On the use of Pareto filters in the multi-objective optimization of energy systems: Application to reverse osmosis desalination plants integrated with solar collectors.

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Abstract

In this paper, we explore the use of Pareto filters as a mean to aid decision-making in the multi-objective optimization of energy systems. The key idea is to narrow down the number of Pareto points generated during the calculations in order to make it easier to identify the best of them. We illustrate the capabilities of our approach through its application to the design of reverse osmosis desalination plants considering simultaneously the unitary production cost and environmental impact. By using the so called epsilon-constraint method, we obtain a set of Pareto solutions each achieving a unique combination of cost and environmental impact. We then apply a filtering procedure to reduce substantially the number of Pareto designs thereby facilitating the task of decision-makers.

1. Introduction

Multi-objective optimization (MOO) has recently gained wider interest in process systems engineering, and particularly in green engineering, where economic and environmental objectives must be accounted for at the design step.

Ideally, we would like to include in the MOO model as many objectives as possible so as to cover all relevant aspects of the problem. However, this may lead to large computational burdens. Furthermore, the analysis of the Pareto solutions and their visual interpretation gets more difficult as one increases the number of objectives in the model [1]. A solution out of the entire Pareto set must be finally selected, and this task is likely to be hard, particularly when several objectives must be considered simultaneously.

Several methods have been proposed to rank alternatives in multi-criteria decision-making. The most popular techniques are the Analytical Hierarchy Process and outranking strategies (ELECTRE and PROMETHEE). In the area of energy systems, they have been widely applied in energy planning applications and in the optimization of renewable energy systems [2]. In addition to these techniques, we can find some filtering methods that aim to retain a subset of particularly appealing Pareto optimal solutions.

Branke et al. suggested new evolutionary algorithm comprising user's preference by defining linear maximum and minimum trade-off functions, guiding the interest of a decision-maker toward a particular region of Pareto set [3]. Later Deb proposed modified domination criterion for handling problems with a convex Pareto-optimal front [4]. Farina and Amato introduced the dominance concept based on fuzzy optimality being non-preference based and allowing to produce reduced Pareto sets [5]. Branke et al. in his later study proposed an evolutionary algorithm which narrows Pareto set to the “knee” region, the region where the small variation of one objective leads to a great deterioration in at least one other objective [6]. Deb suggested robust multi objective procedures to obtain robust Pareto frontier, thus avoiding possible perturbations [7]. Some other strategies to reduce the

Pareto set were proposed by different authors: normal constraint method by Messac et al. [8], a decomposition strategy by Montusiewicz and Osyczka [9] and etc.

In a seminar paper, Das introduced the concept of order of efficiency k, which can be used to assess the quality of the Pareto solutions. This concept allows ranking the Pareto solutions according to their order of efficiency to finally retain those that show better efficiency for further inspection [10]. We will provide further details on this later in the article.

As already mentioned before, in this work we apply the concept of Pareto filters to the design of reverse osmosis plants. The lack of potable water in the world has led to a dramatic increase in the number of desalination facilities. [11]. These processes are energetically intensive, causing large amounts of CO_2 emissions [12-14].

Governments are seeking for ways to make them more sustainable, with one promising option being their integration with renewable energy sources, like solar energy [15] Different models have been proposed to simulate the behavior of a reverse osmosis plant and maximize their energy efficiency. Most of them are limited in scope as they cover only some aspects of the problem. Particularly, some of them have focused on improving the membrane performance [16].
Maximizing the performance of the membrane typically results in a reduction of the electricity consumption and associated environmental impact. Other approaches have been proposed to minimize the total production cost [17-18], while some works have assessed the environmental performance of these facilities. These studies have revealed that combining fossil fuels with renewable energy sources lowers the environmental impact substantially.

2. Problem statement

The core of our methodology is the use of Pareto filters in the postoptimal analysis of the Pareto solutions. To illustrate the capabilities of our approach, we use as a test bed the design of reverse osmosis plants integrated with solar collectors.

