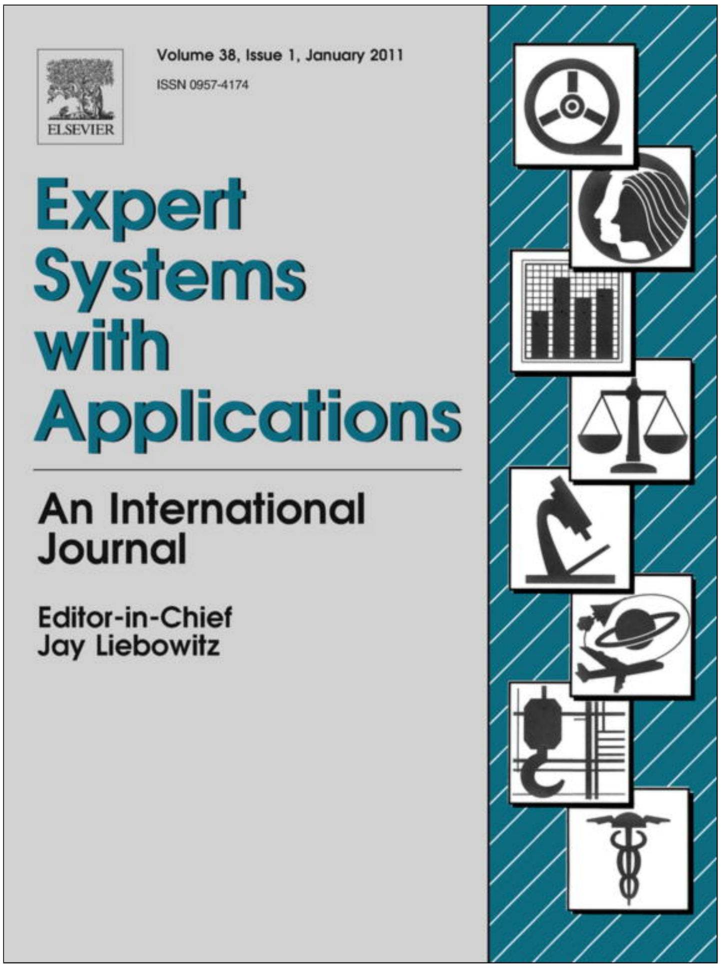
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Including different kinds of preferences in a multi-objective ant algorithm for time and space assembly line balancing on different Nissan scenarios

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ABSTRACT

Most of the decision support systems for balancing industrial assembly lines are designed to report a huge number of possible line configurations, according to several criteria. In this contribution, we tackle a more realistic variant of the classical assembly line problem formulation, time and space assembly line balancing. Our goal is to study the influence of incorporating user preferences based on Nissan automotive domain knowledge to guide the multi-objective search process with two different aims. First, to reduce the number of equally preferred assembly line configurations (i.e., solutions in the decision space) according to Nissan plants requirements. Second, to only provide the plant managers with configurations of their contextual interest in the objective space (i.e., solutions within their preferred Pareto front region) based on real-world economical variables. We face the said problem with a multi-objective ant colony optimisation algorithm. Using the real data of the Nissan Pathfinder engine, a solid empirical study is carried out to obtain the most useful solutions for the decision makers in six different Nissan scenarios around the world.

1. Introduction

An assembly line is made up of a number of workstations, arranged in series and in parallel, through which the work progresses on a product flows, thus composing a flow-oriented production system. Production items of a single type (single-model) or of several types (mixed-model) visit stations successively, where a subset of tasks of known duration are performed on them. Assembly lines are of great importance in the industrial production of high quantity standardised commodities and more recently even gained importance in low volume production of customised products (Boysen, Fliedner, & Scholl, 2008).

The assembly line configuration involves determining an optimal assignment of a subset of tasks to each station of the plant fulfilling certain time and precedence restrictions. In short, the goal is to achieve a grouping of tasks that minimises the inefficiency of the line or its total downtime and that respects all the constraints imposed on the tasks and on the stations. Such problem is called assembly line balancing (ALB) (Scholl, 1999) and arises in mass manufacturing with a significant regularity both for the first-time installation of the line or when reconfiguring it. It is thus a very complex combinatorial optimisation problem (known to be NP-hard) of great relevance for managers and practitioners.

Due to this reason, ALB has been an active field of research over more than half a century and a large branch of research has been developed to support practical assembly line configuration planning by suited optimisation models. The first family of "academic" problems modelling this situation was known as Simple Assembly Line Balancing Problems (SALBP) (Baybars, 1986; Scholl, 1999), and only considers the assignment of each task to a single station in such a way that all the precedence constraints are satisfied and no station workload time is greater than the line cycle time. When other considerations are added to those of the SALBP family, the problems are known in the literature by the name of General Assembly Line Balancing Problems (GALBP). An up-to-date analysis of the bibliography and available state of the art procedures can be found in Scholl and Becker (2006) for the SALBP family of problems, and in Becker and Scholl (2006) for the GALBP ones. Moreover, a generic classification scheme for the field of ALB considering many different variants is also provided in a recent paper by Boysen, Fliedner, and Scholl (2007).

In spite of the great amount of proposed SALBP extensions, there remains a gap between requirements of real configuration problems and the status of research (Boysen et al., 2008). This gap could be due to different reasons making the mathematical models far from real-world assembly systems: (i) the consideration of a single or only a few SALBP practical extensions at a time, when

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real-world assembly systems require a lot of these extensions to be considered simultaneously; (ii) their formulation as a single-objective problem, when the overall assembly objectives (such as production rate, cost of operation, buffer space, etc.) are of a multi-dimensional character (Malakooti & Kumar, 1996); and (iii) the existence of several interesting characteristics present in practical line balancing problems are still not covered by any of the existing models.

As a result of the observation of the ALB operation in an automotive Nissan plant from Barcelona, Spain, Bautista and Pereira recently proposed a SALBP extension aiming to take a step ahead on the latter issue. They considered an additional space constraint to get a simplified but closer version to real-world problems, defining the time and space assembly line balancing problem (TSALBP) (Bautista & Pereira, 2007). TSALBP presents eight variants depending on three optimisation criteria: m (the number of stations), c (the cycle time), and A (the area of the stations). In this paper, we tackle the 1/3 variant of the TSALBP, which tries to jointly minimise the number of stations and their area for a given product cycle time, a complex and realistic multi-criteria problem in the automotive industry.

Multi-criteria optimisation (Chankong & Haimes, 1983; Ehrgott, 2000; Gal, Stewart, & Hanne, 1999; Steuer, 1986) is a major area of research and applications in operations research (OR) and management sciences. Multi-objective optimisation (MOO) problems as the said TSALBP variant are frequently encountered in practice. There are often different criteria measuring the "quality" of a solution and it is not possible to select a most important criterion or to combine them into a single-objective function. In the context of ALB, and in relation with the TSALBP-1/3, consider for example a plant manager that has to define an assembly line configuration or to balance again an existing line to satisfy a given annual production rate (i.e., fulfilling a specific cycle time) with a clear space restriction related to the available place in her or his current plant. Each possible valid line configuration satisfying the cycle time will require a different number of stations – that the decision maker (DM) also wants to minimise as much as possible to reduce the staff costs- and will occupy a concrete area – that must also be minimised for obvious industrial cost reasons-. In such case, company managers would like to have an algorithm to compute a set of good solutions (instead of a single solution) with various trade-offs between the two different criteria (i.e., the number of stations and the area of these stations in the assembly line configuration), so they can select the most desirable solution after inspecting the various alternatives.

