requires an operation time for its execution $t_j > 0$ that is determined as a function of the manufacturing technologies and the employed resources. Each station k has a workload time $t(S_k)$ which is equal to the sum of the processing times of its assigned tasks (workload of the station) and cannot exceed the cycle time of the assembly line, c.

Each task j is assigned to a single station k and has a set of direct "preceding tasks" P_j which must be accomplished before j is started. These constraints are normally represented by means of an acyclic precedence graph. The vertices of the graph represent the tasks where a directed arc (i, j) indicates that, on the production line, task i must finish before the start of task j.

Recently and because of the need of introducing space constraints in ALB, researchers started to additionally consider the linear area (i.e., one dimensional length needed by workers) associated to each task j by means of a new model variable a_j. Each station k has also a linear area $a(S_k)$ which is equal to the sum of the areas required by the tasks assigned to it (S_k). The linear area of the assembly line A is the highest linear area of the stations, defined by $A = max_{k=1,2,\ldots,m} a(S_k)$. This new family of models is called TSALBP (Bautista and Pereira 2007) and introduces additional space features to ALB.

TSALBP states that, for a set of n tasks, restricted by the precedence graph, and with their temporal t_j and spatial a_j attributes ($1 \leq j \leq n$), each task must be assigned to a single station in a way that: (i) every precedence constraint is satisfied, (ii) no station workload time ($t(S_k)$) is greater than the cycle time (c), and (iii) linear area required by any station ($a(S_k)$) is not greater than the available linear area per station (A).

2.2 Multiobjective optimization

Multiobjective optimization considers multi-criteria decision problems involving more than one objective function to be optimized simultaneously (Miettinen 1999; Greco et al. 2005; Ehrgott 2006; Branke et al. 2008). Typically in multiobjective optimization there is not a single solution that simultaneously optimizes each objective. Instead, there is a set of Pareto optimal solutions. A solution is called non-dominated or Pareto-optimal if none of the objective functions can be improved in value without degrading one or more of the other objective values. The set of Pareto optimal solutions is often called the Pareto front. Multiobjective optimization can be mathematically described by $min_{x \in T} F(x)$ where $F(x) = [f_1(x), \ldots, f_m(x)]$ is the m-dimensional function to be optimized and T is the set of constraints applied to the decision variables of the problem x: $T = \{x \in \mathbb{R}^n : g(x) = 0, h(x) \geq 0\}$.

These optimization problems arise when optimal decisions need to be taken in the presence of trade-offs between two or more conflicting objectives. This is the case of ALB and specifically, the TSALBP, where some models consider the need of optimizing more than one objective at the same time. For instance, the majority of the TSALBP variants consider the joint minimization of the cycle time c, linear area of stations A, and number of stations m (Bautista and Pereira 2007).

Metaheuristics are a family of approximate non-linear optimization techniques that provide acceptable solutions in a reasonable time even when problems are hard and complex (Talbi 2009). Population-based metaheuristics such as evolutionary algorithms are well-suited for handling complex multi-objective problems (Mukhopadhyay et al. 2014). One of the most well-known metaheuristic for tackling multiobjective problems is evolutionary multiobjective optimization (EMO) (Deb et al. 2002; Coello et al. 2007). These EMO algorithms are one of the most popular approaches to generate Pareto optimal solutions by evolving a set of solutions simultaneously in one run and in a reasonable time (Coello et al. 2007; Talbi 2009; Shen and Yao 2015). In the past 20 years, EMO received much attention and researchers have applied it to many areas (Eiben and Smith 2015), showing successful applications in problems such as scheduling (Zhu et al. 2016), manufacturing systems (Shen and Yao 2015; Rada-Vilela et al. 2013; Chica et al. 2011), and industrial robotics (Gao and Zhang 2015). The main advantage of these algorithms for solving multicriteria problems is the fact that they typically generate sets of various non-dominated solutions, allowing the computation of an approximation of the entire Pareto front. Some of the most popular EMO algorithms in the literature are NSGA-II (Deb et al. 2002) and MOEA-D (Zhang and Li 2007).

2.3 Robust optimization

2.3.1 Robustness definition and robust EMO

The traditional formulation of optimization problems, both single and multiobjective, is inherently static and deterministic. However, reality is dynamic and uncertain: environmental parameters fluctuate, materials wear down, processing or transportation times vary, clients change their demands, etc (Beyer and Sendhoff 2007; Ben-Tal et al. 2009). When uncertainty is not added to the optimization process, the optimized solutions for those systems can be unstable and sensitive to small changes.

There are different robustness concepts in the literature, see e.g. (Beyer and Sendhoff 2007; Ben-Tal and Nemirovski 2002; Bertsimas et al. 2011). A way to tackle with this uncertainty in optimization is by providing solutions to the optimization problem with a high degree of robustness. One of the most common way to obtain robust solutions is to calculate the desired robustness measures and the related (robust) constraints explicitly (Beyer and Sendhoff 2007). In some cases, as ours, robustness measures are included in the original problem formulation as additional constraints or objective functions. Therefore, the problem properly handles uncertainty but still has a deterministic mathematical formulation.

With respect to EMO, the work of Deb and Gupta (2006) is the first and one of the most important contributions in introducing robustness in this kind of algorithms. The authors define a robust solution as one which is least sensitive to the perturbation of the decision variables in its neighborhood. More recently, Mirjalili and Lewis (2015) proposed performance metrics for robust EMO and Gaspar-Cunha et al. (2014) presented sets of robust test problems accounting for the different types of robustness cases and non-dominated solutions were classified according to their degree of robustness.

2.3.2 Robust assembly line balancing

In this publication we focus on the uncertainty coming from changes of the environmental and operating conditions which are changes in the demand for the products to be assembled. These uncertainties are modeled through the input quantities provided by the environment of the system to be optimized (also known as Type I variations in Tsui and Mistree 1996).

With respect to ALB, one of the most common ways of finding robust solutions is to search for the solutions that perform well across all possible scenarios (Battaïa and Dolgui 2013). Using this approach, Xu and Xiao (2011) dealt with the mixed ALB problem variant and proposed a lexicographic-order on the α-worst case scenario (i.e., a scenario for which the system performs equally or better than for $\alpha \times 100\%$ of all scenarios). The majority of the approaches existing in the literature for robust ALB are based on considering uncertainty in the input attributes of the tasks, such as operation time, by defining interval values or by setting different plausible scenarios (i.e., set of possible values for the input attributes depending on past actions or historical data). The most used robust criteria rely on the worst case by using traditional min-max or variations of it (Dolgui and Kovalev 2012; Simaria et al. 2009; Xu and Xiao 2011; Saif et al. 2014).