The scheme of the process is sketched in Fig.1. It consists of several units: desalination unit, solar Rankine cycle (includes Rankine cycle and solar field) and thermal energy storage. The filtration of saline water takes place in the reverse osmosis desalination unit. The energy for the reverse osmosis high pressure pump is provided by the solar Rankine cycle, which is powered by a system comprising solar collectors, a gas fired heater and a thermal energy storage. Further details on the system can be found in [19, 20]. The goal of the analysis is to find the design and operating conditions that optimize simultaneously the economic and environmental performance of the system. The design task can be posed in mathematical terms as the following multi-objective MINLP:

$$\begin{aligned} &\min \left\{ f_1(x,y),\ldots,f_N(x,y) \right\} \\ &s.t. \qquad h(x,y) = 0 \\ &\qquad\qquad g(x,y) \le 0 \end{aligned}$$

where x and y denote the continuous and binary variables of the problem, respectively, and f(x, y) are the objectives (specific total cost and specific environmental impact) considered in the analysis. The solution to this model is given by a set of Pareto alternatives or optimal system designs each achieving a unique combination of operating condition, process design and consequently objectives. Standard MOO algorithms calculate a large enough set of Pareto points that are provided to decision-makers, which are supposed to decide which optimal solution is “the best”. In the section that follows we propose a method to narrow down the number of such alternatives.

3. Methodology

<u>Model development</u>

We develop in first place a model of a desalination plant whose energy demand is partially covered using solar energy. The economic and environmental performances of the system are assessed in terms of unitary production cost and environmental load, respectively. The latter is defined as the damage caused by the production of one cubic meter of potable water in different impact categories. We therefore considered a total of 12 objectives in the optimization model: specific total cost, specific total impact and 10 individual environmental metrics. For environmental impact assessment we use Life Cycle Assessment methodology and particularly Ecoindicator-99. Details of the model are provided in Salcedo et al. [19] and Antipova et al. [20].

Pareto solutions

With the model of the system at hand, we generate next a set of Pareto solutions using any available MOO solution method. Without loss of generality we employ here the epsilon-constraint method, which consists of solving a set of auxiliary single-objective problems in which one objective is defined as main objective while the others are transferred to auxiliary constraints that bound them within some allowable limits. The advantage of this method is that it allows dealing with non-convex solution boundary. To generate the Pareto points, we follow a heuristic approach based on solving a set of bi-criteria problems, in each of which the cost is optimized against every single environmental impact category. Further details on this heuristic can be found elsewhere [1].

Normalization of the Pareto optimal solutions

Before applying the filters we have to align the values measured in different scales at one scale to facilitate their comparison. To this end, we use a normalization method that consists of dividing the objectives values of each solution by the maximum value attained over all the Pareto points.

Filters

After normalizing the solutions, we apply the Pareto filters. Particularly, we propose the sequential use of two filters (codes). The first rules out repeated solutions according to a given accuracy, while the second generates a reduced pool of solutions with a good performance (quantified according to an efficiency metric). We provide further details on the filters in the next sections.

Smart filter

This filter removes redundant solutions (solutions with the same objectives values) considering a given tolerance, that is, a specified interval around the normalized value of the objective function. The algorithm keeps only one Pareto solution among those falling in this interval, the rest are discarded from the solutions´ pool. By varying the tolerance interval, one can modify the number of solutions discarded. Hence, the size of the reduced Pareto set can vary depending on the tolerance, the larger is the tolerance, the more solutions is discarded from the pool and the less solutions is kept.

Figure 2 illustrates how the filter works. We show a solution in the figure with a shaded region defined around it. Any other solution FNs' falling inside this region is said to be indistinguishable from it, and automatically removed from the pool. This filter starts by comparing solution FN1 with the rest, and then removing those points inside the shaded region defined around the reference point. After comparing all the points, we pick the next candidate solution and repeat the procedure again. In this example, solutions FN2 and FN5 lie within the specified tolerance of 2Δt, so they are considered indistinguishable with the reference points (FN1 and FN4 correspondingly) and thus are discarded from the pool.

In mathematical terms, to filter the solutions we use the following algorithm based on that presented by Mattson et al [21]:

Let FNs be one of the NS normalized solutions of the normalized Pareto set (i.e., FNs~fns,1,:::,fns,NO) obtained through steps 2 and 3 of the solution approach, and let SOS be the set containing all these solutions. The application of the filter comprises the following steps.

1. Define tolerance Δt, a set of rejected solutions SOR = ∅, a set of candidate solutions SOC = ∅ and start iteration counters s(SOR) = 0 and ss(SOC) = 0.
2. ***While*** s < NS,
   (a) s = s + 1
   (b) If ¬∃ FN_s |FN_s Ï SOS, return to 2.a. Else:

(c) While ss < NS,

i. ss = ss + 1 π

ii. If ¬∃ FN_{ss} |FN_{ss} Î SOS, return to 2.c.i. Else:

iii. If s = ss, return to 2.c.i. Else, if $fn_{s,b} - fn_{ss,b} \leq \Delta t$ " b, let SOR = SOR $\grave{E}_F$ N_{ss} and SOS = SOS\SOR.