Ant Colony Optimisation (ACO) (Dorigo & Stützle, 2004; Mullen, Monekosso, Barman, & Remagnino, 2009) is a metaheuristic approach for solving hard combinatorial optimisation problems. The inspiring source of ACO is the pheromone trail laying and following behaviour of real ants which use pheromones as a communication medium. In analogy to the biological example, ACO is based on the indirect communication of a colony of simple agents, called (artificial) ants, mediated by (artificial) pheromone trails. The pheromone trails in ACO serve as a distributed, numerical information which the ants use to probabilistically construct solutions to the problem being solved and which they adapt during the algorithm's execution to reflect their search experience. Some examples of applications of ACO algorithms to production and management science are assembly line balancing, production, project scheduling, and flowshop optimisation (Abdallah, Emara, Dorrah, & Bahgat, 2009; Bautista & Pereira, 2007; Behnamian, Zandieh, & Fatemi Ghomi, 2009; Merkle, Middendorf, & Schmeck, 2002; Sabuncuoglu, Erel, & Alp, in press). Recently, multi-objective ant colony optimisation (MOACO) algorithms have been shown as powerful search techniques to solve complex MO NP-hard problems (Angus & Woodward, 2009; García Martínez, Cordón, & Herrera, 2007).

In Chica, Cordón, Damas, and Bautista (2010) Chica, Cordón, Damas, Bautista, and Pereira (2008b), we proposed the use of MOACO to solve the TSALBP-1/3. In those contributions, our novel procedure based on the Multiple Ant Colony System (MACS) algorithm (Barán & Schaerer, 2003) clearly outperformed the well-known NSGA-II (Deb, Pratap, Agarwal, & Meyarivan, 2002), the state-of-the-art evolutionary multi-objective optimisation (EMO) algorithm.

Nevertheless, although with the latter approach we managed to obtain a successful automatic procedure to solve the problem, providing very good approximations of the "efficient frontier", it still presents an important drawback. Sometimes, in real-world problems, the experts do not want to evaluate so many solutions and they feel much more comfortable on dealing with a smaller number of the most interesting solutions. This can be done by locating the search in a specific Pareto front region or just by considering a smaller Pareto set. In our problem, due to its realistic nature and the absence of any information on DM preferences, large Pareto sets with a huge number of different solutions are not suitable. On the one hand, plant managers can be overwhelmed with the excessive number of solutions found in the efficient solutions set, many of them being different ALB configurations sharing the same objective values. On the other hand, they can be only interested in a local objective trade-off corresponding to a specific portion of the efficient frontier collecting those most appealing solutions to their industrial context. Any other efficient solution, although theoretically valid for the problem-solving in any context, would not be interesting for them.

Therefore, the need of using explicit knowledge allowing us to guide the multi-objective search and to get the more interesting solutions for the plant DM in charge of the ALB in our problem becomes clear. As we are specifically interested on the TSALBP in automotive industry scenarios, in the current contribution we aim to extend the latter proposal for the TSALBP-1/3 based on MACS by incorporating problem-specific information provided by the Nissan plant experts. To do so, we introduce some novel procedures for incorporating preference information into a MOACO algorithm in order to simplify the DM task. These models will use an *a priori* approach to incorporate the Nissan managers' expertise elicited in the form of preferences both in the decision variable and the objective space. Notice that, this comprises a novelty since *a priori* approaches have been less used in MOACO, EMO and other metaheuristics for MOO (Coello, Lamont, & Van Veldhuizen, 2007; Jones, Mirrazavi, & Tamiz, 2002) than, for instance *a posteriori* approaches, which postpone the inclusion of preferences until the search process is finished. Nevertheless, we should note that the presented procedures are generic and can be applied without problems to any other TSALBP domain or even to other kinds of MOO problems.

Our preferences in the decision variable space will aim to discriminate between those promising line configurations having the same objective values, i.e., the same trade-off between the number of stations and their area (some preliminary work was done in Chica, Cordón, Damas, Bautista, & Pereira (2008a)). In the same conditions, a Nissan DM would prefer a solution with a more balanced stations configuration since it provides less human resources' conflicts. In this way, the efficient solutions set size will be reduced by providing the plant manager with only a single line configuration for each objective value trade-off. Additionally, we will show how the use of this kind of preference information also increases the quality of the Pareto front approximation by increasing the MACS convergence capability.

Meanwhile, the preferences in the objective space will deal with an even more important task to ease the Nissan plant manager's task. It will aim to reduce the efficient frontier size by focusing only on the most interesting specific portion to the DM according to the economic factors of the country where the Nissan plant is located.

These preferences will change with respect to the final location of the industrial plant (scenario). Hence, we will use six real scenarios around the world and two distinct approaches to incorporate preferences in the objective space into the MACS algorithm: (a) by units of importance, and (b) by setting a set of goals (some preliminary work in the latter approach was done in Chica, Cordón, Damas, & Bautista (2009)). They will be based on two preference incorporation models existing in EMO (Branke, Kaubler, & Schmeck, 2001; Deb, 1999).

Our MACS algorithm with preferences will be tested on both academic real-like TSALBP-1/3 instances and a real-world Nissan instance which has specific peculiarities with respect to the others. The latter corresponds to the assembly process of the Nissan Pathfinder engine, developed at the Nissan industrial plant in Barcelona (Spain). Real scenarios and cost data are used to test the behaviour of the algorithms.

The paper is structured as follows. In Section 2, the problem formulation, our MOACO proposal, and the experiments configuration are explained. Then, the preferences in the decision space to filter equally-preferred solutions and their experimentation are detailed in Section 3. In Section 4, we introduce the need of incorporating more advanced preferences in the objective space and we check out the performance of the resulting algorithms on different Nissan scenarios. Finally, some concluding remarks are discussed in Section 5.

2. Preliminaries

The problem description and our MOACO approach to the TSALBP-1/3 are presented in the first two sections. In the third section, a brief summary on the usual way to incorporate preferences in MOO is provided. Besides, we present the experimental setup and the tackled problem instances.

2.1. The time and space assembly line balancing problem

The manufacturing of a production item is divided up into a set V of n tasks. 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 resources employed. Each station k is assigned to a subset of tasks S_k ($S_k \subseteq V$), called its workload. Each task j must be assigned to a single station k.

Each task j has a set of direct predecessors, P_j, which must be accomplished before starting it. These constraints are normally represented by means of an acyclic precedence graph, whose vertices stand for the tasks and where a directed arc (i,j) indicates that task i must be finished before starting task j on the production line. Thus, if $i \in S_h$ and $j \in S_k$, then $h \leqslant k$ must be fulfilled. Each station k presents a station workload time $t(S_k)$ that is equal to the sum of the tasks' lengths assigned to the station k.

In general, SALBP (Scholl, 1999) focus on grouping together the tasks belonging to the set V in workstations by an efficient and coherent way. In short, the goal is to achieve a grouping of tasks that minimises the inefficiency of the line or its total downtime satisfying all the constraints imposed on the tasks and on the stations. The literature includes a large variety of exact and heuristic problem-solving procedures as well as metaheuristics applied to the SALBP (Baybars, 1986; Talbot, Patterson, & Gehrlein, 1986).

However, this SALBP does not model the real industry situation in an accurate way. For example, the need of introducing space constraints in assembly lines design can be easily justified since: (i) there are some constraints to the maximum allowable movement of the workers that directly limit the length of the workstation and the available space, (ii) the required tools and components to be assembled should be distributed along the sides of the line so, if several tasks requiring large areas for their supplies are put together, the workstation would be unfeasible; and (iii) the change of product which will need to be assembled keeping the same production plant (line reconfiguration) sometimes causes additional requirements of space.

