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Benefits of robust multiobjective optimization for flexible automotive assembly line balancing

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Abstract Assuming certain and homogeneous demand is not realistic. Demand changes are frequent and decision makers must take into account the risk of not considering this uncertainty. The automotive industry is an example of these changing conditions. Manufacturers must adapt their decisions when balancing the assembly line and consider different flexible solutions to the problem. 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 and simulation techniques to generate realistic demand sets with 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 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

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such as Ford, General Motors, and Chrysler have begun overhauling some of their previously specialized car-assembly plants into "flexible factories" to 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, dramatic changes in the demand of the products' type could drive to unstable assembly line balancing and to the need of constant re-balancing operations (Chica et al 2016). These production changes might be managed by building flexibility and reconfigurability *a priori* into the manufacturing system as *a posteriori* adaptation corresponds to the reaction of an already existing manufacturing system to changes in the product (ElMaraghy and AlGeddawy 2012). 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 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 (Deb et al 2002, Coello et al 2007) 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). In the automotive industry and specifically, when assembling engines, the variety of the final products has been increased in the last decades (Garcia-Sabater et al 2012). These product 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 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 line.

New optimization models such as those considering robust solutions (Roy 2010, Beyer and Sendhoff 2007) have emerged, given their possible benefits to managerial decisions in the production system of the plant. In this work, we will focus on one of the most recent multiobjective robust ALB models (the r-TSALBP (Chica et al 2016)) to study a set of ALB solutions with different flexibility characteristics to a real automotive case study. The r-TSALBP integrates the concepts of robust optimization and multiobjective optimization (Coello et al 2007) to find the most efficient and flexible assembly line configurations also having a low impact on the management of the plant. The model links robustness with the flexibility of an assembly line configuration when demand changes according to a set of real production plans. The model identifies and measures how robust a line configuration is for a set of production plans according to both operation time and linear area.

We apply the methods to a real engine assembly line of the Nissan automotive industrial plant in Barcelona (Spain). First, we 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 the adaptive IDEA (Chica et al 2016) 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 sub-populations of solutions and by adapting the size of both populations depending on the robustness of the Pareto archive every generation.

Within the robust assembly line framework we propose and study three non-robustness metrics of the assembly line configurations, g_1^c, g_2^c, and g_3^c, with respect to the set of production plans. These temporal non-robustness functions, based on overloaded stations by plans, provide a way to identify the most critical workstations in terms of flexibility for changing production plans. The results of the case study are evaluated in terms of the managerial and industrial advantages for the company and how not using a robust approach can generate difficulties in several departments of the organization.

Additionally, we include a novel methodology in the robust framework by making use of a 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 complex systems under uncertainty (Borshchev and Filippov 2004) because a well-validated simulation model can capture the system variation in a realistic way while still producing results that can be made as accurate as desired and supporting the existing complexity. 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).

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 1,000 different demand plans. The use of the latter simulation method allows us to better measure the reliability of the robustness of the configuration solutions. We compare the values of the robustness metrics for the non-robust and robust approaches and flexibility of them when using simulation as part of the risk management process. Finally, the managerial implications and effects of implementing the evaluated line configuration are discussed.

The structure of this paper is organized in five main parts starting from this introduction. Section 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 including the temporal non-robustness functions). Then, Section 3 explains the case study used in our work and the methods' details. Section 4 describes the experimental results. Finally, Section 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 (Section 2.1). Later, multiobjective and robust optimization are described in Sections 2.2 and 2.3, respectively. How simulation can be used as a tool in optimization under uncertainty is presented in Section 2.4. Finally, a multiobjective model for ALB that considers uncertainty in its formulation is described in Section 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 focuses 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). Each station $k = \{1, 2, ..., m\}$ is assigned to a subset of tasks S_k ($S_k \subseteq J$) which is 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 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 vertexes 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 also consider the linear area a_j associated to each task j (Bautista and Pereira 2007). Then, each station k has also an available station linear area $a(S_k)$ which is equal to the maximum of the sum of linear areas required by the tasks assigned to all the stations: $A = max_{k=1,2,\ldots,m} A_k$, where A_k is given by the sum of the linear area of all the assigned tasks to station 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 optimization problems involving more than one objective function to be optimized simultaneously (Deb et al 2002, Coello et al 2007). Multiobjective 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 optimization of the cycle time c, linear area of stations A, and number of stations m (Bautista and Pereira 2007).