(d) End while

(e) Restart iteration counter ss = 0.

3. End ***while***

4. Make SOC = SOS

[21,22]

<u>*Order of efficiency filter*</u>

This filter makes use of the concept of order of efficiency (optimality), which allows ranking Pareto solutions according to a common metric. This concept was suggested by [10] and later applied to metabolic models by Pozo et al. [22].

We next formally state the concept of Pareto optimality of order k. Let D be a discrete set of points or design options (in the x-space), and F(D) the projection of the discrete set of alternatives in the objective space, i.e. F(D) ={F(x):x∈D} . For all possible k-element subsets of n given criteria (1≤k≤ n), a point x*∈D is referred to as efficient of order k, if F(x*) is not dominated by any member of F(D) for any of the k-element subsets of objectives, which implies that there does not exist any feasible x** such that $f_j(x^{**}) \leq f_j(x^*)$ for all j ∈ $\{i_1, i_2, \ldots, i_k\}$ and $f_j(x^{**}) < f_j(x^*)$ for some j ∈ $\{i_1, i_2, \ldots, i_k\}$. Note that if x* is efficient of order k, it is efficient of order k+1. The point with lowest order of efficiency represents the “best” point for the decision maker, and corresponds to the utopia point.

By definition, the utopia point has efficiency of order 1. Points with lower efficiency values are more “balanced”, and therefore “better”. The closer the value of k gets to 1, the closer the solution gets to the utopia point. The concept of efficiency was later expanded in scope giving rise to the more general concept of efficiency of order k with degree m. As will be discussed in detail later in this article, this more general concept enables further reductions of the Pareto set. Particularly, we follow here the approach suggested by

Pozo et al. [22] which consists of applying the concept of order of efficiency recursively to a progressively smaller Pareto set until the number of Pareto solutions retained is small enough.

Figure 3 provides an illustrative example of the concept of Pareto efficiency of order Q. Consider we have a MOO problem with 3 objectives: cost and four different environmental impacts. Assume we have 3 solutions plotted as lines on the graph whose objectives values are normalized as described previously, so that the minimum of each objective represents its best possible value. As seen, all 3 solutions are Pareto optimal, and therefore efficient of order 3, since none of them improves any of the others simultaneously in all of the objectives. We next identify possible subsets of 2 objectives. For instance, if we discard function f3 from the pool of objectives (see Figure 3.b), none of the solutions will be dominated by others. If we discard f1 and consider another reduced set of objectives (f2, f3) how it is shown on the Figure 3.c, solution s2 and s3 are dominated by s1, which means that solutions s2 and s3 cannot be efficient of order 2 and stay with the efficiency of order 3. If we discard f2 from the pool and get the reduced set of the objectives (f1, f3) we find out that s2 dominates s1 and s3, thus is a non-dominated solution in the full space of objectives as well as in any of the reduced sets of the objectives, so it is efficient of order 2. Considering this concept we can compare the solutions in the original space of the objectives and in this particular case we can remove 2 solutions out of 3 while we decrease the order of efficiency. We select s2 as the best solution out of 3 Pareto optimal solutions. Note that the concept of efficiency of order Q is stronger than the Pareto optimality condition, and can thus be used to further reduce the Pareto set.

3. Application to the engineering problems. Case study of a desalination plant coupled with Rankine cycle and thermal energy storage.

We apply our approach to the design of desalination plants. The plant aims to fulfill a certain amount of potable water. The data used in the calculations can be found in [19, 20].

We derive a MOO model that accounts for economic and environmental concerns simultaneously. The environmental performance of the system is assessed via life cycle assessment (LCA), a methodology that quantifies the environmental impact over the life cycle of a product or process. In our case, we quantify the damage associated with the production of a certain amount of potable water. To evaluate the environmental impact, we use the Eco-indicator 99, an LCA-based environmental assessment method that accounts for 10 impacts aggregated into 3 damage categories: human health, ecosystem quality and resources depletion. Hence, the model comprises 12 objective functions: unitary production cost (economic performance), and 11 environmental impacts in different damage categories (environmental performance). We calculate 11 bi-criteria problems (unit production cost vs each of the 11 environmental impacts separately). The solutions from this set are optimal in terms of the 11 objectives. The post optimal analysis aims to identify the most convenient solutions from this large set of points. To this end, we use the Pareto filters described above.