A spatial constraint may be considered by associating a required area a_j to each task j and an available area A_k to each station k that, for the sake of simplicity, we shall assume to be identical for every station and equal to A:$A = \max_{k \in \{1 \ldots n\}} \{A_k\}$. Thus, each station k requires a station area $a(S_k)$ that is equal to the sum of areas required by the tasks assigned to station k.

This leads us to a new family of problems called TSALBP in Bautista and Pereira (2007). It may be stated as: given a set of n tasks with their temporal t_j and spatial a_j attributes ($1 \leqslant j \leqslant n$) and a precedence graph, each task must be assigned to a single station such that: (i) every precedence constraint is satisfied, (ii) no station workload time ($t(S_k)$) is greater than the cycle time (c), and (iii) no area required by any station ($a(S_k)$) is greater than the available area per station (A).

TSALBP presents eight variants depending on three optimisation criteria: m (the number of stations), c (the cycle time), and A (the area of the stations). Within these variants there are four multi-objective problems and we will tackle one of them, the TSALBP-1/3. It consists of minimising the number of stations m and the station area A, given a fixed value of the cycle time c. We chose this variant because it is quite realistic in the automotive industry. The main supporting reasons for our decision were: (i) the annual production of an industry plant is usually set by some market objectives specified by the company. This rate and other minor aspects influence the specification of a fixed cycle time c, so the assembly line needs to be balanced again taking into account the new cycle time. (ii) When we set the cycle time c, we need to search for the best number of stations m because the factory must achieve the demand with the minimum number of workers. Furthermore, searching for the station area is a justified objective because it can reduce the workers' movements and the components and system tools transfers. (iii) Some values for the objective m, the number of stations, are not allowed in real conditions because in automotive factories the number of workers are decided in advance and some changes can occur during a project or periods of time. (iv) Not only the number of stations but also some station areas may be unreachable. Undesirable areas are those which are too small or too large because they can generate disturbing conditions for workers or annoying and unnecessary movements among the stations, respectively.

2.2. A MACS algorithm to solve the TSALBP-1/3 variant

In this section, we review our ACO proposal for solving the TSALBP-1/3. It is based on the MACS algorithm, which was proposed by Barán and Schaerer (2003) as an extension of Ant Colony System (Dorigo & Gambardella, 1997) to deal with multi-objective problems. The complete MACS description can be found in Barán and Schaerer (2003), and our proposal is detailed in depth in Chica et al. (2010).

MACS uses one pheromone trail matrix, τ, and several heuristic information functions, η^k (in our case, η^0 for the duration time of each task t_j, and η^1 for their area a_j). The transition rule is slightly modified to attend to both heuristic information functions. Since MACS is Pareto-based, the pheromone trails are updated using the current non-dominated set of solutions (Pareto archive).

In our problem, although one solution is an assignment of different tasks to different stations, its construction cannot be performed similarly to other assignment problems because the number of stations is not fixed. Indeed, this is a variable to be minimised and we have to deal with the important issue of satisfying precedence constraints. Using a constructive and station-oriented approach (as usually done for the SALBP, Scholl & Becker, 2006) we can face the precedence problem. Thus, our algorithm will open a station and select one task among every candidate till a stopping criterion is reached. Then, a new station is opened to be filled.

We analysed different settings for the heuristic information but the experiments showed that the performance of the algorithm is better if it is not considered (see Chica, Cordón, Damas, Bautista, & Pereira, in press). Therefore, the new preference incorporation proposals in this contribution are based on a MACS algorithm only guided by the pheromone trail information.

This pheromone trail information has to memorise which tasks are the most appropriate to be assigned to a station. Hence, pheromone has to be associated to a pair $(station_k, task_j)$, $k = 1,\ldots,m$, $j = 1,\ldots,n$, so our pheromone trail matrix has a bi-dimensional nature. We have used two station-oriented single-objective greedy algorithms to obtain the initial pheromone value τ_0.

In addition, we introduced a new mechanism in the construction algorithm to close a station according to a probability distribution, given by the filling rate of the station. It helps the algorithm reach more diverse solutions from closing stations by a probabilistic process:

$$p(closing) = \frac{\sum_{\forall i \in S_k} t_i}{c}$$

This probability is computed at each construction step so its value is progressively increased. Once it has been computed, a random number is generated to decide if the station is closed or not at that time.

Furthermore, there is a need to look for a better intensification-diversification trade-off. This objective can be achieved by means of introducing different filling thresholds associated to the ants that build the solution, so the solution construction procedure is modified. In this way, before deciding the closing of the station, the ant's filling threshold must be overcome. Thus, the higher the ant's threshold, the more filled the station will be because there will be less possibilities to close the station during its construction process.

In this way, the ants population will show a highly diverse search behaviour, allowing the algorithm to properly explore the different parts of the optimal Pareto front by spreading the generated solutions.

2.3. Handling preferences in MOO

There have been much work on regarding how and when to incorporate decisions from the DM into the search process. Numerous techniques have been applied to solve multi-criteria problems considering the DM domain knowledge such as outranking relations, utility functions, preference relations, or desired goals (Chankong & Haimes, 1983; Ehrgott, 2000).

One of the most important question is the moment when the DM is required to provide preference information. There are basically three ways of doing so (Ehrgott, 2000):

- *Prior to the search (a priori approaches)*: There is a considerable body of work in OR involving approaches performing prior articulation of preferences. The main difficulty and disadvantage of the approach is finding this preliminary global preference information.
- *During the search (interactive approaches): Interactive* approaches have been normally favoured by researchers because of the DM can get better perceptions influenced by the total set of elements in a situation or perhaps, some preferences cannot be expressed analytically but with a set of beliefs. Thus, the OR community has been working with this approach for a long time.

Table 1
Used parameter values.

Parameter	Value	Parameter	Value
Number of runs	10	Number of ants	10
Maximum run time	900 s	β	2
PC specifications	Intel Pentium™ D	ρ	0.2
	2 CPUs at 2.80 GHz	q_0	0.2
Operating system	CentOS Linux 4.0	Ants' thresholds	{0.2,0.4,0.6,0.7,0.9}
	GCC 3.4.6		(2 ants per threshold)

- *After the search (a posteriori approaches)*: The main advantage of incorporating preferences after the search is that no utility function is required for the analysis. However, many real-world problems are too large and complex to be solved using this technique, or even the number of elements of the Pareto optimal set that tends to be generated is normally too large to allow an effective analysis from the DM.

Concerning the field of EMO and other metaheuristics for MOO, most of the existing work is mainly based on *a posteriori* approaches where the only intervention of DMs is done once the algorithm has reached the best possible approximation of the efficient solutions set. However, this is sometimes problematic as the process of selecting the most convenient set of solutions from a complete efficient set is not particularly trivial. In most of the cases, the DM is unable to choose a solution among the hundreds or thousands computed (Miettinen, 1999).

Nevertheless, in the last few years we can find several EMO approaches based on eliciting goal information prior to the search (*a* priori approaches) (Cvetkovic & Parmee, 2002; Deb & Branke, 2005) as well as handling preferences during the search (interactive approaches, as done for instance in Phelps & Koksalan (2003), and in Molina, Santana, Hernández-Díaz, Coello, & Caballero (2009)), which are becoming more and more usual and important. A comprehensive survey on the incorporation of preferences in EMO is studied in Coello et al. (2007). In addition, some EMO researchers are starting to define a global framework considering multi-criteria decision making (MCDM) as a conjunction of three components: search, preference trade-offs, and interactive visualisation (Bonissone, 2008).

2.4. Experimental setup and problem instances

The problem instances and the parameter values used in this contribution are detailed in the next two sections.

2.4.1. Problem instances

Three real-like problem instances with different features have been selected for the experimentation: `barthol2`, `barthold`, and `weemag`. Originally, these instances were SALBP-1 instances[1] only having time information. However, we have created their area information by reverting the task graph to make them bi-objective (as done in Bautista & Pereira (2007)).