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.

Evolutionary multiobjective optimization (EMO) algorithms are one of the most popular approaches to generate Pareto optimal solutions to a multiobjective optimization problem (Deb et al 2002, Coello et al 2007, Talbi 2009). Currently, most of the EMO algorithms apply Pareto-based ranking schemes. 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

The traditional formulation of optimization problems, both single and multi-objective, 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). When uncertainty is not added to the optimization process, the optimized solutions for those systems are unstable and sensitive to small changes. A way to tackle with this uncertainty in optimization is by providing solutions to the optimization problem with a high degree of robustness. This robustness indicates how the solutions to the optimization problem remain relatively unchanged when exposed to uncertain conditions (Beyer and Sendhoff 2007, Ferreira et al 2008).

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. The majority of the approaches existing in the literature for robust ALB are based on considering uncertain tasks attributes by defining interval values or by setting different scenarios. 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 line life cycle.

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. Papakostas et al (2014) proposed a model for minimizing time and cost through a set of demand profiles but they used single-objective particle swarm optimization. Finally, a novel multiobjective genetic algorithm to find the most robust solutions for TSALBP was proposed in Chica et al

(2016) where two separated populations of solutions are evolved through the running of the algorithm.

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). However, simulation is not an optimization tool on its own and simulation experiments need to be designed in order to gain an understanding of the models behavior with respect to both decision and probability spaces.

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.).

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.

Regarding unbalanced assembly lines some authors has 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 TSALP, 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 will describe a mathematical model for ALB related to the latter concepts. This is a multiobjective optimization problem which models uncertainty in the demand and which could be solved by robust optimization methods together with/or simulation techniques. The model is called r-TSALBP and is a multiobjective TSALBP variant which minimizes the number of stations m and their linear area A (Chica et al 2016).

This model assumes the realistic case where the processing time of a specific operation is different when an engine is assembled for a truck or a van. If demand changes and more products with higher processing time requirements have to be assembled, the workload of the stations will necessary increase. Therefore, the r-TSALBP model incorporates the flexibility of an assembly line configuration when demand changes based on a set of real production plans. These production plans define the demand of a set of mixed products to be assembled in the line. The goal of this model is to identify the flexibility of an assembly line configuration for a set of production plans by computing the overload of each station and production plan using temporal and spatial functions.

r-TSALBP includes a set I of product types. Thus, 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 line configuration which belongs to the set. The same applies to the spatial features of the line tasks but, in this paper, we focus the uncertainty in the temporal feature of the ALB problem. For a complete mathematical definition of the model see Chica et al (2016).

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 reference line configuration. Typically, this reference plan ε^0 is the one having a balanced demand for the products of I.

Given a production plan $\varepsilon \in \mathrm{E}$, defined by a demand vector $\overrightarrow{d}_\varepsilon = (d_{1\varepsilon}, d_{2\varepsilon}, ..., d_{|I|\varepsilon})$, we can determine the average processing time of task $j \in J$ for this plan ε by Equation 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 $D_\varepsilon = \sum_{i=1}^{|I|} d_{i\varepsilon}$. In the next two sub-sections we specifically define the r-TSALBP non-robustness functions and how to use them as constraints to be used with an optimization method.

2.5.1 Temporal non-robustness functions

The r-TSALBP formulation adds temporal functions to measure the overload of the workstations and production plans with respect to the cycle time c. These functions 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 $\varepsilon \in \mathrm{E}$ ($\sum_{j \in S_k} \bar{t}_{j\varepsilon}$) exceeds the cycle time c, and 0 otherwise. These non-robustness functions are defined as follows:

– g_c^1: Rate of overloading production plans (Equation 2).