Dolgui and Kovalev (2012) proposed an ALB model and a dynamic programming method to minimize the cycle time by following a worst scenario approach; while Li and Gao (2014) characterized unstable demand in manual mixed-model assembly lines by several representative scenarios. Another well-known uncertainty focus in ALB is the time: task times have uncertain values by defining intervals or known distributions. For instance, Gurevsky et al. (2012) dealt with the SALBP-E when having task times within intervals and proposed a way to find a compromise between the objective function minimization and a stability ratio . A related stability study was done in Gurevsky et al. (2013) but for the case of an ALB problem where a workstation can have several workplaces, there are exclusion constraints, and the processing times of the tasks can vary during the cycle of the assembly line.

Chica et al. (2013) also defined a set of scenarios and proposed a visual representation of the optimal solutions to quantitatively measure and represent how robust the assembly line configuration is on the set of scenarios or production plans. The work of Papakostas et al. (2014) also evaluated a posteriori the solutions of a model for minimizing time and cost through a set of demand profiles but they used single-objective particle swarm optimization.

2.4 Simulation when optimizing under uncertainty

Simulation techniques allow the modeling of complex systems in a natural way (Nance and Sargent 2002; Gass and Assad 2005). These techniques can be incorporated into optimization models without a mathematical sophistication and the computational time typically stays manageable (Lucas et al. 2015). Simulation techniques can be considered as a powerful tool to detect and evaluate those situations where risks could appear and also provide with a robust optimization solution. Although there are different kinds of simulation, Monte Carlo simulation has been proved to be useful for obtaining numerical solutions to complex problems which cannot be efficiently solved by using analytic approaches (Kroese et al. 2014). This kind of simulation is defined as a set of techniques that make use of random number generation to solve certain stochastic or deterministic problems. Hence, by using this simulation approach, a solving method can be naturally extended to consider a different distribution for each stochastic variable.

EMO methods can make use of simulation paradigms to be employed when solving optimization problems under uncertainty (Juan et al. 2016, 2015). This extension of EMO algorithms is oriented to efficiently tackle an optimization problem involving stochastic components. The stochastic components can be either located in the objective function (e.g., random customers demands, random processing times, etc.) or in the set of constraints (e.g., customers demands that must be satisfied with a given probability, deadlines that must be met with a given probability, etc.).

As mentioned before, several works in the literature deal with the combination of EMO algorithms and robust optimization (Beyer and Sendhoff 2007). However, just a few of them also use Monte Carlo simulation. Deb and Gupta (2006) explained two procedures to introduce the robustness concept into multi-objective optimization and demonstrated their benefits for a particular engineering design problem. One work in the literature which proposes a similar approach to ours is the one of Sahali et al. (2015). They developed and implemented a genetic algorithm, based on an evaluation mechanism of objective functions, which integrate the Monte Carlo simulation to calculate the robustness of the objective function and different constraints. We will use Monte Carlo simulation as our simulation method.

Regarding unbalanced assembly lines some authors have used simulation to investigate them, for example taking into account their operation time means, coefficients of variation and/or buffer sizes (Shaaban and Hudson 2012). In the particular case of the TSALBP, uncertainty may appear in different parts of the optimization process such as the uncertain demand of the products (Chica et al. 2013, 2016). Several particular scenarios can be generally stated in order to test the robustness of solutions. However, we might miss risk situations if solutions are just tested with a small number of discrete scenarios. Therefore, simulating a high number of possible scenarios will have a great impact in the evaluation of how assembly line configurations behave under these conditions. We could obtain a more realistic measure of robustness by taking into account a higher number of more diverse risk situations for the set of production plans.

2.5 Mathematical definition of the r-TSALBP

In this section we describe the mathematical model for a multiobjective robust ALB. This is a multiobjective optimization problem which models uncertainty in the demand by setting production plans as an input. The model can be solved by robust optimization methods with or without simulation techniques. This model is called r-TSALBP and is a multiobjective TSALBP variant which minimizes two objectives: the number of stations (m) and their linear area (A).

The r-TSALBP model incorporates the concept of flexibility which means an assembly line configuration able to cope with demand changes. These demand changes are defined through production plans which set the mix of products to be assembled in the assembly line. The goal of this model is to identify the most flexible assembly line configurations for a set of production plans by searching for the most robust solutions based on three non-robustness temporal metrics.

In this model, we assume that two workers are assigned to each station and therefore, by minimizing the number of stations, we implicitly minimize the number of workers because the factory must meet the demand with the minimum number of workers (Chica et al. 2010). With respect to the machinery and required tools, the r-TSALBP assumes that the required tools and components to be assembled should be distributed along the sides of the line. In addition, in the automotive industry, some operations can only be performed on one side of the line. Then, the linear area of the stations restricts the physical space where tools and materials can be placed.

2.5.1 Introducing uncertainty by production plans

r-TSALBP manages the uncertainty in the demand of products by including a set I of product types. Being J the set of tasks to be assembled, a task $j \in J$ requires a processing time of t_{ji} for assembling product $i \in I$. r-TSALBP refers Ψ to the set of assembly line configurations and ψ to a specific assembly line configuration which belongs to the set. The same applies to the spatial features of the tasks of the assembly line but, in this paper, we focus the uncertainty in the temporal feature of the ALB problem.

We define E as the set of realistic production plans to model the demand variation of the mix of products to be assembled. One of the plans of E is called the reference production plan, ε^0, and ψ^0 is its assembly line configuration of reference. Typically, this reference plan ε^0 is the one having a balanced demand for the products of I.

Given a production plan $\varepsilon \in E$, defined by a demand vector $\overrightarrow{d}_\varepsilon = (d_{1\varepsilon}, d_{2\varepsilon}, \ldots, d_{|I|\varepsilon})$, we can determine the average processing time of task $j \in J$ for this plan ε by Eq. 1:

$$\bar{t}_{j\varepsilon} = \frac{1}{D_\varepsilon} \sum_{i=1}^{|I|} t_{ji} d_{i\varepsilon}, \tag{1}$$

where D_ε is the global demand of plan ε given by $D_\varepsilon = \sum_{i=1}^{|I|} d_{i\varepsilon}$.

Table 1 shows the main variables and parameters of the r-TSALBP. Additionally, Table 2 shows the associated restrictions of the proposed model.

Equations 2 and 3 show the two objective functions of the r-TSALBP model. The first equation defines the number of stations of the assembly line configuration while the second one sets the one dimensional linear area (i.e., maximum length for each station) of the assembly line.

$$f^1(x) = m = \sum_{k=1}^{UB_m} \max_{j \in J} \{x_{jk}\}, \tag{2}$$

$$f^2(x) = A = \max_{k \in K} \left\{ \sum_{j=1}^{|J|} a_j x_{jk} \right\}. \tag{3}$$

In the next two sub-sections we first define the r-TSALBP non-robustness metrics and second, how to use them as constraints within an optimization method to find flexible assembly line solutions.

