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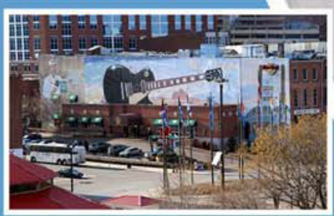

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Integration of an EMO-based Preference Elicitation Scheme into a Multi-objective ACO Algorithm for Time and Space Assembly Line Balancing

Manuel Chica, Óscar Cordón, Sergio Damas and Joaquín Bautista

Abstract— **In this paper, we consider the incorporation of user preferences based on Nissan automotive company's domain knowledge into a multi-objective search process for assembly line balancing. We focus on the Time and Space Assembly Line Balancing problem, a more realistic variant of this family of problems considering the joint minimisation of the number of stations and their area in the assembly line configuration. The multi-objective optimisation algorithm considered is based on Ant Colony Optimisation, a research area where the consideration of multi-criteria decision making issues is still not extended. The proposed approach borrows a successful preference scheme from the evolutionary multi-objective optimisation community, which provides experts with solutions of their contextual interest in the objective space. The expressions of the considered preferences are based on the Nissan plant designer's expert knowledge and on real-world economical variables. Using the real data of the Nissan Pathfinder engine, an experimental study is carried out to obtain the most preferred solutions for the decision makers in six different Nissan scenarios.**

I. 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 production of high quantity standardised commodities and more recently even gained importance in low volume production of customised products [1].

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) [2] 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.

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Bautista and Pereira recently proposed a more realistic framework, the Time and Space Assembly Line Balancing Problem (TSALBP) [3]. This framework considers an additional space constraint to become a simplified but closer version to real-world problems. In this paper we tackle the 1/3 variant of the TSALBP, which tries to minimise the number of stations and their area for a given product cycle time, a very complex and realistic multi-criteria problem in the automotive industry.

In our previous work [4], we successfully solved the TSALBP-1/3 by means of a multi-objective ant colony optimisation (MOACO) proposal [5], the Multiple Ant Colony System (MACS) algorithm [6]. In [7], the latter work was extended by incorporating problem-specific information provided by the plant experts in the form of *a priori* preferences 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. We based our study on the idea that in the same conditions, a Nissan decision maker (DM) would prefer a solution with a more balanced stations configuration since it provides less human resources' conflicts. Thus, the size of the efficient solutions set was reduced by providing the plant manager with only a single line configuration for each objective value trade-off.

In this contribution, we aim to extend the latter work by incorporating the elicitation of preferences in the objective space, tackling an even more important task to ease the Nissan plant manager's work: the reduction of the efficient frontier size by only focusing 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 to incorporate preferences in the objective space into the MACS algorithm. Preferences will be defined by setting goals and using the evolutionary multi-objective optimisation (EMO) preference incorporation model proposed by Deb in [8], [9]. The use of such a scheme in a MOACO algorithm constitutes one of the novelties of this work.

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 II, the problem formulation and our MOACO proposal are explained. Then, a brief study on the different ways of incorporating preferences in multi-objective optimisation (MOO) in general, and metaheuristics for MOO, in particular, is shown in Section III. In Section IV, real industrial costs and variables to elicitate preferences are introduced. We explain Deb's approach, the experimental setup, and check out the performance of the resulting preference-based MOACO algorithm on different Nissan scenarios in Section V. Finally, some concluding remarks are discussed in Section VI.

II. Preliminaries

In this section the problem preliminaries and our previous MOACO proposal are presented. First, an overview of the assembly line balancing problem is discussed. Then, the main features of the MACS algorithm are briefly described. In the last subsection, the experimental setup is shown.

A. 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 employed resources. Each station k is assigned to a subset of tasks S_k ($S_k \subseteq V$), called its workload. A task j is assigned to a 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 $h \leq k$ 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. SALBP [2] focuses on grouping tasks in workstations by an efficient and coherent way. There is a large variety of exact and heuristic problem-solving procedures for it [10].