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

– g_c^2: Rate of overloaded stations with respect to the allowed workload time (Equation 3).

$$g_c^2 = \frac{1}{m} \sum_{k=1}^{|K|} \max_{\varepsilon \in \mathrm{E}} y_{k\varepsilon}^c. \tag{3}$$

– 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 (Equation 4).

$$g_c^3 = g_c^3(x) = \frac{1}{\Delta^c \sum_{\varepsilon=1}^{|\mathrm{E}|} \sum_{k=1}^{|K|} y_{k\varepsilon}^c} \sum_{\varepsilon=1}^{|\mathrm{E}|} \sum_{k=1}^{|K|} (\max\{0, \sum_{j=1}^{|J|} \bar{t}_{j\varepsilon} x_{jk} - c\}), \tag{4}$$

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.

2.5.2 Use of the r-TSALBP temporal non-robustness functions as constraints

One way to incorporate the temporal non-robustness functions defined in Section 2.5.1 to the r-TSALBP model is to use them as constraints during the optimization process. In this way, solutions which do not fulfill the temporal constraints of Equation 5 are not valid (i.e., unfeasible solutions):

$$g_c^1 \le \tilde{g}_c^1;\ g_c^2 \le \tilde{g}_c^2;\ g_c^3 \le \tilde{g}_c^3, \tag{5}$$

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 functions (g_c). Analogously, we can define the robustness temporal functions 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 temporal constraints of Equation 5 by $\tilde{g}_c^1 = 1 - \tilde{r}_c^1$, $\tilde{g}_c^2 = 1 - \tilde{r}_c^2$, and $\tilde{g}_c^3 = 1 - \tilde{r}_c^3$. This process can be seen as an *a priori* decision making scheme (see Section 2.2).

An illustrative example of the use of this constraint is the following. Let set the decision-maker robustness preference $\tilde{r}_c^1$ to 0.6 (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, Section 3.1 shows the data collected for the experimentation and later, Section 3.2 describes the methods and parameters used for running the computational experience.

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 line assembles up to nine different types of engines $(P_1, P_2, ..., P_9)$. 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. 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.

Fig. 1 Nissan Pathfinder engine, assembled in the industrial line of the case study.

Under conditions of demand equilibrium (i.e., equal demand for the all the engines) and a cycle time of 3 minutes, the line is balanced by 21 workstations with an average length of 4 meters each. However, the engines' demand is not usually homogeneous or identical for the nine types of engines. This fact means that, although the 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 hours uniformly distributed in two shifts. Table 1 shows the most usual 23 demand plans for the company. Seven of these 23 plans have been selected as the representative demand plans

Table 1 Units of demand of 23 production plans for the nine engine types ($P_1, P_2, ..., P_9$) during a 13.5 hours day divided into two shifts.

	Family									
	4x4			Vans		Trucks				
Plan	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	Total
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

for a working day: 1, 2, 3, 6, 9, 12, and 18. These seven plans will be used to search and evaluate the most robust assembly line configuration solutions.

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 1,620, 1,575, 1,470, 1,350, 1,425, 1,530, 1,500, 1,380, and 1,650cs 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 1,483cs in plan 12, in contrast to 1,532cs in plan 9. Appendix C of the supplemental material file shows the weighted processing times of all the 140 assembly operations according to the seven selected 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 Section 2.5 with the seven representative production plans of the Nissan engine (described in previous Section 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 (Chica et al 2011). 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 seconds. Both algorithms use a population size $pop = 100$ 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 2.40GHz, 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 Simulation method

Additionally, we run a Monte Carlo simulation process to evaluate the uncertainty response in the tasks' processing time. Thanks to the use of this 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. 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 combinations are possible by always considering that the total number of assembled engines per day is 270.

The Monte Carlo simulation is built by using the 23 productions plans defined in Table 1 of Section 3.1. We use a triangular probability distribution

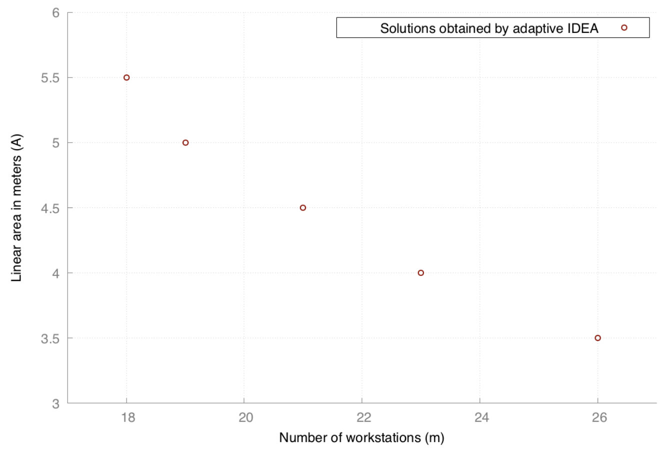

Fig. 2 Pareto front with different assembly line configurations for the same Nissan instance solved by the adaptive IDEA.