The model was implemented in GAMS and solved using CONOPT on an Athlon(tm) II X2 B24, processor 2.99GHz, 3.49 GB of RAM. To solve every bi-criteria problem, we use the epsilon-constraint method, which provides a total of 288 feasible solutions. These solutions are normalized by dividing the objective function values by the maximum value attained over all objectives. Figure 4 depicts these solutions in a Parallel coordinates plot, where the horizontal axis represents the objectives and the vertical axis shows the performance attained by each solution in every objective. The objectives we consider are given in the Table 1.

Table1. Objectives

Number of objective	Objective
1	Specific total cost (STC)
2	Eco-99
3	Acidification and eutrophication
4	Toxic emissions
5	Land occupation and conversion

6	Carcinogenic effects
7	Climatic change
8	Ionizing radiation
9	Ozone layer depletion
10	Respiratory effects
11	Extraction of fossil fuels
12	Extraction of minerals

Hence, every line in this plot represents a single design operating under a set of specific conditions. All such designs are Pareto optimal, as their corresponding lines intersect in at least one point, that is, there is no single line that improves any of the others in all the objectives simultaneously. Furthermore, some objectives show large variability (i.e., difference between the upper and lower bound above 0.8: 2,7-12), others medium (difference between bounds between 0.5 and 0.8: 3,5,6), and others a small one (difference between bounds below 0.5: 1,4). It can also be observed, how some of the lines in the plot are parallel, indicating the existence of correlated objectives, while others intersect in at least one point, showing the opposite. Note that this topic is investigated in more detail in [22].

The Pareto solutions are filtered next using the Smart Pareto filter fixing a tolerance $t = 0.01$, which allows for a reduction of the Pareto set from 288 to 186 points (102 solutions were very close to each other considering the aforementioned tolerance).

We apply next the second type of Pareto filter: the order of efficiency filter. We start by imposing $Q=11$ and search for non-dominated solutions in any of the subsets of cardinality Q. This allows reducing the number of Pareto solutions from 186 to 66 alternatives. The same procedure is repeated for decreasing values of Q until an empty set of solutions is identified, which occurs for $Q= 6$. In particular, 66 solutions were found to be efficient of order 11, 65 efficient of order 10, 60 efficient of order 9, 29 efficient of order 8, and 7 efficient of order 7.

Figures 5 and 6 show the minimum and maximum objective values (i.e., lower and upper bounds, respectively) among those solutions retained for a given Q. These plots provide valuable insight on how much quality is lost as we decrease the efficiency order. The proximity of the lower bound of a set of solutions to the lower bound of the original set is an indicator of the quality of the set. Particularly, if the lower bound of a set is close to the lower bound of the original set, then it will contain solutions with objective function values close to the best possible performance that can be attained in each criterion.

As observed in Figure 5, the lower bound of the sets of efficiency of order 12, 11, 10, 9 and 8 are the same (except for objective 1, in which the set of order 12 shows slightly better performance than the rest), while the lower bound of the set of efficiency of order 7 is significantly larger than the rest. This last set of solutions therefore perform well on average, but at the expense of sacrificing (i.e., ruling out) points with very good performance in some criteria and poor in other objectives. With regard to the upper bounds, they drop from the set of order 12 to the sets of order 11, 10, 9, 8, and then again from the second group of sets to the set efficient of order 7. This is because as we move to smaller efficiency orders, we gradually discard extreme solutions that perform well only in a subset of objectives (but show very poor performance in others). Hence, we conclude from this analysis that the filters allow keeping the size of the set of solutions low while still preserving its quality to a large extent.

The results of gradual filtering by smart filter are given in Table 2.

Table 2. Number of solutions for reduced Pareto of different optimality orders

Order of efficiency	11	10	9	8	7	6
Number of solutions	66	65	60	29	7	0

4. Conclusions

To analyze all possible alternatives of Pareto set and to suggest the best ones based on this analysis is not a trivial task. In the current study a combination of two filters was suggested to test its efficiency being applied to the problem of selecting the appropriate design for a reverse osmosis desalination plant coupled with a Rankine cycle and thermal energy storage. As a result the solution space of feasible solutions was reduced and the possible choice narrowed. Thus, instead of implementing computationally intensive and time-consuming analysis of all possible solutions we executed 2-steps filtering procedure to identify the “best " solution in terms of objective functions.