Table 1 Main parameters and variables of the r-TSALBP model

J	Set of all the elementary processing tasks of the line ($j = 1, \ldots, \|J\|$)
n	Number of tasks of the line: $n = \|J\|$
K	Set of workstations ($k = 1, \ldots, \|K\|$), $\|K\|$ is equal to objective m
c	Cycle time of the assembly line
Ψ	Set of line configurations ($\psi = 1, \ldots, \|\Psi\|$)
E	Set of demand production plans ($\varepsilon = 1, \ldots, \|E\|$)
$\bar{t}_{j\varepsilon}$	Average processing time of the elementary task $j \in J$ (measured at normal work pace) in production plan $\varepsilon \in E$
a_j	Linear area of the elementary task $j \in J$
P_j	Set of immediate "preceding tasks" which must be accomplished before j is started
UB_m	Upper bound of the number of stations. It is equal to the number of tasks
Δ^c	Maximum exceeding time for all the stations $k \in K$ at normal work pace. $\Delta^c = \gamma_c c$
x_{jk}	Binary variable being 1 if task $j \in J$ is assigned to station $k \in K$. Otherwise its value is 0
S_k	Subset of tasks assigned to each station $k \in K : S_k = \{j \in J : x_{jk} = 1\}$ (referred as the workload of the station)
$y^c_{k\varepsilon}$	Binary variable being 1 if the processing time required in station $k \in K$ for the production plan $\varepsilon \in E$ ($\sum_{j \in S_k} \bar{t}_{j\varepsilon}$) exceeds the cycle time c. Otherwise, 0

Table 2 Restrictions of the r-TSALBP model

Binary condition of the station-task assignment variable:
$x_{jk} \in \{0, 1\}, \quad (j = 1, \ldots, \|J\|; k = 1, \ldots, \|K\|)$
Binary conditions to denote variables exceeding time and/or linear area, respectively:
$y^c_{k\varepsilon} \in \{0, 1\}, \quad (k = 1, \ldots, \|K\|; \varepsilon = 1, \ldots, \|E\|)$
Every task must be assigned to just one single station:
$\sum_{k=1}^{\|K\|} x_{jk} = 1, \quad (j = 1, \ldots, \|J\|)$
Every station must contain at least one task:
$\sum_{j=1}^{\|J\|} x_{jk} \geq 1, \quad (k = 1, \ldots, \|K\|)$
The assignment cannot violate the immediate precedence relations:
$\sum_{k=1}^{\|K\|} k(x_{ik} - x_{jk}) \leq 0, \quad (i \in P_j, j = 1, \ldots, \|J\|)$
The station workload time cannot exceed the maximum cycle time (including the defined allowance):
$\sum_{j=1}^{\|J\|} \bar{t}_{j\varepsilon} x_{jk} \leq (c + \Delta^c y^c_{k\varepsilon}), \quad (k = 1, \ldots, \|K\|; \varepsilon = 1, \ldots, \|E\|)$
The sum of linear areas of tasks assigned to a station cannot exceed the maximum linear area of the assembly line:
$\sum_{j=1}^{\|J\|} a_j x_{jk} \leq A. \quad (k = 1, \ldots, \|K\|)$

2.5.2 *Temporal non-robustness metrics*

The r-TSALBP formulation adds metrics to measure the overload of the workstations and production plans with respect to the cycle time c. These metrics are normalized to [0, 1] and make use of $y^c_{k\varepsilon}$, a binary variable being 1 if the processing time required in station $k \in K$ for the production plan $\varepsilon \in \mathrm{E}$ $\left(\sum_{j \in S_k} \bar{t}_{j\varepsilon}\right)$ exceeds the cycle time c, and 0 otherwise. These non-robustness metrics are defined as follows:

- g^1_c: Rate of overloading production plans which overload at least one station k (Eq. 4).

$$g^1_c = \frac{1}{\mid \mathrm{E} \mid} \sum_{\varepsilon=1}^{|\mathrm{E}|} \max_{k \in K} y^c_{k\varepsilon}. \tag{4}$$

- g^2_c: Rate of overloaded stations, by at least one production plan, with respect to the allowed workload time (Eq. 5, where m is the number or stations). Note that g^2_c is a dynamic rate as it depends on the number of stations of the configuration m, one of the objectives to be minimized in the model.

$$g_c^2 = \frac{1}{m} \sum_{k=1}^{|K|} \max_{\varepsilon \in \mathrm{E}} y_{k\varepsilon}^c. \tag{5}$$

- g_c^3: Proportion of exceeding processing time of the stations in all the plans with respect to the maximum exceeding time and number of overloaded stations (Eq. 6).

$$g_c^3 = g_c^3(x) = \frac{1}{\Delta^c \sum_{\varepsilon=1}^{|\mathrm{E}|} \sum_{k=1}^{|K|} y_{k\varepsilon}^c} \sum_{\varepsilon=1}^{|\mathrm{E}|} \sum_{k=1}^{|K|} \left(\max \left\{ 0, \sum_{j=1}^{|J|} \bar{t}_{j\varepsilon} x_{jk} - c \right\} \right), \tag{6}$$

where Δ^c is the maximum allowable processing time above cycle time for any workstation at a normal work pace. To ease the decision maker definition of the model, Δ^c is usually defined as $\Delta^c = \gamma_c c$ where γ_c is a flexibility control parameter for exceeding cycle time.

2.5.3 Using the temporal non-robustness metrics as constraints of the model

We use the temporal non-robustness metrics defined in Sect. 2.5.2 as constraints within the optimization model. Using these constraints we are able to inject the robustness concept during the optimization process by filtering those solutions which do not fulfill the temporal constraints. These non-robust solutions are not valid for the multiobjective optimization method (i.e., unfeasible solutions). The following constraints define the robust and non-robust solutions:

$$g_c^1 \le \tilde{g}_c^1; g_c^2 \le \tilde{g}_c^2; \quad g_c^3 \le \tilde{g}_c^3,$$

where $\{\tilde{g}_c^1, \tilde{g}_c^2, \tilde{g}_c^3\}$ are parameters defined in [0, 1] that restrict the temporal non-robustness metrics.

Analogously, we can define the robustness temporal ratios as $r_c = 1 - g_c$. A decision maker could inject their preferences about her/his desired robustness level by using minimum temporal robustness parameters $\tilde{r}_c^1$, $\tilde{r}_c^2$, and $\tilde{r}_c^3$. These parameters define the latter temporal constraints by $\tilde{g}_c^1 = 1 - \tilde{r}_c^1$, $\tilde{g}_c^2 = 1 - \tilde{r}_c^2$, and $\tilde{g}_c^3 = 1 - \tilde{r}_c^3$. An illustrative example of the use of this constraint is the following: the decision-maker robustness preference $\tilde{r}_c^1$ is set to 0.6 and then, the non-robustness parameter $\tilde{g}_c^1$ is equal to 0.4. A feasible solution for the r-TSALBP will be a solution which is robust in the 60% of the production plans (according to the workload of the stations).

3 The automotive case study

In this section we describe the case study used in this paper. First, Sect. 3.1 shows the data collected for the experimentation and later, Sect. 3.2 describes the methods and parameters used for running the computational experiments.