to represent the behavior of the processing times of each engine P_i. This triangular distribution is depicted by the maximum, minimum, and average for each product in the 23 production plans. We have chosen the triangular distribution as it provides a simple and realistic representation of the probability distribution when sample data is limited, as in our case, and there is no need for a high number of parameters for the distribution.

Once the probability distribution to represent the behavior of the processing times of each engine is obtained, we can generate a high number of random demands for all of them and create a set of thousands of production plans to evaluate the robustness of the assembly line configurations. We will show and analyze the results of this simulation approach in Section 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 seven 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 and linear area). The first one corresponds to a 18-stations assembly line which needs a linear area of 5.5 meters (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 meters (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 meters (ζ_3 with $m = 23$ and $A = 4$).

Tables 2 and 3 show two line configurations both having 23 stations and 4 meters of linear area. These two configuration 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. 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 Appendix A of the supplemental material.

Table 2 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									

Table 3 Assembly configuration line with objectives $m = 23$ and $A = 4$ (ζ_3^R) found by a robust multiobjective 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						

4.2 Robustness evaluation using the Nissan production plans

As mentioned before, seven plans (1, 2, 3, 6, 9, 12, and 18) have been selected from Table 1 as representative demand plans for a working day. Using these plans we can test the behavior of the assembly line configurations. Tables 4 and 5 show the workload of the 23 stations for the two line configurations ζ_3^N and ζ_3^R, provided by the non-robust and robust EMO algorithms. In these tables we can see the stations' workload for the seven 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 of the 18-stations and 21-stations assembly line configurations are available in Appendix B of the supplemental material of this paper.

We can see that, for solution ζ_3^N found by the non-robust EMO algorithm (Table 4), 3 of the 23 workstations (11, 17, and 18) need more processing time than the available cycle time (i.e., 180s) 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. However, this is not happening for solution ζ_3^R, given by the robust adaptive IDEA method (Table 5). 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 4 Stations workload and overloaded values for each production plan of the line configuration (ζ_3^N) with 23 stations and 4 meters, 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 5 Stations workload and overloaded values for each production plan of the line configuration (ζ_3^R) with 23 stations and 4 meters, 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 6 Metric values for the six assembly configuration lines.

	ζ_1, (18, 5.5)		ζ_2, (21, 4.5)		ζ_3, (23, 4)	
Metrics	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)

Table 6 shows the corresponding robustness metric values for the found assembly line configurations. These metrics g_c^1, g_c^2, g_c^3, and r_c^1, r_c^2, r_c^3 summarize the non-robustness and robustness of the line configurations, respectively. They are useful for a decision maker as they provide information about how flexible the configuration is and the possible managerial impact of adopting one or another solution. We will discuss the managerial impact related to these metric values in next Section 5.

The rows of Table 6 show, for each of the three non-dominated solutions, the number of stations and linear area needed (m, A) as well as the three metric values for the configurations given by the non-robust and robust EMO algorithms. In light of this table, we can state that:

- 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 than in the 18-stations configurations. All the plans overload at least one workstation (metric g_c^1), 13%

Table 7 Metric values for the six assembly configuration lines for the Monte Carlo simulated production plans.

	$\zeta_1, (18, 5.5)$		$\zeta_2, (21, 4.5)$		$\zeta_3, (23, 4)$	
	Non-robust	Robust	Non-robust	Robust	Non-robust	Robust
Metrics	ζ_1^N	ζ_1^R	ζ_2^N	ζ_2^R	ζ_3^N	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)

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, seven representative demand plans (plans 1, 2, 3, 6, 9, 12, and 18 from Table 1) were taken into account for running evaluating the robustness in the proposed EMO algorithms. Simulation techniques can help to extend the evaluation of the flexibility of the assembly line configurations by using a higher number of demand plans instead of using a small number of them.