The practice shows that applying the filters for Pareto set solutions can play a significant role in decision making representing a powerful tool for selecting the best possible alternative. It allows choosing the best options out of the range the feasible equally “important” options. One of the applications for these filters was illustrated in this study.

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Nomenclature

D – set of the points(design alternatives)

F(D) – projection of D in the space of objectives

f(i) – objective function

i - solution

k - number of elements in subset

n - number of objectives

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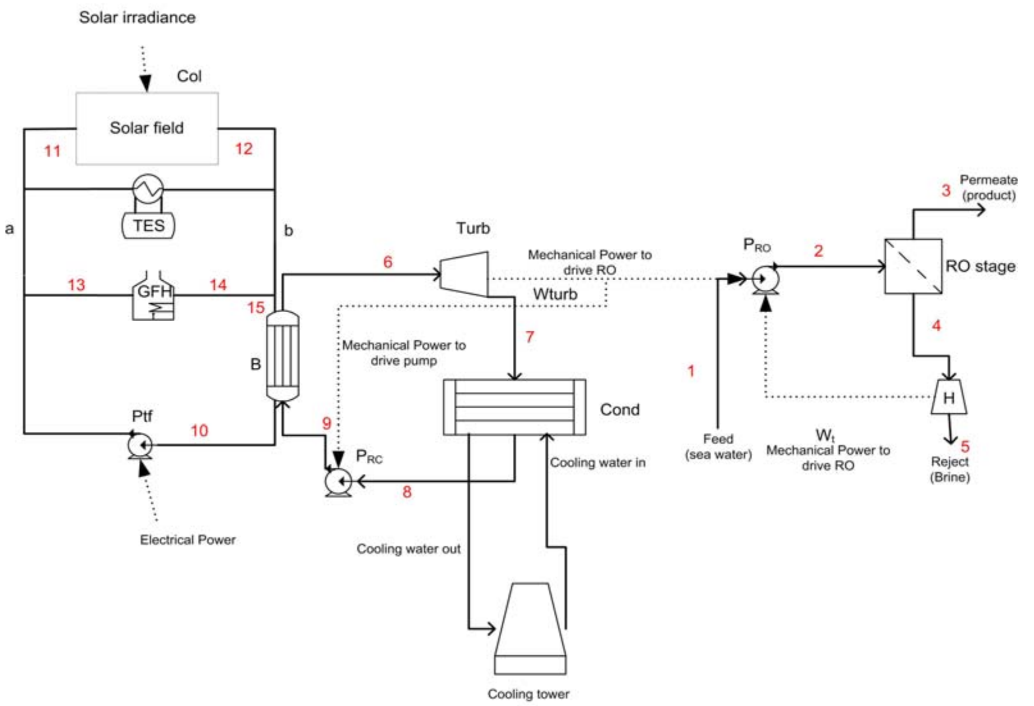
Figures



Solar irradiance
Col
Solar field
11
12
TES
a
b
13
GFH
14
15
B
Ptf
10
Electrical Power
Turb
6
Mechanical Power to drive RO
Wturb
Mechanical Power to drive pump
7
9
P_RC
8
Cond
Cooling water in
Cooling water out
Cooling tower
1
Feed (sea water)
P_RO
2
RO stage
3
Permeate (product)
4
H
5
Reject (Brine)
W_t
Mechanical Power to drive RO

Figure1. Process scheme of the reverse osmosis desalination plant coupled with solar thermal power plant.