The need of introducing space constraints in the assembly lines' design is based on two main reasons: (a) the length of the workstation is limited in the majority of the situations, and (b) the required tools and components to be assembled should be distributed along the sides of the line. Hence, an area 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 it to be identical for every station and equal to $A : A = max_{\forall k \in \{1..n\}}\{A_k\}$. 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 [3]. It may be stated as: given a set of n tasks with their temporal t_j and spatial a_j attributes ($1 \leq j \leq n$) 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 since the annual production of an industrial plant (and therefore, the cycle time c) is usually set by some market objectives. Besides, the search for the best number of stations and areas makes sense if we want to reduce costs and make workers' day better by setting up less crowded stations. For more information we refer to [4].

B. A MACS algorithm to solve TSALBP 1/3

In this section, a brief summary of our previous multi-objective proposal based on the MACS algorithm is presented. The complete MACS description can be found in [6], and our proposal is detailed in [4].

MACS was proposed as an extension of ACS [11] to deal with multi-objective problems. 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).

Since the number of stations is not fixed, we use a constructive and station-oriented approach (as usually done for the SALBP [10]) to face the precedence problem. Thus, our algorithm will open a station and select one task till a stopping criterion is reached. Then, a new station is again opened to be filled.

Experiments showed that the performance is better if MACS is only guided by the pheromone trail information. Such 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 $(station_k, task_j)$, $k = 1...n$, $j = 1...n$, so our pheromone trail matrix is bi-dimensional. We used two station-oriented single-objective greedy algorithms to obtain the initial pheromone value τ_0.

We also 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: $p(closing) = \left(\sum_{\forall i \in S_k} t_i\right) / c$. It helps the algorithm to reach more diverse solutions for closing stations by a deterministic process. The probability is computed at each construction step so its value is progressively increased. Then, a random number is generated to decide if the station is closed.

Besides, there is a need to achieve a better intensification-diversification trade-off. That was achieved by introducing different filling thresholds associated to the ants. These thresholds make the different ants have a different search behaviour. The higher the ant's threshold, the more filled the station will be (there will be less possibilities to close the station during its creation process).

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

III. HANDLING PREFERENCES IN MOO AND EMO

From the operations research (OR) perspective, there has been much work on how and when to incorporate decisions from the DM into the search process. Numerous techniques have been applied to solve multi-criteria decision making (MCDM) problems considering the DM domain knowledge such as outranking relations, utility functions, preference relations or desired goals [12], [13].

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 [13]:

- **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 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.
- **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 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 one solution among hundreds or thousands [14].

Nevertheless, in the last few years we can find several EMO approaches based on eliciting goal information prior to the search (*a priori* approaches) [9], [15] as well as handling preferences during the search (interactive approaches, as done for instance in [16] and in [17]), which are becoming more and more usual and important. A comprehensive survey on the incorporation of preferences in EMO is presented in [18]. In addition, some EMO researchers are starting to define a global framework to consider MCDM as a conjunction of three components: search, preference trade-offs, and interactive visualisation [19].

IV. NISSAN SCENARIOS BASED ON THE MANUFACTURING LOCATION COSTS

When a DM has a set of possible solutions (the non-dominated solutions of the efficient 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 is used in this paper (taken from the International Labour Organisation [1]) and US dollars are considered as currency. Other indicators related to labour costs might be used as well (productivity, working hours, etc.).
- **Industrial space cost**: directly associated to the area A. In our case, it was collected from the 2007 Industrial Space Across the World report [2]. The used units for space cost are US dollars per square feet in one year.

Naturally, the 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 consider its possible location, that is, there is not enough information for the MOO algorithm to search for the desired efficient solution set. 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 (scenarios). All the Nissan scenarios over the world are red-coloured in Figure 1. We have selected six of these countries to carry out our study, which together with their real costs [3] are shown in Table I.