In addition, we have considered a real-world problem corresponding to the assembly process of the Nissan Pathfinder engine, developed at the Nissan industrial plant in Barcelona (Spain).[2] The assembly of these engines is divided in 378 operation tasks

[1] Available at: http://www.assembly-line-balancing.de.

[2] The problem has been simplified by merging the data of the different kinds of engines that are assembled in the industrial cell.

(grouped into 140). For more details about the Nissan instance, the interested reader is referred to Bautista and Pereira (2007), in which all the tasks and their time and area information are specified.

2.4.2. Parameter values

The initial MACS algorithm and all its variants with preferences which will be introduced in the next two sections have been run 10 times with 10 different seeds for each of the three real-like instances and the Nissan instance. Every considered parameter value is shown in Table 1.

3. Preferences in the decision space to reduce the number of efficient solutions for the TSALBP

We have included preferences in the decision space to discriminate between those solutions having the same objective values, i.e., the same values for the number of stations and their area (notice that, some preliminary work on this issue was done in Chica et al. (2008a)). First, the description of these DM preferences, based on the Nissan factories observation, is given. Then, some experimentation is done and the behaviour of the MACS variants with and without preferences is analysed.

3.1. Description of the used preferences for an idle module-phase of production

Although the most usual application of preferences is aimed to guide the search to the specific Pareto front regions which are interesting for the DM (see Section 4), we also considered that applying them on the decision variable space could be beneficial for our framework.

Despite it is convenient to have a set of possible useful assembly line configurations for the plant (see for instance, Dar-El & Rubinovitch, 1979), the reduction of the number of solutions presenting the same objective values is highly justified in the TSALBP. In this way, it will relieve managers for the tiring task of checking an extremely large number of possible solutions for the line balancing of their plant.

Thus, it is important to establish some rules, based on the expert preferences, to choose among those solutions the most appropriate one according to the specific industrial context. This addition of domain knowledge (using an *a priori* approach) (Bonissone, Subbu, Eklund, & Kiehl, 2006; Coello et al., 2007) will allow us to derive a Pareto set composed of a smaller number of more likely solutions for the final user as well as it induces a better convergence to the actual efficient frontier as a collateral effect.

In view of our observations of real Nissan plants, we can discriminate between two solutions (assembly line configurations) with the same cycle time, number of stations and area (c, m and A values) changing the original dominance relation by considering the following preferences based on Nissan domain knowledge:

(a) The workload of the plant must be well-balanced in every station. For m stations, all the station workload times $t(S_k)$ for $k = 1,\ldots,m$ are alike. Due to this information, and considering the same number of employees per station, a well-balanced plant provides less human resources' conflicts. Likewise, it eliminates the need of programming shifts among the workers of the different stations.
(b) The needed space for toolboxes and other worker's instruments must be as similar as possible. This preference aims to offer solutions in which every worker has the same working conditions. If we reduce the extra effort in movements and the crowding feeling, that will eliminate industrial disputes.

As can be seen, these industrial concepts have not got the importance of the m and A objectives. Thus, considering them as additional criteria and establishing a lexicographic order is not appropriate for the problem. However, the "know-how" represented by (a) and (b) can be formulated by means of preference measures allowing us to establish a priority between similar solutions:

$$P_t(\sigma) = \sum_{k=1}^{m}(c - t(S_k))^2, \quad P_a(\sigma) = \sum_{k=1}^{m}(A - a(S_k))^2$$

where σ represents a solution (assembly line configuration) with known c, A and m values. S_k is the set of tasks assigned to the k-th station in σ.

Bearing in mind these measures, the following preferences-based dominance relations can be considered:

Table 2
Unary metrics for `barthol2`, `barthold`, `Nissan`, and `weemag` instances.

	Mean (standard deviation)			
	`barthol2`	`barthold`	`Nissan`	`weemag`
	Number of non-dominated solutions			
MACS	13.5 (2.84)	12 (1.41)	571.9 (81.08)	15.6 (4.39)
MACS preferences	10.8 (1.47)	12 (1.18)	7.2 (0.75)	7.9 (1.22)
	Number of different Pareto front solutions			
MACS	12.8 (2.79)	11 (0.89)	7.6 (1.02)	8.2 (1.54)
MACS preferences	10.8 (1.47)	12 (1.18)	7.2 (0.75)	7.8 (1.17)
	Metric S			
MACS	391719.09 (1204.82)	725348.19 (2127.41)	8889.75 (0.65)	65148.1 (5.66)
MACS preferences	391410.59 (166.44)	726.088 (2202.85)	8864.45 (31.9)	65151.6 (17.49)
	*Metric M2**			
MACS	10.86 (2.07)	9.49 (0.58)	6.88 (0.78)	7.46 (1.26)
MACS preferences	9.38 (1.2)	10.19 (0.97)	6.54 (0.65)	7.15 (1.06)
	*Metric M3**			
MACS	61.99 (12.92)	407.91 (20.95)	21.12 (1.31)	24.61 (1)
MACS preferences	64.82 (6.56)	403.31 (23.33)	19.62 (2.63)	24.39 (1.62)
	Number of applications of preferences-based dominance			
MACS preferences	8.3 (3.02)	5.6 (2.88)	935.4 (231.36)	39.5 (18.19)

Definition 1. A solution σ_1 is said to partially dominate (i.e., to be more preferable for the plant DM than) another solution σ_2 with respect to time – with both having identical *c*, *A*, and *m* values – if $P_t(\sigma_1) < P_t(\sigma_2)$.

Definition 2. A solution σ_1 is said to partially dominate (i.e., to be more preferable for the plant DM than) another solution σ_2 with respect to space – with both having identical *c*, *A*, and *m* values – if $P_a(\sigma_1) < P_a(\sigma_2)$.

Definition 3. A solution σ_1 is said to completely dominate (i.e., to be totally preferable for the plant DM than) another solution σ_2 with respect to time and space – with both having identical *c*, *A*, and *m* values – if: $[P_t(\sigma_1) \leqslant P_t(\sigma_2)] \wedge [P_a(\sigma_1) < P_a(\sigma_2)] \vee [P_t(\sigma_1) < P_t(\sigma_2)] \wedge [P_a(\sigma_1) \leqslant P_a(\sigma_2)]$

Of course, the decision between two solutions with different *c*, *A* and *m* values is made by using the traditional dominance relationship.

3.2. Experiments and analysis of results

Comparing different optimisation techniques empirically always involve the notion of performance and it is not an easy task. Thus, we have used more than a single MOO performance index of different kinds (as proposed in Zitzler, Thiele, Laumanns, Fonseca, & Grunert da Fonseca (2003)): the number of total and different (in the objective space) efficient solutions returned by each algorithm, as well as the *S*, $M2^*$ and $M3^*$ metrics. *S*, the hypervolume metric, measures the volume enclosed by the generated Pareto front (it is the most used because it can determine the quality of the obtained Pareto front in terms of both convergence and extension), $M2^*$ evaluates the distribution of the solutions, and $M3^*$ evaluates the extent of the obtained Pareto fronts[3] (see Coello et al. (2007) for a more detailed explanation on multi-objective performance indices, classically called metrics). In addition, the number of applications of the preferences-based dominance criterion is also shown in Table 2.