3.1 Industrial data description

The cases study involves the data of the engines' assembly line of the Nissan Motor Iberica plant, located in Barcelona. This assembly line assembles up to nine different types of engines ($P_1, P_2, \ldots, P_9$). Figure 1 shows one of these engines, the one of the Nissan Pathfinder. The number of elementary tasks for manufacturing one engine is 380 but for simplification, those tasks were grouped in 140 operations. Information about preceding tasks, operating times, and area is shown in Appendix C of the supplemental material file. All of the engines have different destinations and features. The first three engines, P_1, P_2, P_3, are for 4x4 vehicles. Engines P_4 and P_5 are for vans; and the last four types (P_6–P_9) are for commercial trucks of medium tonnage.

Under conditions of demand equilibrium (i.e., equal demand for the all the engines) and a cycle time of 3 min, the assembly line is balanced by 21 workstations with an average length of 4 m each. However, the engines' demand is not usually homogeneous or identical for the nine types of engines. This fact means that, although the assembly line maintains a daily production of 270 units, it should be able to adapt to different production plans based on the partial demands of each type of engine.

The present case study has a cycle time of $c = 180$ s, which allows to manufacture 270 engines for an effective day of 13.5 h uniformly distributed in two shifts. Table 3 shows the most usual(-236.100l1987792(be)]TJ50[(able)-103(cycle)-254103(pla

Table 3 Units of demand of 23 production plans for the nine engine types ($P_1, P_2, \ldots, P_9$) during a 13.5 h day divided into two shifts

Plan	Family									Total
	4 × 4			Vans		Trucks				
	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	
1	30	30	30	30	30	30	30	30	30	270
2	30	30	30	45	45	23	23	22	22	270
3	10	10	10	60	60	30	30	30	30	270
4	40	40	40	15	15	30	30	30	30	270
5	40	40	40	60	60	8	8	7	7	270
6	50	50	50	30	30	15	15	15	15	270
7	20	20	20	75	75	15	15	15	15	270
8	20	20	20	30	30	38	38	37	37	270
9	70	70	70	15	15	8	8	7	7	270
10	10	10	10	105	105	8	8	7	7	270
11	10	10	10	15	15	53	53	52	52	270
12	24	23	23	45	45	28	28	27	27	270
13	37	37	36	35	35	23	23	22	22	270
14	37	37	36	45	45	18	18	17	17	270
15	24	23	23	55	55	23	23	22	22	270
16	30	30	30	35	35	28	28	27	27	270
17	30	30	30	55	55	18	18	17	17	270
18	60	60	60	30	30	8	8	7	7	270
19	10	10	10	90	90	15	15	15	15	270
20	20	20	20	15	15	45	45	45	45	270
21	60	60	60	15	15	15	15	15	15	270
22	20	20	20	90	90	8	8	7	7	270
23	10	10	10	30	30	45	45	45	45	270

Each of the latter production plans leads to a weighted average process time for the 140 tasks of the case study. For example, task $j = 13$ has processing times of 1620, 1575, 1470, 1350, 1425, 1530, 1500, 1380, and 1650 cs for engines from type P_1 to P_9, respectively. Meanwhile, the corresponding demands to these engines according to plan number 12 are: 24, 23, 23, 45, 45, 28, 28, 27 and 27 units. Therefore, the weighted average of the process time for operation $j = 13$ is 1483 cs in plan 12, in contrast to 1532 cs in plan 9. For more data about the production plans and tasks processing times, the supplemental material file shows the weighted processing times of all the 140 assembly operations according to the seven representative plans.

3.2 Experimental setup

3.2.1 Parameters for the optimization methods

In order to obtain the results for the case study we use the r-TSALBP model defined in Sect. 2.5 with the production plans of the Nissan engine (described in previous Sect. 3.1). For this case, the reference plan ε^0 for the r-TSALBP is the one having a balanced demand for all the products of I (i.e., first plan with 30 products of each type of engine).

The minimum robustness value injected by the decision maker prior to the search as their preferences are $\tilde{r}_c^1 = 0.75$, $\tilde{r}_c^2 = 0.9$, $\tilde{r}_c^3 = 0.95$. These values will determine how robust assembly line solutions are and will influence the final set of non-dominated solutions offered to the decision maker. The allowed exceeding cycle time for each station is $\gamma_c = 0.05$ s.

The experimentation comprises the run of two EMO algorithms to solve the Nissan case study. The first algorithm is an adaptation of the well-known NSGA-II (Deb et al. 2002) for solving the TSALBP. This method does not consider uncertainty in the demand and therefore, solves a traditional ALB problem. The second algorithm is the adaptive IDEA which was proposed in Chica et al. (2016) to solve the r-TSALBP. This extension of the original IDEA (Singh et al. 2008) searches for robust assembly line solutions by dividing the evolutionary algorithm population in two sub-populations. One sub-population only includes robust solutions but the other sub-population includes non-robust solutions to provide the algorithm with a higher diversity. The number of solutions of both populations change during the run of the algorithm and is adapted depending on the robustness of the set of non-dominated solutions at every generation. For more information about this robust EMO please refer to Chica et al. (2016).

The parameters of both EMO algorithms are the following. The stopping criterion is 300 s. Both algorithms use a population size of 100 individuals, a crossover probability $p_c = 0.8$, and a mutation probability $p_m = 0.1$. In the specific case of the adaptive IDEA, the unfeasibility ratio α_I is set to 0.2 and the Pareto robustness ratio Δ_r is set to 0.5 after running a preliminary experimentation. Also, both algorithms were run 15 times with different random seeds setting the run time as the stopping criterion. All the algorithms were launched in the same computer: Intel Xeon^{TM} E5530 with two CPUs at 2.40 GHz, 3.7 Gbytes of memory, and Scientific Linux 6.4 as operating system and we use the same framework and programming language (C++) for the development of the algorithms.

3.2.2 Monte Carlo simulation method

The probability distributions of the demands for each kind of engine are unknown. As said, the company provided the most representative scenarios with the most probable demands but more production plans (i.e., scenarios) can emerge. In order to generate more representative scenarios with the available demand information, we extract statistical information of the demand for each engine (such as minimum, maximum, average, or median) from the production plans.

A set of different engines' demand values are built once we have obtained the probability distributions which represent the processing times of each engine. These demand values are used to create a set of thousands of new production plans. This way we can generate similar demands to the most common but not exactly equal and then, to characterize a probability distribution that fits the empirical data of the production plans as good as possible.

We will use the Monte Carlo simulation to calculate the robustness of the solutions in all the generated scenarios. Thanks to the use of this Monte Carlo simulation technique, a deeper analysis can be done. Monte Carlo simulation was chosen to perform this process because of its simplicity and appropriateness for evaluating a set of artificially generated demand plans. Several studies demonstrate that Monte Carlo simulation has many advantages over conventional methods in the estimation of uncertainty (Gilks et al. 1996; Coleman and Steele 1995). The simulation process is fast and allows us to calculate the robustness metrics for a large number of scenarios. Therefore, risk evaluations with a high number of engines' demand combinations are possible by always considering that the total number of assembled engines per day is 270.