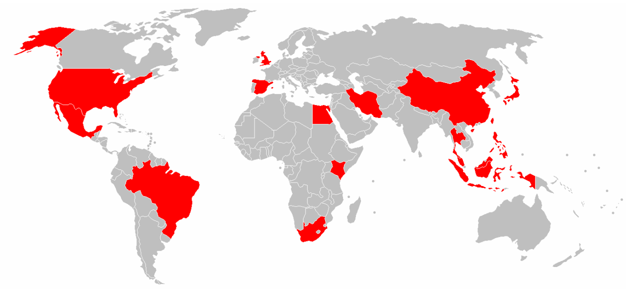

Fig. 1. World locations of Nissan Motors factories.

[1] http://laborsta.ilo.org

[2] Reported by Cushman & Wakefield Research, http://www.cushwake.com

[3] 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)).

TABLE I

LABOUR COST, PRODUCTIVITY AND INDUSTRIAL SPACE 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

From this data, industrial experts are able to set the 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 space 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.

V. SETTING THE PREFERENCES BY MEANS OF GOALS FOR THE OBJECTIVES m AND A

In this section, we first introduce the EMO-based preference elicitation scheme which will be included in our MOACO algorithm. Then, the experimental setup and the analysis of results are presented.

A. Deb's approach for EMO-based preference elicitation

The aim of goal programming is finding a solution which minimises the deviation d between the achievement of the goal and the aspiration target t [20]. 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* ($f(x) \leq t$), *greater-than-equal-to* ($f(x) \geq t$), *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 a Nissan expert, as done in Table II. We have not considered the *greater-than-equal-to* relation since it does not make sense in a minimisation problem like ours.

Deb proposed a technique to transform goal programming into MOO problems which are then solved using an EMO algorithm [8], [9]. The objective function of the EMO algorithm attempts to minimise the absolute deviation from targets to objectives. This approach was only used to perform the transformation from goals to objectives in [8]. However, it can be also used to incorporate preferences into any MOO algorithm, like our MACS algorithm for the TSALBP-1/3.

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

Here, the operator $\langle\rangle$ returns the value of the operand if it is positive, otherwise it gives value zero. We have translated

TABLE II

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

Goal	Objective function
$f_i(x) \leq t_j$	minimise $\langle f_j(x) - t_j \rangle$
$f_i(x) \geq t_j$	minimise $\langle t_j - f_j(x) \rangle$
$f_i(x) = t_j$	minimise $\lvert f_j(x) - t_j \rvert$
$f_i(x) \in [t_j^l, t_j^u]$	minimise $max(\langle t_j^l - f_j(x) \rangle, \langle f_j(x) - t_j^u \rangle)$

our preference goals for each country in Table II 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 area (objective A), and Japan is more interested in a trade-off between them.

B. Experimental setup

The problem instances and the parameter values used in this contribution are detailed as follows:

1) Problem instances: Three real-like problem instances with different features have been selected for the experiments: `barthol2`, `barthold`, and `weemag`. Originally, these instances were SALBP-1 instances [4] only having time information. However, we created their area information by reverting the task graph to make them bi-objective (as in [3]).

In addition, we considered a real-world problem corresponding to the assembly process of the Nissan Pathfinder engine, developed at the Nissan industrial plant in Barcelona (Spain) [5]. The assembly of these engines is divided in 378 operation tasks (grouped into 140). For more details about the Nissan instance, the reader is referred to [3], in which all the tasks and their time and area information are specified.

2) Parameter values: The initial MACS algorithm and all its variants with preferences have been run ten times with ten different seeds for each of the three real-like instances and the Nissan instance. Every considered parameter value is shown in Table III.