On the other hand, we have considered the binary metric *C* (Coello et al., 2007) to compare the obtained Pareto sets. Fig. 1 shows boxplots based on that metric which compare MACS with and without preferences by calculating the dominance degree of their respective generated efficient set approximations. Each rectangle contains four boxplots (from left to right, `barthol2`, `barthold`, `Nissan`, and `weemag`) representing the distribution of the *C* values for the ordered pair of algorithms. Each box refers to algorithm *A* associated with the corresponding row (i.e., either MACS with or without preferences) and algorithm *B* associated with the corresponding column (i.e., the other one) and gives the fraction of *B* covered by *A* (*C*(*A*,*B*)).

In the view of the obtained results, the preferences-based MACS variant shows the best convergence and reduces the number of non-dominated solutions with the same objective values as expected while keeping a similar value of different solutions. In some cases, this reduction is quite important (see `Nissan` instance, from an average of 571.9 solutions to 7.2), thus significantly reducing the complexity of the desired solution selection for the plant DM. We should also highlight that the real-world instance of Nissan is the most appropriate to use preferences based on domain knowledge. Indeed, the number of applications of the preferences-based dominance is the highest one. Regarding the *C* metric analysis represented in Fig. 1, we can notice the similar convergence of MACS with and without preferences. Nevertheless, the preferences-based MACS variant seems to outperform MACS in some instances.

The graphical representation of the aggregated Pareto fronts[4] for the `barthol2` instance is shown in Fig. 2. We can arrive to the same previous conclusions by observing it. MACS with and without preferences achieve a very similar convergence, and even in some cases the former gets slightly better results. We have only included the obtained Pareto front for this problem instance for the lack of space but pretty similar behaviours are obtained in the remainder.

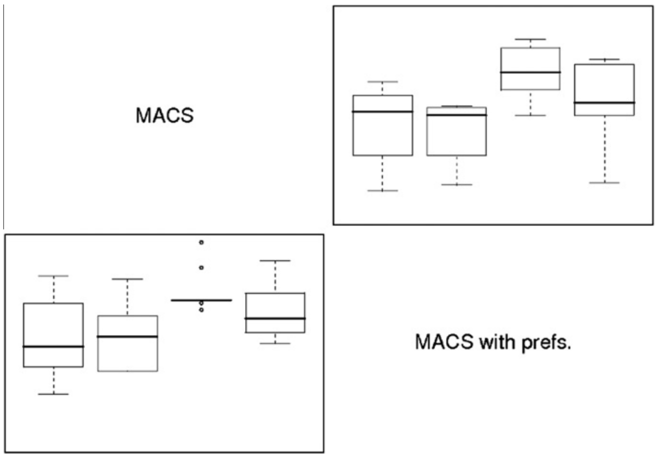

Fig. 1. *C* metric values represented by means of boxplots for every problem instance (from left to right, `barthol2`, `barthold`, `Nissan`, and `weemag`).

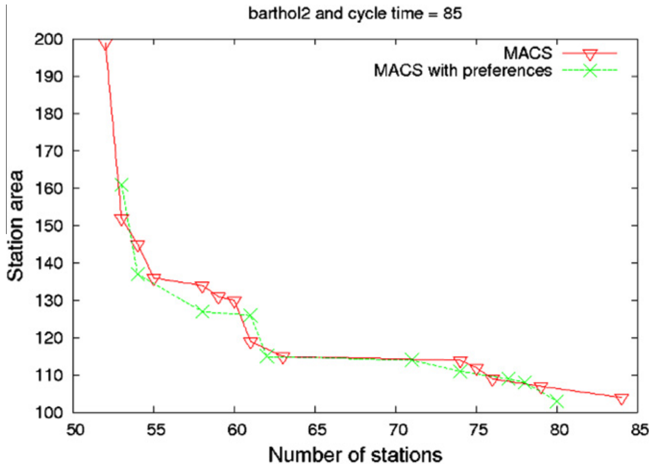

Fig. 2. The Pareto front for the `barthol2` problem instance.

Table 3
Upper and lower bounds for the considered instances.

Problem instance	*m*		*A*	
	Lower	Upper	Lower	Upper
`barthol2`	50	90	70	200
`barthold`	7	30	250	800
`weemag`	30	60	40	70
`Nissan`	16	40	16	40

[3] $M1^*$ has not been applied because we do not know the optimal efficient frontier for the problem instances.

[4] In order to be able to properly show all the algorithm's runs at one time, we merged the approximations of the efficient frontiers it obtained in different runs preserving only the global efficient solutions in an aggregated Pareto front.

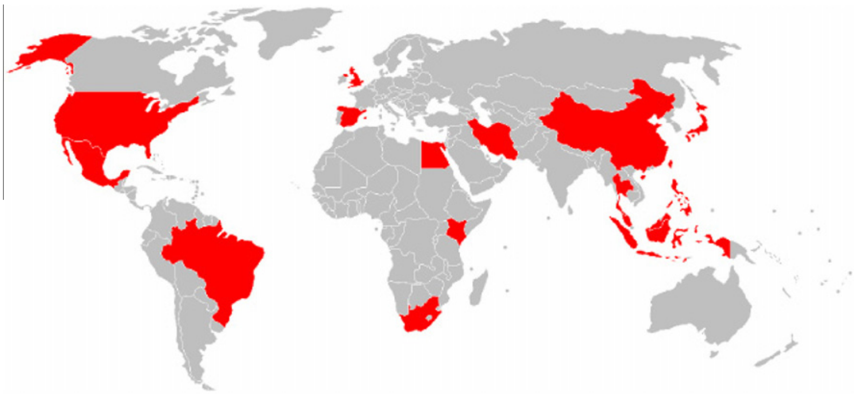

Fig. 3. World locations of Nissan Motors factories.

4. Advanced objective space preferences to guide the search to the interesting TSALBP Pareto front region

In Section 3, we defined a criterion that allowed us to discriminate among line configurations having the same values of *c*, *m*, and *A* from an industrial point of view. However, this is a useful mechanism but unfortunately it is not enough because of the realistic nature of TSALBP. Therefore, we should provide managers with only interesting and helpful solutions for their specific industrial context, instead of providing them with all the possible best solutions for their problems regardless the location of the plant. We will incorporate this explicit knowledge in the objective space using the Nissan expertise, considering again an *a priori* approach.

In the next sections, we describe the Nissan problem-specific knowledge as well as various EMO preference incorporation mechanisms which will be embedded in our MACS algorithm to handle *a priori* preferences. Figures with the obtained Pareto fronts are included to show and analyse the results of the experimentation in every case.

4.1. Removing unattainable assembly line configurations from the obtained Pareto sets

As said in Section 2.3, if explicit domain-knowledge is not considered, the multi-objective algorithm can provide a vast set of solutions. Obviously, every efficient solution, although valid to solve the tackled problem, is not always appropriate in every specific real industrial design context, as the MOO algorithm does not take those conditions into account by itself while the DM does. Hence, providing plant managers with some TSALBP solutions that are known in advance not to be attainable or interesting for them is meaningless. In our problem, line configurations with extreme values of *m* or *A* must be directly discarded because of the following reasons:

1. An assembly line configuration with a very large number of stations and a small area may be dangerous with respect to the industrial implantation. This behaviour can be explained since, for a single assembly line, the management of a high number of employees can negatively condition the near future. Staff management is even more complicated in our problem context, the automotive industry. On the other hand, solutions having a low number of stations with a large area are prone to be problematic when assembly lines need to be restarted and the absenteeism level is appreciable.
2. If we consider the value of the area, the same extreme values must be avoided. Industrial configurations with an extremely high area for the stations will result in an inefficient process since workers' movements will take a lot of time. In contrast, the end result of adopting configurations with a low area will cause the workers' discomfort and their productivity will decrease.

Consequently, the obtained efficient set could be restricted to upper and lower bounds for both objectives, the number of stations *m* and their area *A*, prior to the run of the MOACO algorithm. None of the solutions being out of these bounds will be considered in the search process as they will never be useful line configurations for the DM of the plant. Table 3 shows these bounds, set by plant's DMs, for our problem instances as well as for the real case of Nissan.