A Monte Carlo simulation of 1000 runs is built by generating probability distributions of the engines' demand taking into account the provided 23 productions plans (defined in Table 3 of Sect. 3.1). Specifically, we used a triangular probability distribution to represent the behavior of the processing times of each engine P_i. This triangular distribution is depicted by the maximum, minimum, and average values for each product in the 23 production plans. We have chosen the triangular distribution as it is a simple and realistic representation of the probability distribution when sample data is limited. Also, it does not need a high number of parameters for the generating the probability distribution.

We will show and analyze the results of this Monte Carlo simulation approach using the additional generated production plans in the next Sect. 4.3.

4 Experimental results

This section explains the considered computational experiments to study the robustness of the assembly lines under scenarios of uncertain products' demand. First, six different assembly line configurations are selected from the results of two EMO algorithms. Later, some experiments are performed by considering Nissan production plans to evaluate the robustness of the six configurations. Finally, we show how a simulation technique is used as a tool to intensively use thousands of plans and compare the robustness metrics obtained for the six assembly line configurations.

4.1 Obtaining a set of non-dominated solutions for the assembly line

We obtain a set of non-dominated solutions for the two r-TSALBP objectives by using the two EMO algorithms. Figure 2 shows different non-dominated solutions obtained using the adaptive IDEA algorithm. These non-dominated solutions are possible configurations, with a minimum level of robustness for the decision maker. All of them are equally preferable as they minimize both conflicting objectives, number of stations m and their linear area A, with different values.

For studying the impact and analyzing the managerial insights of selecting different assembly line configurations, three of these non-dominated solutions are selected from the set of assembly line configurations. These solutions trade one objective off for the other (number of stations m and linear area A). Please note that, as stated before, our model assumes that two workers are assigned to one station and therefore, the minimization of the number of stations implicitly minimize the number of workers. The first one corresponds to a 18-stations assembly line which needs a linear area of 5.5 m (ζ_1 with $m = 18$ and $A = 5.5$); the second one corresponds to a 21-stations assembly line which requires a linear area of 4.5 m (ζ_2 with $m = 21$ and $A = 4.5$); and the third one corresponds to a 23-stations assembly line which needs a linear area of 4 m (ζ_3 with $m = 23$ and $A = 4$).

Tables 4 and 5 depict two different assembly line configurations which have 23 stations and 4 m of linear area and ζ_3^R. These configuration of the assembly lines were respectively obtained by a standard multiobjective method (ζ_3^N), and a robust multiobjective method, adaptive IDEA, (ζ_3^R). As already explained, the adaptive IDEA incorporates mechanisms to address robustness through temporal constraints.

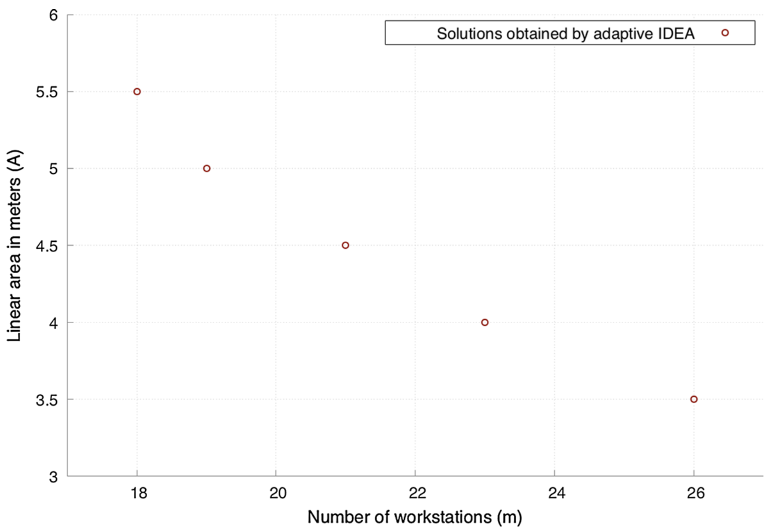

Fig. 2 Pareto front with different assembly line configurations for a Nissan instance, obtained by the adaptive IDEA when minimizing the two objectives of the r-TSALBP model (number of stations m and their area A)

Table 4 Assembly configuration line with objectives $m = 23$ and $A = 4$ (ζ_3^N) found by a standard (non-robust) multiobjective method, NSGA-II

k	$j \in S_k$										
1	1	9	10								
2	3	4	5	7	8	11					
3	6	13	14	16	18						
4	12	15	17	19	20						
5	21	22	23	24	26	27					
6	25	28	29	30							
7	31	32	33	34	35	36	37				
8	38	39	40	41	42						
9	43	44	45	49	59	60					
10	46	47	48	50	51	52	53	54			
11	55	56	57	58	61	62	63	64	65		
12	2	66	67								
13	68	69	70	71	72						
14	73	74	75	76	77						
15	78	79	80	81	82	83	86				
16	84	85	87	88	89	90	91	92	94		
17	93	95	98	99	100	101	102				
18	103	104	105	106	108	109	110	111	112	113	114	115
19	107	116	117	118	119	120					
20	121	131	132	134	135						
21	97	122	128	136	137	138	139				
22	123	124	125	126	127	129	130				
23	96	133	140								

Similar tables for the 18-stations solutions, (ζ_1^N and ζ_1^R), and 21-stations solutions (ζ_2^N and ζ_2^R), are shown in the supplemental material file of this paper.

4.2 Robustness evaluation using the Nissan production plans

Using the Nissan production plans we can test the behavior of the assembly line configurations. Tables 6 and 7 show the workload of the non-robust and robust assembly line configurations (referred as ζ_3^N and ζ_3^R) which are formed by 23 stations of 4 m for the seven selected plans because of the lack of space. In these tables we can see the stations' workload for the selected plans in each of the columns. Also, the last two columns show the overload times and the maximum exceeding time for all the stations $k \in K$ (i.e., Δ^c). Again, similar tables are available in the supplemental material file for the 18-stations and 21-stations assembly line configurations.

Table 5 Assembly configuration line with objectives $m = 23$ and $A = 4$ (ζ_3^R) found by a robust multi-objective algorithm, adaptive IDEA

k	$j \in S_k$											
1	1	9	10									
2	3	5	7	8	11	13						
3	4	6	14	15								
4	16	17	20									
5	12	18	19	21	22	26	27					
6	23	24	25	28	29	30						
7	31	32	33	34	35	36						
8	2	37	38	39	40							
9	41	42	43	44								
10	45	46	47	48	49	50	51	59	60			
11	52	53	54	55	56							
12	57	58	61	62	63	64	66					
13	65	67	68	69	71	72						
14	70	73	74	75	79							
15	76	77	78	80	81	82						
16	83	84	85	86	87	88	89	90				
17	91	92	94	98	99	100						
18	95	101	102	103	104	105	106	107	108	109	110	111
19	93	112	113	114	115	116	117	118				
20	119	120	121	122	123	124						
21	125	126	128	131	132	134						
22	127	129	130	135	136	137	138					
23	96	97	133	139	140							

We can see that, for the 23-stations solution ζ_3^N found by the non-robust EMO algorithm (Table 6), 3 of the 23 workstations (11, 17, and 18) need more processing time than the available cycle time, i.e., more than 180 s (in bold, Table 6), to assemble the 270 engines in some of the plans considered. It means that these stations are overloaded when the demand plans are not the one of reference.