Figure 3 shows how the stations are overloaded when simulating 1,000 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 7 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 seven plans. 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 seven 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

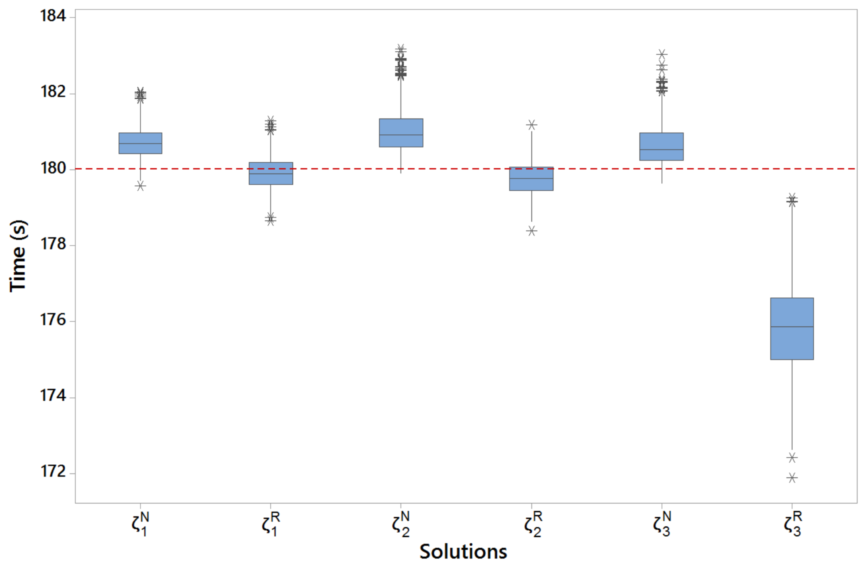

Fig. 3 Overloaded time of the workstations for the six assembly line configurations using a Monte Carlo simulation to generate 1,000 different production plans.

of the assembly line are affected (g_c^2 metric) and when so, by just a low exceeding workload time (g_c^3 metric).
– 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 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 seven production plans.

5 Final discussion and concluding remarks

Changing the demand of the products to be assembled can generate disharmony between the required work (planning department) and the capacity of the assembly line (production department). These differences need changes in the production system of the company and can disrupt the production of the required items to customers. When the global demand varies with respect to the reference plan, there are some adverse effects on the production line. The main effects for the global demand changes are the next two:

- An increase of the number of workstations in order to satisfy the new production plans when we have higher global demands than expected.
- The reduction of workers when the global demand decreases and then, dead periods can arise in the assembly line.

The latter two 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). The second effect, i.e., the workers' reduction, can be considered easier to manage. This is true from the technological point of view. However, from the human resources point of view, these re-adjustments are more complex: processing the new allocations, training the unskilled workers towards a more multi-tasking work, and also having a new line configuration.

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 line (reference plan):

- Increase/decrease of the number of workplaces to satisfy the temporal restrictions of the assembly line while keeping the total cycle time and linear area required for the workstations.
- A clear modification of the workload of the stations (minimum in two of them) by keeping the number of workplaces, cycle time, and linear area required for the assembly line.

The latter first effect has managerial consequences, similar to the first two effects. If the global demand is unchanged, the temporal attributes of the processing tasks for all the types of products are similar, and then, the new situation will have slight differences with respect to the initial one. But here again, workers will need to be re-trained in accordance to the tasks and associated workstations. The measurements of these workers' health and work conditions must support strategic and long-term operational cost-saving plans such as reduced or shifted work-force size or different allocated working hours.

All the latter effects and damaging managerial consequences for the production line and company itself can be alleviated by using our proposed multi-objective robust models. Our case study from the Nissan assembly line showed how our robust TSALBP model, EMO algorithms, and 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 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 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 meters, ζ_2 with 21 stations of 4.5 meters, and ζ_3 with 23 stations of 4 meters. 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 simulation techniques 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 the Monte Carlo 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 1,000 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 functions 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 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 1,000 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 meters 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. These issues are related with the possible actions of the human resources department. 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 reference line configuration, 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 contribution 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) 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 (2016).

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