4.2. Manufacturing location costs based on Nissan expert knowledge

When a DM has a set of possible solutions (the non-dominated solutions of the Pareto set) one of the most used criterion to choose one or a subset of them is taking into account their cost of development. In order to define some cost variables in the TSALBP with the latter aim, we will consider two types of operational costs:

- *Labour cost*: Associated to the employees (and consequently, to the number of stations *m*). It is defined as an average labour cost per employee in the manufacture of motor vehicles industry group. Real data are used in this paper (taken from the International Labour Organisation[5]) and US dollars are considered as currency. Other indicators related to labour costs might be used as well (productivity, working hours, etc.).
- *Industrial cost*: Directly associated to the station maintenance cost. In order to collect objective data, we consider that cost is proportional to the station area *A*. In our case, it was collected from the 2007 Industrial Space Across the World report.[6] The used units for industrial cost are US dollars per square feet in one year.

Naturally, both operational costs are not fixed. Their differences are subject to the location a manager wants to set up the factory. Thus, one efficient solution (assembly line configuration) is not well-defined enough if we do not take into account its possible location, that is, there is not enough information for the MOACO algorithm to search for the desired efficient solution set (Coello et al., 2007). Since our real-world problem belongs to a Nissan industrial plant, the candidate locations for the industrial solution may perfectly be one of the actual Nissan factory locations (scenar-

[5] http://laborsta.ilo.org.
[6] Reported by Cushman & Wakefield Research, http://www.cushwake.com.

Table 4
Labour cost, productivity, and industrial cost.

Country	Labour cost per hour ($)	Productivity	Labour cost biased by productivity	Industrial space ($/sq.ft.year)
Spain	28.36	21.67	1.31	15.59
Japan	30.60	25.61	1.19	19.51
Brazil	8.79	7.99	1.10	10.05
UK	31.61	30.13	1.05	28.91
USA	30.39	35.29	0.86	11.52
Mexico	6.57	9.24	0.71	5.02

Table 5
Units of importance for both objectives.

Country	Labour cost (objective f_1:m)	Industrial space cost (objective f_2:A)
Brazil	2	0.2
Spain	1.5	0.1
Japan	0	0
Mexico	0	0
USA	0.2	1.25
UK	0.2	3

ios). All the different Nissan Motors manufacturing locations all over the world are red[7]-coloured in Fig. 3. We have selected six of these countries to carry out our study, which together with their real costs[8] are shown in Table 4, in a descending order of labour cost-productivity ratio.

From this data, industrial experts are able to set units of importance to the achievement of the two objectives, the number of stations m, and their area A, in order to define some preferences, or even to set some goals depending on the countries the industrial plant wants to be established. For example, in those countries where the industrial cost (respectively, the labour cost) is quite expensive, the objective m (respectively, the objective A) will be more important to be minimised and hence its weight will be higher.

4.3. Setting the plant manager preferences by means of units of importance for the m and A objectives

Sometimes, it is quite difficult to exactly define the weighting of different optimisation criteria, although the user has usually some notions about what range of weightings might be reasonable. In Branke et al. (2001), the authors present a simple and intuitive way to integrate user's preference into an EMO algorithm by defining linear maximum and minimum trade-off functions.

In the Guided Multi-Objective Evolutionary Algorithm (G-MOEA) proposed by Branke et al. (2001), user preferences are taken into account by modifying the definition of dominance. The approach allows the DM to specify, for each pair of objectives, maximally acceptable trade-offs. For example, in the case of two objectives, the DM could define that an improvement by one unit in objective f_2 is worth a degradation of objective f_1 by at most a_{12} units. Similarly, a gain in objective f_1 by one unit is worth at most a_{21} units of objective f_2.

In our case, an expert can provide our MACS algorithm for the TSALBP-1/3 variant with the same units of importance for each country location bearing in mind the costs of Table 4. A possible definition for these units is shown in Table 5.

This information is then used to modify the traditional dominance scheme as follows:

$$x \succ y \leftrightarrow (f_1(x) + a_{12}f_2(x) \leqslant f_1(y) + a_{12}f_2(y)) \wedge (a_{21}f_1(x) + f_2(x) \leqslant a_{21}f_1(y) + f_2(y))$$

With this dominance scheme, only a part of the original Pareto front remains non-dominated. This region is bounded by the solutions where the trade-off functions are tangent to the optimal efficient frontier. The original dominance criterion can be considered just as a special case of the guided dominance criterion by choosing $a_{12} = a_{21} = \infty$.

In the case of two objectives, as ours, the guided dominance criterion corresponds to the standard dominance principle together with a suitably transformed objective space. It is thus sufficient to replace the original objectives with two auxiliary objectives Ω_1 and Ω_2 and use them together with the standard dominance principle (Deb & Branke, 2005):

$$\Omega_1 = f_1(x) + a_{12}f_2(x), \quad \Omega_2 = a_{21}f_1(x) + f_2(x)$$

In the case of the MACS algorithm, the transformation of the dominance relation is as simple as in an evolutionary algorithm. We have applied directly these modified relations to our scheme with the units of importance of Table 5.

The obtained aggregated Pareto fronts are shown in Figs. 4 and 5 for every problem instance. The "MACS no specific location" line

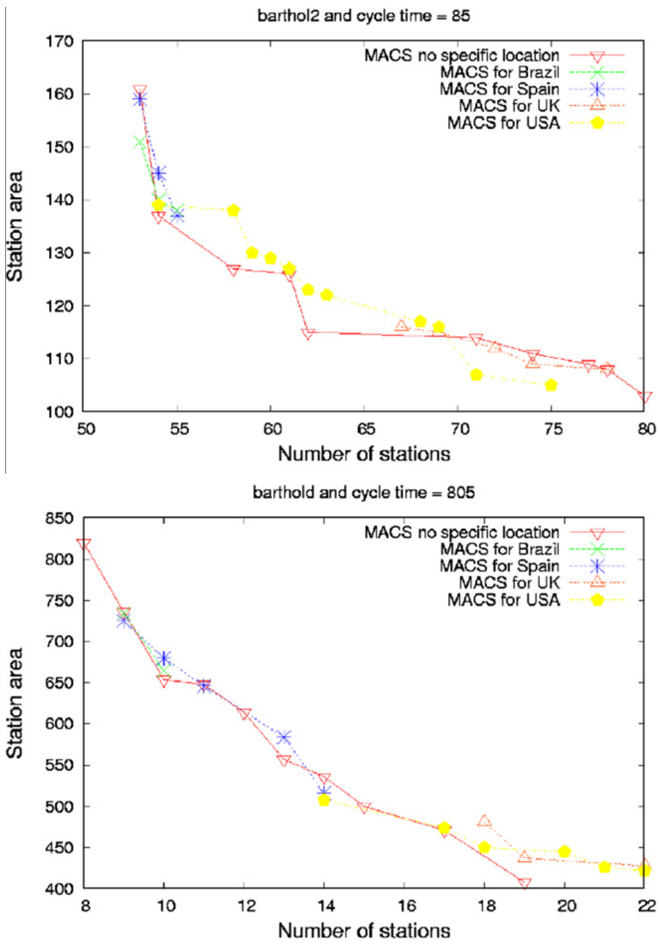

Fig. 4. Pareto fronts for the `barthol2` and `barthold` instances for different scenarios using Branke's units of importance alternative.

[7] For interpretation of the references to colour in Fig. 3, the reader is referred to the web version of this paper.