On the contrary, this situation is not happening for the 23-stations solution ζ_3^R, given by the robust adaptive IDEA method (Table 7). With this robust method, all the stations can support the uncertainty defined by the different production plans and therefore, the assembly line is not overloaded by different task processing times. We have similar results for the other two assembly line configurations ζ_1 and ζ_2 with 18 and 21 stations, respectively. In these two cases (see supplemental material file), the standard EMO algorithm provides assembly line solutions where the stations are overloaded more frequently than the configuration found by the robust multiobjective method.

Table 6 Stations workload and overloaded values for the seven selected production plans of the assembly line configuration (ζ_3^N) with 23 stations and 4 m, obtained with a non-robust EMO algorithm (note that $\Delta_c = max\{0, t(S_k) - c\}$)

k	$t_{plan1}(S_k)$	$t_{plan2}(S_k)$	$t_{plan3}(S_k)$	$t_{plan6}(S_k)$	$t_{plan9}(S_k)$	$t_{plan12}(S_k)$	$t_{plan18}(S_k)$	$\sum_\epsilon y^c_{k\epsilon}$	Δ_c
1	110	109.58	108.95	110.24	110.87	109.5	110.35	0	0
2	170	169.53	169.14	169.98	170.37	169.54	169.94	0	0
3	133	132.78	131.39	134.14	135.53	132.43	134.72	0	0
4	113	112.99	113.19	112.80	112.6	113.03	112.7	0	0
5	59	59.10	58.92	59.25	59.43	59.01	59.39	0	0
6	85	85.18	85.81	84.55	83.92	85.33	84.32	0	0
7	110	109.93	109.65	110.27	110.54	109.84	110.37	0	0
8	90	89.83	90.58	89.06	88.3	90.15	88.6	0	0
9	95	94.93	94.42	95.44	95.95	94.79	95.66	0	0
10	175	175.64	175.78	175.47	175.33	175.5	175.72	0	0
11	180	**180.41**	**182.8**	177.95	175.51	**181.09**	176.93	3	2.85
12	100	99.83	99.82	99.84	99.86	99.91	99.77	0	0
13	120	119.64	119.74	119.52	119.42	119.8	119.29	0	0
14	100	100.12	99.55	100.73	101.31	99.86	101.08	0	0
15	105	105	105.51	104.5	103.99	105.15	104.25	0	0
16	165	165.05	165.13	164.99	164.91	165.07	164.97	0	0
17	180	179.39	178.17	**180.68**	**181.91**	179.13	**180.99**	3	1.91
18	180	179.88	179.23	**180.53**	**181.18**	179.69	**180.8**	3	1.18
19	140	139.79	139.57	140.01	140.23	139.77	140.01	0	0
20	145	145.17	144.58	145.78	146.37	144.94	146.16	0	0
21	140	139.78	139.81	139.76	139.72	139.85	139.63	0	0
22	140	139.84	140.1	139.58	139.33	139.99	139.38	0	0
23	155	156.16	157.28	154.96	153.83	156.23	154.97	0	0
c_{max}	180.00	180.41	182.85	180.68	181.91	181.09	180.99	182.85	

Table 8 shows the corresponding robustness metric values for the found assembly line configurations. The first row shows the number of stations and linear area needed (m, A) for each configuration solution. The second row distinguishes between the non-dominated solutions given by the non-robust and the robust EMO algorithm. The remaining three rows show the metrics g_c^1, g_c^2, g_c^3, and r_c^1, r_c^2, r_c^3, which summarize the non-robustness and robustness of the assembly line configurations, respectively.

These metrics' values are useful for a decision maker as they provide information about how flexible the configuration is and the possible managerial impact (i.e., impact on other departments of the organization) when adopting one or another solution. In light of this table, we can see that:

Table 7 Stations workload and overloaded values for the seven selected production plans of the line configuration (ζ_3^R) with 23 stations and 4 m, obtained with a robust EMO algorithm (note that $\Delta_c = max\{0, t(S_k) - c\}$)

k	$t_{plan1}(S_k)$	$t_{plan2}(S_k)$	$t_{plan3}(S_k)$	$t_{plan6}(S_k)$	$t_{plan9}(S_k)$	$t_{plan12}(S_k)$	$t_{plan18}(S_k)$	$\sum_\epsilon y_{k\epsilon}^c$	Δ_c
1	110	109.58	108.95	110.24	110.87	109.5	110.35	0	0
2	125	124.49	124.75	124.26	124	124.74	123.87	0	0
3	138	138.19	136.43	139.96	141.71	137.55	140.93	0	0
4	93	92.86	92.96	92.76	92.66	92.91	92.64	0	0
5	82	81.72	81.23	82.19	82.68	81.67	82.30	0	0
6	122	122.32	123.08	121.54	120.79	122.46	121.33	0	0
7	95	94.89	94.76	95.07	95.20	94.87	95.08	0	0
8	105	105.06	105.29	104.84	104.61	105.13	104.75	0	0
9	115	114.68	115.05	114.29	113.93	114.94	113.95	0	0
10	170	170.54	170.84	170.27	169.97	170.46	170.39	0	0
11	90	89.97	89.58	90.34	90.73	89.87	90.52	0	0
12	155	155.57	157.88	153.25	150.95	156.15	152.39	0	0
13	110	109.73	109.96	109.5	109.27	109.91	109.25	0	0
14	120	119.59	118.61	120.6	121.58	119.36	120.88	0	0
15	70	70.45	70.79	70.12	69.78	70.40	70.17	0	0
16	160	159.93	160.37	159.51	159.07	160.11	159.26	0	0
17	170	169.19	168.56	169.91	170.54	169.2	169.82	0	0
18	170	170.46	169.76	171.15	171.86	170.07	171.73	0	0
19	165	164.63	163.96	165.31	165.98	164.51	165.46	0	0
20	125	124.61	124.16	125.05	125.49	124.59	125.07	0	0
21	160	160.07	160.57	159.61	159.11	160.23	159.4	0	0
22	165	164.91	164.56	165.24	165.59	164.83	165.37	0	0
23	175	176.08	177.06	175.02	174.04	176.13	175.07	0	0
c_{max}	175	176.08	177.06	175.02	174.04	176.13	175.07	177.06	