C. Analysis of results

The Pareto fronts generated by MACS with goals for the different scenarios explained in Section V-A are shown in

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

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

TABLE III

USED PARAMETER VALUES

Parameter	Value
Number of runs	10
Max. run time	900 seconds
PC Specs.	Intel Pentium^{TM} D
	2 CPUs at 2.80GHz
Operating System	CentOS Linux 4.0
	GCC 3.4.6
Number of ants	10
β	2
ρ	0.2
q_0	0.2
Ants' thresholds	$\{0.2, 0.4, 0.6, 0.7, 0.9\}$
	(2 ants per threshold)

Figures 2 and 3. We can check how the MACS algorithm for a given location behaves in comparison with MACS for the other locations. These approximations of the efficient frontiers show how the use of goals in the different scenarios gets solutions belonging to different areas.

The solutions for the Spanish plant manager will have the lowest number of stations as well as 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 the `barthol2` instance (Figure 2), 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. Hence, we can conclude the preference scheme is working properly when it is incorporated into the MACS algorithm.

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. Generally, the convergence of the algorithm incorporating goal preferences is the same than in "MACS no specific location", although sometimes the set of solutions belonging to "MACS no specific location" achieves better convergence than the ones from location-specific MACS.

In order to check the latter statement and to measure the performance of the variants of the algorithms, we have considered the binary coverage metric C [18] to compare the obtained Pareto sets. Graphics in Figure 4 are box-plots [21] based on C metric which compare the different algorithms two by two by calculating the dominance degree of their respective Pareto sets. Each rectangle contains four box-plots representing the distribution of the C values for a certain ordered pair of algorithms in our four problem instances. Each box refers to algorithm A in the corresponding row and algorithm B in the corresponding column and gives the fraction of B covered by A $(C(A, B))$. In Figure 4, the top right box represents the fraction of solutions of MACS for UK covered by the non-dominated sets produced by MACS no location. In each box, the minimum and maximum values are the lowest and highest lines, the upper and lower ends of the box are the upper and lower quartiles, and a thick line

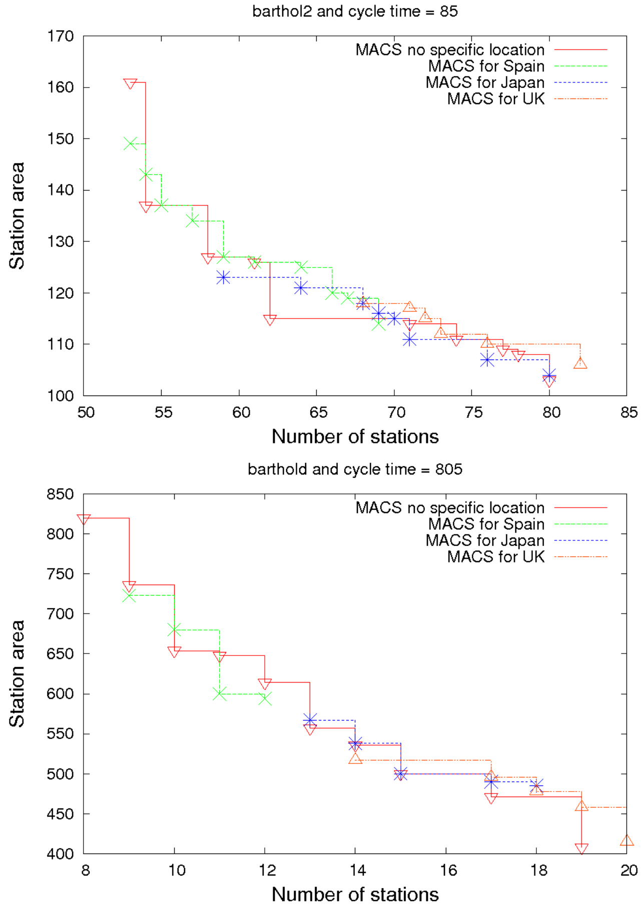

Fig. 2. Pareto fronts for the `barthol2` and `barthold` instances for different scenarios using Deb's alternative.

within the box shows the median.

In Figure 4 we can see how MACS for Japan gets a low number of solutions dominated by the other algorithms. The reason is that MACS for Japan spreads its search along all the Pareto front region, and this is not done by the other variants. In general, a slightly better convergence of MACS without preferences with respect to MACS with preferences can be observed.