[8] Productivity is measured as the Gross Domestic Product (purchasing power parity (PPP) converted) per hour worked. This is the value of all final goods and services produced within a nation in a given year, divided by the total annual hours worked (source: Groningen Growth and Development Centre (University of Groningen)).

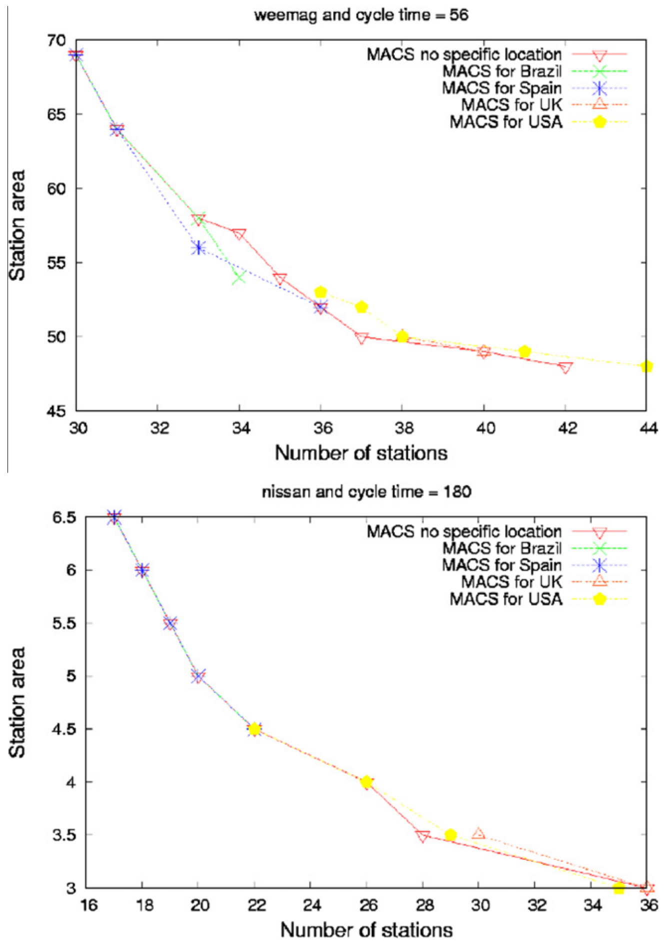

Fig. 5. Pareto fronts for the `weemag` and `Nissan` instances for different scenarios using Branke's units of importance alternative.

shows the Pareto front achieved by the MACS algorithm without considering any preference information (i.e., units of importance in this case). This line also corresponds to the case of Japan and Mexico, which have no discrimination between objectives (see Table 5). The other lines show the MACS outputs with the different units of importance of Brazil, Spain, UK, and USA.

The main idea we get from the observation of the figures is the correct focus on a different efficient frontier region depending on the scenario and its weights of importance. It can be clearly seen how a plant manager from UK will not obtain the same solutions than another from Brazil or Spain in every problem instance. However, depending on the instance, the features of the Pareto fronts for the same scenario can change. For example, the USA scenario gets much more solutions and a wider efficient solution set in the `barthol2` instance than in `weemag`. Thus, to get a more fine-grained front it is necessary to study the specific instance in depth and to set different units of importance for each of them.

Generally, Brazil and UK scenarios are more interested in the extremes of the Pareto fronts since their units of importance are clearly towards one objective (as stated, that happens because of the high difference between the costs associated to each of the two objectives). When the deviation of the units of importance are high, as in these cases, the obtained approximations of the efficient frontiers are narrower than in Spain and USA scenarios, in which the area of interest is more vaguely described.

We should notice that, in some instances and locations, the MACS variants with units of importance cannot achieve an equal convergence to the efficient frontier than the "MACS no specific location", which is able to get some efficient solutions not provided by the other MACS variants.

4.4. Setting the plant manager preferences by means of goals for the objectives m and A

The aim of goal programming is to find a solution which will minimise the deviation d between the achievement of the goal and the aspiration target t (Romero, 1991). These goals can be used as a set of preferences defined by the expert. There can be different types of goal criteria, from which we have chosen four of the most important, that is: *less-than-equal-to* ($f(x) \leqslant t$), *greater-than-equal-to* ($f(x) \geqslant t$), *equal-to* ($f(x) = t$) and *within a range* ($f(x) \in [t^l, t^u]$). For example, we can set that the total area of an industry plant I could be less than a number of specified squared metres or our number of stations needs to be, if possible, within an interval of 100 and 200. In our specified scenarios, some preference relations can be established by an expert, as done in Table 6 (Chica et al., 2009). We have not considered the *greater-than-equal-to* relation since it does not make sense in a minimisation problem like the TSALBP.

Deb proposed a technique to transform goal programming into MOO problems which are then solved using an EMO algorithm (Deb, 1999; Deb & Branke, 2005). The objective function of the EMO algorithm attempts to minimise the absolute deviation from the targets to the objectives. This approach was only used to perform the transformation from goals to objectives in Deb (1999). However, it can be also used to incorporate preferences into any MOO algorithm, like our MACS algorithm for the TSALBP-1/3 variant.

The goal programming problem can be modified to incorporate preferences to the objective function by changing the original objective functions as follows:

Goal	Objective function
$f_i(x) \leqslant t_j$	Minimise $\langle f_j(x) - t_j \rangle$
$f_i(x) \geqslant t_j$	Minimise $\langle t_j - f_j(x) \rangle$
$f_i(x) = t_j$	Minimise $\lvert f_j(x) - t_j \rvert$
$f_i(x) \in \left[t_j^l, t_j^u\right]$	Minimise $\max\left(\left\langle t_j^l - f_j(x)\right\rangle, \left\langle f_j(x) - t_j^u\right\rangle\right)$

Here, the operator $\langle\ \rangle$ returns the value of the operand if it is positive, otherwise it gives value zero. We have translated our preference goals for each country in Table 6 to modified objective functions following the conversion of Deb's approach. Since our defined goals are generic, our six initial scenarios have been grouped into only three, that is, Spain, Japan, and UK. Due to their economic characteristics, Spain is focused on line configurations that give more importance to the labour costs (objective m, the number of stations), UK needs solutions with less industrial cost (i.e., objective

Table 6
Goal criteria for our objectives: number of stations m, and the area A (different relational operators are used for each instance).

Problem instance	Spain	Japan	UK
`barthol2` ($=, \leqslant$)	$m = 51$ $A \leqslant 120$	$m = 60$ $A \leqslant 100$	$m = 68$ $A \leqslant 90$
`barthold` ($\in, \leqslant$)	$m \leqslant 8$ $A \leqslant 650$	$m \leqslant 14$ $A \leqslant 500$	$m \leqslant 16$ $A \leqslant 400$
`weemag` ($\leqslant, \in$)	$m \leqslant 30$ $A \in [56,61]$	$m \leqslant 35$ $A \in [46,51]$	$m \leqslant 45$ $A \in [40,45]$
`Nissan+` ($=, =$)	$m = 16$ $A = 5.7$	$m = 23$ $A = 3.8$	$m = 27$ $A = 3$