Table 8 Metric values for the six assembly configuration lines

Metrics	Configuration ζ_1 $(m = 18, A = 5.5)$		Configuration ζ_2 $(m = 21, A = 4.5)$		Configuration ζ_3 $(m = 23, A = 4)$	
	Non-robust ζ_1^N	Robust ζ_1^R	Non-robust ζ_2^N	Robust ζ_2^R	Non-robust ζ_3^N	Robust ζ_3^R
$g_c^1(r_c^1)$	1 (0)	0	1 (0)	0.17 (0.83)	1 (0)	0 (1)
$g_c^2(r_c^2)$	0.22 (0.78)	0 (1)	0.24 (0.76)	0.05 (0.95)	0.13 (0.87)	0 (1)
$g_c^3(r_c^3)$	0.09 (0.91)	0 (1)	0.09 (0.91)	0.02 (0.98)	0.13 (0.87)	0 (1)

- For ζ_1^N (i.e., the 18-stations assembly line configuration given by the standard EMO algorithm), the rate of overloaded production plans with respect to the allowed workload time g_c^1 is 1. It means that 100% of plans overload, at least, one station. On the contrary, the robust EMO algorithm provides with a configuration ζ_1^R which is not overloaded in any of the stations. The second robustness metric g_2^c indicates that the number of overloaded stations with respect to the allowed workload time is not very high (i.e., 22%) for the configuration given by the standard EMO algorithm, although this metric value is lower for the configuration given by the robust adaptive IDEA (i.e., 0%). Finally, the third robustness metric g_3^c, which shows the exceeding processing time for all the workstations, is 9% for the configuration ζ_1^N given by the standard EMO algorithm. In contrast, this value drops to 0% in the solution ζ_1^R given by the robust EMO algorithm.
- Metric values corresponding to the 21-stations assembly line configuration ζ_2^N given by the standard EMO algorithm are very similar to the ones obtained for the 18-stations configuration with the same algorithm. On the other hand, the solution obtained with the robust EMO algorithm is less robust than the corresponding 18-stations assembly line, but still those metric values lead to confirm that the robustness of the solution is higher than the obtained by the standard algorithm. Decision makers can still use this additional information when choosing the best solution for the company.
- For ζ_3, the 23-stations assembly line configuration, we see that the robust method can get again a totally robust configuration. Metric values for the non-robust configuration ζ_3^N are similar to 18-stations configurations. All the plans overload at least one workstation (metric g_c^1), 13% of the workstations are overloaded at least in one plan (g_2^c), and the exceeding processing time of the stations is almost the 13% of the maximum exceeding time of the overloaded stations (metric g_3^c).

4.3 Extending the set of production plans through simulation

In the previous experimentation, the provided demand plans were taken into account for running evaluating the robustness in the proposed EMO algorithms. But Monte Carlo simulation can help us to extend the evaluation of the robustness of the assembly line configurations by using a higher number of demand plans instead of using the reduced number of them.

One of the potential disadvantages of Monte Carlo simulation is that a single run of trials does not indicate by itself the reliability of the results. However, the greater the number of Monte Carlo simulation trials, the more "stable" will be the output standard deviation (that is, the standard uncertainty of the measuring). This property of Monte Carlo simulation can thus be used as a direct method for determining the number of trials for a given application. We have tried different number of scenarios, checked the output standard deviations, and chosen the number of simulations that start to provide really small changes in standard deviation. In this case, it was 1000 scenarios.

Figure 3 shows how the stations are overloaded when simulating 1000 production plans with different engines' demands. The box-plot shows the results for the six assembly line solutions of 18, 21, and 23 stations (ζ_1, ζ_2, and ζ_3) when obtained by non-robust (ζ^N) and robust (ζ^R) EMO algorithms. This box-plot allows us to visually identify the solutions that present a more flexible behavior when evaluating the risk of having a diverse and high number of production plans. The red line of the box-plot sets the available cycle time c of the assembly line to better visualize what configurations are always below this level.

Additionally, Table 9 provides the robustness metric values g_c^1, g_c^2, g_c^3, r_c^1, r_c^2, and r_c^3 obtained after evaluating all the simulated production plans. We can compare these metric values with respect to the previous ones, obtained without simulation and only the discrete set of the plans provided by Nissan. The analysis of these results can arise the following insights:

- The robustness of the 18-stations assembly line configuration given by the non-robust EMO algorithm ζ_1^N is similar than the one obtained using the discrete set of plans. However, metrics obtained for the configuration given by the robust EMO algorithm ζ_1^R indicate that the flexibility of this configuration is lower and therefore, less robust when a higher number of more diverse plans are considered by means of the Monte Carlo simulation. Nevertheless, taking into account the g_c^1 metric value, there is a significant number of plans which exceed the cycle time but just a few workstations of the assembly line are affected (g_c^2 metric) and when so, by just a low exceeding workload time (g_c^3 metric).

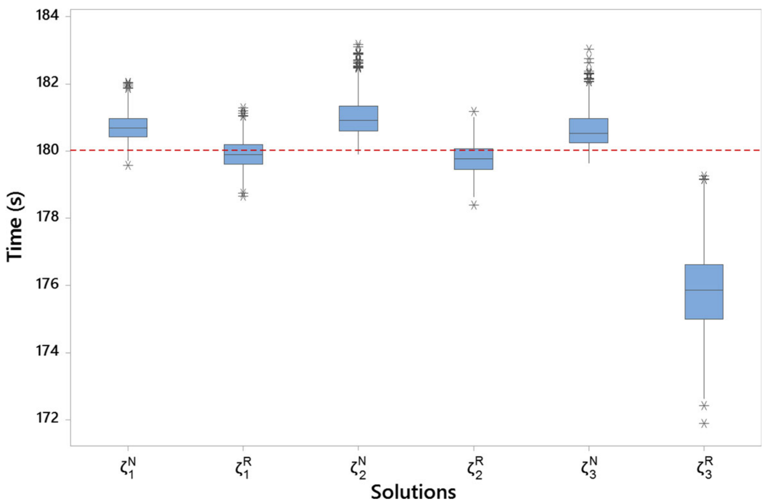

Fig. 3 Overloaded time of the workstations for the six assembly line configurations using a Monte Carlo simulation to generate 1000 different production plans

Table 9 Metric values for the six assembly configuration lines for the Monte Carlo simulated production plans

Metrics	Configuration ζ_1 $(m = 18, A = 5.5)$		Configuration ζ_2 $(m = 21, A = 4.5)$		Configuration ζ_3 $(m = 23, A = 4)$	
	Non-robust ζ_1^N	Robust ζ_1^R	Non-robust ζ_2^N	Robust ζ_2^R	Non-robust ζ_3^N	Robust ζ_3^R
$g_c^1(r_c^1)$	0.96 (0.04)	0.41 (0.59)	0.99 (0.01)	0.30 (0.70)	0.95 (0.05)	0 (1)
$g_c^2(r_c^2)$	0.28 (0.73)	0.11 (0.89)	0.24 (0.76)	0.05 (0.95)	0.13 (0.87)	0 (1)
$g_c^3(r_c^3)$	0.01 (0.99)	0.01 (0.99)	0.02 (0.98)	0.01 (0.99)	0.02 (0.98)	0 (1)

- Both 21-stations assembly line configurations ζ_2 show approximately the same behavior than the 18-stations ones. That is, the robustness of the configuration given by the non-robust EMO algorithm ζ_2^N remains similar when a large number of plans, obtained by a Monte Carlo simulation is performed. However, the robustness of the configuration given by the robust EMO algorithm ζ_2^R seems to get worse robustness as the number of production plans that overload the cycle time of the workstations increases.
- Finally, for the assembly line configuration with 23 stations ζ_3, both robust and non-robust configurations have similar metric values as when using the discrete set of production plans.