VI. CONCLUDING REMARKS

In this contribution, we have studied the inclusion of user preferences in the objective space based on Nissan's domain knowledge to tackle the TSALBP-1/3. A previous MOACO proposal based on the MACS algorithm was extended and improved by using a preference elicitation scheme borrowed from the EMO community. It consists of defining a set of goals to reach only the Pareto front region which has the desirable trade-off between the number of stations m and their area A. 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. The application of these advanced preferences to the different Nissan scenarios

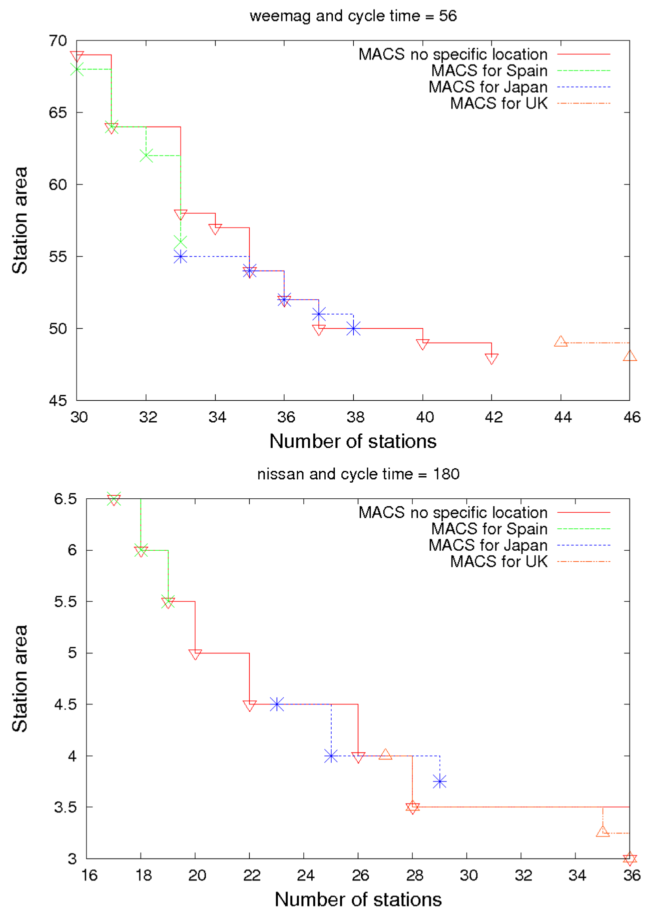

Fig. 3. Pareto fronts for the `weemag` and `Nissan` instances for different scenarios using Deb's alternative.

were actually successful since they helped the 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, and (ii) the use of interactive procedures within the algorithm [17], [22].

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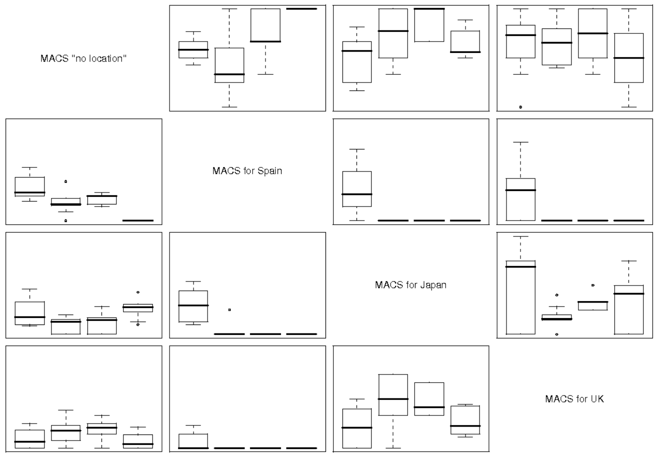

Fig. 4. C metric values represented by boxplots comparing MACS with the specific variants for the different scenarios using Deb's approach.

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