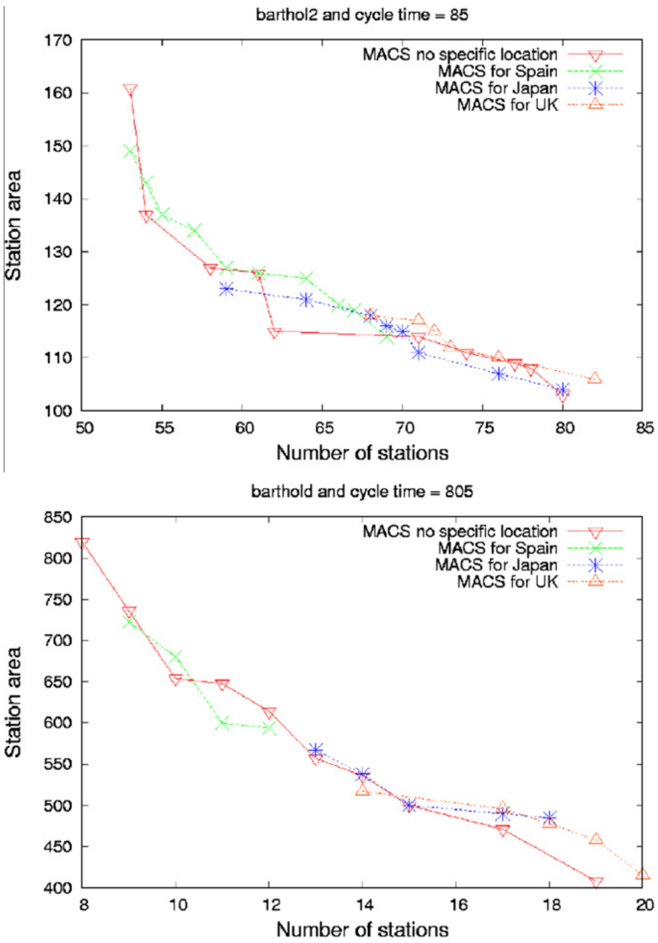

Fig. 6. Pareto fronts for the `barthol2` and `barthold` instances for different scenarios using Deb's alternative.

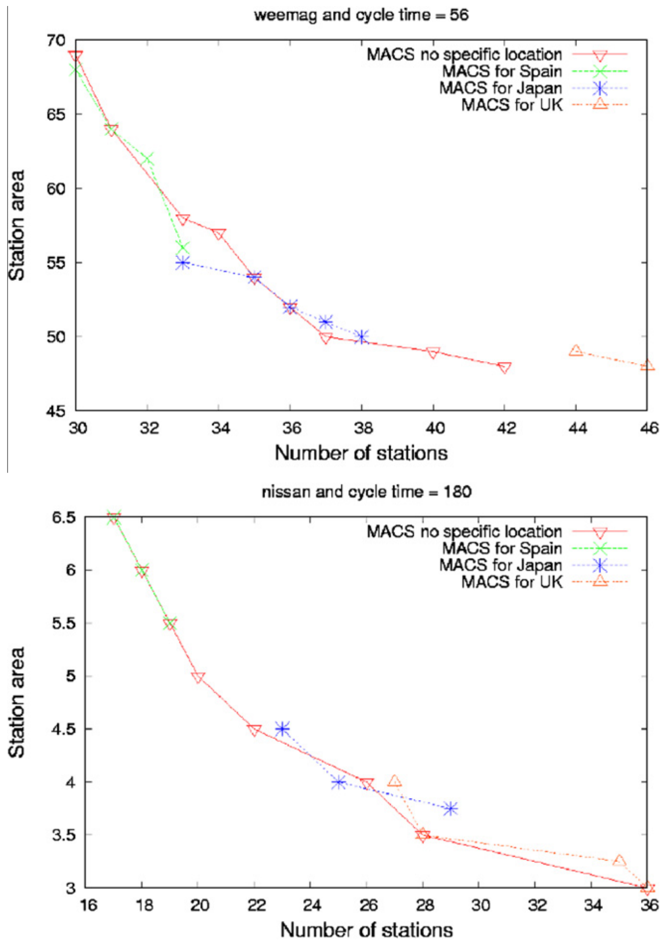

Fig. 7. Pareto fronts for the `weemag` and `Nissan` instances for different scenarios using Deb's alternative.

A, the maximum area of the stations), and Japan is more interested in a trade-off between the two costs. The Pareto fronts generated by MACS with the goals in Table 6 for the different scenarios are shown in Figs. 6 and 7.

These approximations of the efficient frontiers show how the use of goals in the scenarios gets solutions belonging to different areas. The solutions for the Spanish plant manager will have the lowest number of stations while those for the British expert will have the minimum station area of the whole Pareto front. In the case of the Japan scenario, configurations with a good trade-off between number of stations and area are achieved. Only in `barthol2` instance (Fig. 6), Japanese expert's solutions overlap those for the British expert. In the rest of instances, each scenario has its own Pareto front area, distinct to the others.

Generally, the convergence of the algorithm with goal preferences is the same than in "MACS no specific location", although the pseudo-optimal solutions sometimes belongs to "MACS no specific location" and others to a location-specific MACS.

4.5. A comparison between both approaches

In Fig. 8, boxplots based on the *C* metric comparing first, Branke's approach-based MACS variants with the general MACS (we remind that Japan-Mexico location used the MACS algorithm without preferences) and second, MACS variants with Deb's approach are shown. In the first boxplot, we can see how MACS for Japan-Mexico gets a low number of solutions dominated by the other algorithms. The reason is that MACS for Japan-Mexico spreads its search along all the Pareto front region, and this is not done by the other variants. In the second boxplot, the same results for the comparison among MACS variants using goals appear. Although the big picture is the same, a slightly better convergence of MACS without preferences with respect to MACS with preferences can be observed using Deb's goals.

Again, bearing in mind Fig. 8, we can compare how the MACS algorithm for a given location behaves in comparison with MACS for the other locations. In this case, the result of both approaches is quite similar in terms of convergence. Since the location-specific MACS focuses on a different Pareto front region, its solutions will not be dominated by the others and will dominate the rest of the variants' solutions.

Hence, we cannot affirm with no doubt which of both approaches performs better and they can be considered in principle as alternative approaches. The introduction of preferences in the objective space with units of importance, that is, Branke's approach, drive the search towards the interesting solutions for the expert with the same accuracy as Deb's approach using goals does. In addition, the number of solutions got by Branke and Deb's approaches in the different scenarios depends on the problem instance.

However, the main difference of both approaches is the representation of the preferences, since to be able to define goals we need to know exactly which values of our objectives we want to achieve. In contrast, defining our preferences by means of units of importance can be easily done and there is no need to know

Fig. 8. *C* metric values represented by means of boxplots comparing the general MACS with the specific variants for different scenarios using first, Brake's and second, Deb's alternative.

the specific context of each problem instance. In this sense, Branke's approach would be easier to be applied for plant manager DMs in real scenarios.

5. Concluding remarks

In this contribution, we have studied the inclusion of preferences based on domain knowledge to tackle the TSALBP-1/3, both in the decision and objective spaces. A previous MOACO proposal based on the MACS algorithm was extended and improved by using them. Bi-objective variants of three real-like ALB problem instances as well as a real problem from a Nissan industrial plant in Spain have been used in an experimental study for six different Nissan scenarios.

From the obtained results we have found out that the enrichment of MACS with domain knowledge related to the obtaining of a well-balanced configuration of the station workloads and areas provides excellent results. The number of solutions in the Pareto set having the same objective values is reduced, what simplifies the selection of the best assembly line configuration for plant experts as they need to check a lower number of alternatives. Moreover, a better convergence is obtained with respect not to considering the expert knowledge.

Two ways of incorporating preferences in the objective space to achieve only the Pareto front region which has the desirable trade-off between the number of stations *m* and their area *A* were applied by means of units of importance and goals. The application of these advanced preferences to the different Nissan scenarios was actually successful since they helped the MOACO algorithm to provide efficient solutions sets only focused on the solutions that plant managers are more interested on.

Some future works arise from this contribution: (i) more advanced ways of incorporating *a priori* expert knowledge in the algorithm must be studied, and (ii) the use of interactive procedures within the algorithm can also be beneficial (Hanne, 2000; Molina et al., 2009).

Acknowledgements

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