5 Final discussion and concluding remarks

When the global demand varies with respect to the reference plan, there are adverse effects on the production line. The main effects can be an increase of the number of workstations to satisfy new production plans when having a higher global demand, and the reduction of workers when the global demand decreases (i.e., dead periods can arise in the assembly line).

These effects require, with respect to the managerial impact of the production system, significant changes in the production system. Clearly, an increase in the number of workstations needs hiring more workers for the assembly line and also, as a reassignment to new workers is necessary, a training phase for them is required during several weeks with a consequent reduction in the number of products assembled by the company (i.e., the productivity of the automotive company). There are also possible negative effects in the workstations and production line when global demand does not change but there are changes in the production mix with respect to the one considered when balancing the assembly line (reference plan).

All the latter effects and damaging managerial consequences for the production line and company itself can be alleviated by using our proposed multiobjective robust models. Our case study from the Nissan assembly line showed how our robust TSALBP model, EMO algorithms, and Monte Carlo simulation techniques can help the decision maker to find flexible assembly line configurations which have less risk when the demand of the products changes. With our model and methods, it is possible to propose various optimal and robust assembly line configurations (i.e., non-dominated solutions). And additionally, we can measure the flexibility of all the solutions with respect to a reference assembly line configuration.

This is done through robustness metrics applied to an assembly line configuration with respect to a set of demand plans (E). We understand these robustness metrics as the capacity of the assembly line configuration to absorb the possible demand variations in the set of products to be assembled in the same assembly line (I). Therefore, an assembly line configuration is more robust when less changes are needed to adapt the assembly line to new incoming demand scenarios.

Multiobjective optimization methods as those based on EMO offer the decision maker a set of equally-preferable alternative solutions. Also, EMO algorithms offer a manager a set of equally-preferred solutions for the assembly line and these solutions can be restricted by injecting decision maker preferences prior to the search. For the Nissan case study, three different assembly line configurations were selected from the Pareto front resulted from the optimization process: ζ_1 with 18 stations of 5.5 m, ζ_2 with 21 stations of 4.5 m, and ζ_3 with 23 stations of 4 m. These three solutions present different objective values for the decision maker. We obtained and analyzed in the experimentation two options for each one: ζ^R with a robust EMO algorithm and ζ^N without it.

We explored the values for the non-robustness metrics g_1^c, g_2^c, and g_3^c and robustness metrics r_1^c, r_2^c, and r_3^c for the latter six solutions. These metrics show different information about the flexibility of the solutions in terms of overloaded stations by a set of production plans. The use of Monte Carlos simulation helped us to provide more certainty about when a solution is robust as we will be able to compute these metrics in a higher number of future scenarios. We showed that a way of improving the risk evaluation of the assembly line configuration is by means of simulation approaches. Thanks to this simulation, the values of the robustness metrics are calculated by taking into account a high number of simulated demand plans. In our experiments we first used a discrete set of plans and later enriched the robust approach by generating 1000 different demand plans in order to evaluate the robustness of the six selected assembly configurations.

The r-TSALBP model and its use of temporal robustness ratios as optimization constraint can offer managers a set of non-dominated solutions which can deal with high levels of uncertainty in the demand plans. The robustness achievement of the solutions with respect to these metrics provides information about the kind of managerial actions to apply when adopting the specific assembly line configuration. For instance, we observed that, using the simulated extended set of plans, non-robust solution ζ_1^N would have overloading problems in 27% of the workstations (g_2^c), and an exceeding workload of the 1.3% of the maximum exceeding time (g_3^c). A solution with 23 stations found by a non-robust EMO algorithm, ζ_3^N, will also be overloaded in the 13% (metrics g_2^c and r_c^2), and by almost all the demand plans in, at least, one workstation (metrics g_1^c and r_1^c).

The provided robust assembly line configuration ζ_3^R was totally robust with respect to the defined set of demand plans and the 1000 simulation plans. It means that no changes will probably be needed when the current demand changes. Solutions ζ_1^R and ζ_2^R (i.e., those having 21 stations and 4.5 m of linear area for the stations) did not obtain a full robustness value in the given demand plans but much lower metric values g_1^c, g_2^c, and g_3^c were obtained than in the case of a standard non-robust model and EMO algorithm.

These robust models and built decision support system for assembly lines are useful when the assembly lines are for mixed products and the attributes of the tasks are based on averaged industrial measures such as averaged processing time. Although there are more external implications for the organization, the proposed flexibility information provides with the number of interventions on the assembly line when the demand changes and therefore, the temporal processing features of the tasks of the assembly line. The metrics alert about potential re-adjustments that would cause additional works to be re-scheduled in other shifts or during the weekends. These changes may cause production inefficiencies until achieving the regular capacity of the line. As commented by Eynan and Dong (2012), the process design and capacity investment cannot be just a strategic decisions without considering the effect of the weekly (or daily) decisions such as model mix planning (sequencing) which is the concern of tactical planning.

Additionally, detecting which workstations are the least flexible is useful to find the most problematic workstations if demand changes. Our first proposed metric g_1^c for instance, shows workstations that, under the conditions of the assembly line configuration of reference, need more cycle time to fulfill all the set or simulated production plans. Manufacturing process management technologies can offer the following solutions to solve this issue (Chica et al. 2016): (a) improve the processing time of the industrial tasks, (b) request alternative pieces having less processing time during their assembly (product design department), and (c) set a working pace over the normal activity of the line (Bautista et al. 2015) within the legal and trade union agreements (process engineering).

Nevertheless, the proposed model and given results have limitations. For instance, the r-TSALBP model and its managerial relevance do not apply when we have a production system that is process-oriented. Also, these results are limited when the industry needs to assemble extremely similar models or the demand is constant. In general, this publication is not relevant for industries where changes in the assembly line do not require important changes and they can be easily made.

Future works may focus on adding the current robust EMO algorithms and models with more realistic industrial features such as ergonomic factors (Bautista et al. 2016). Furthermore, and although we have considered uncertain demand in our case study, the use of more advanced simulation-optimization approaches such as simheuristics (Juan et al. 2016; Chica et al. 2017) could promote the integration of simulation techniques within the optimization procedure. Additionally, visualization processes to enhance the decision making process are, in our opinion, another important and promising line in the area. First attempts to support the ALB decision maker with network visualization have been recently done in Trawinski et al. (2018).

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