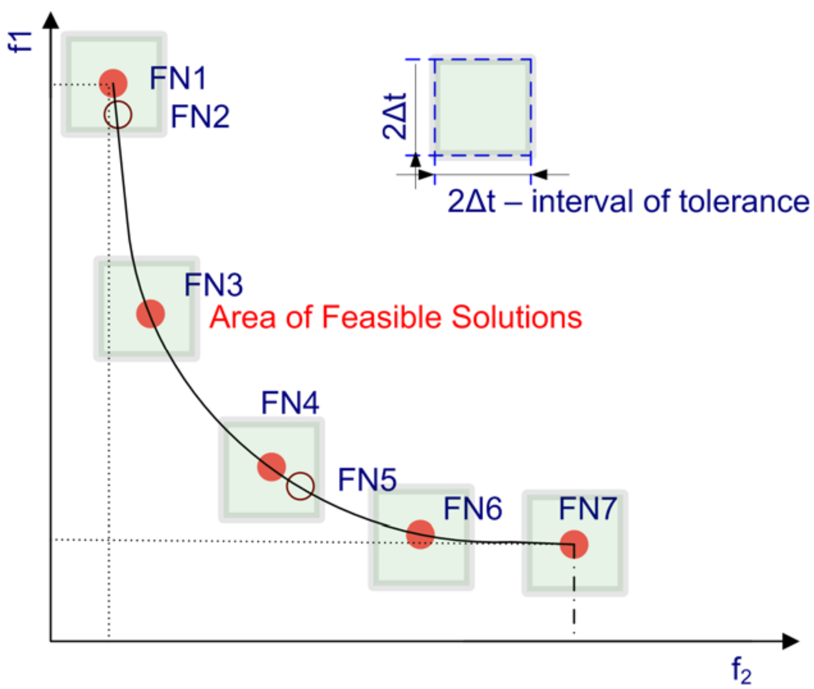


Figure 2. Smart Pareto filter. Tolerance.

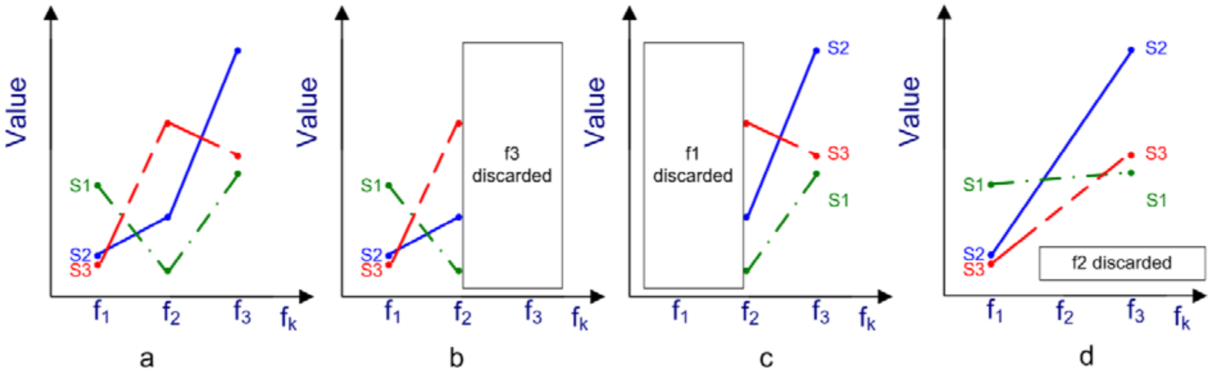


Figure 3. Pareto order of efficiency concept.

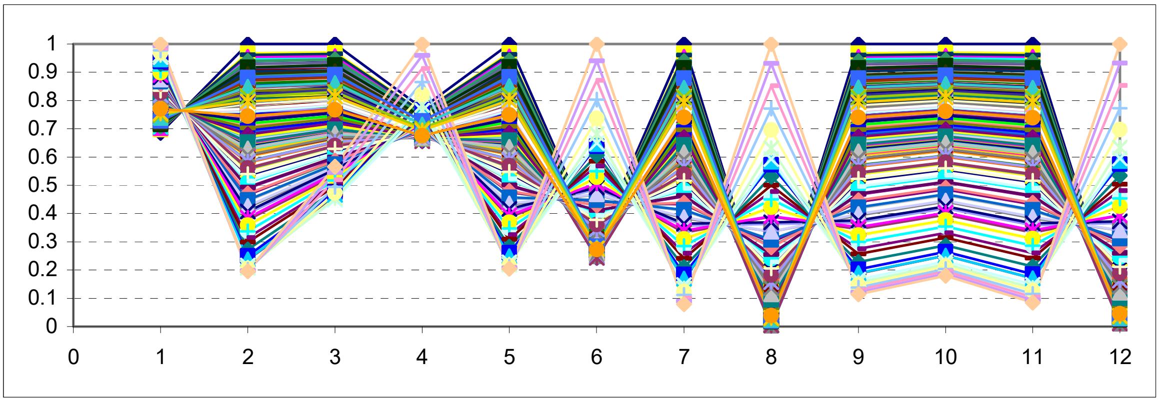


Figure 4. Parallel coordinate plot.

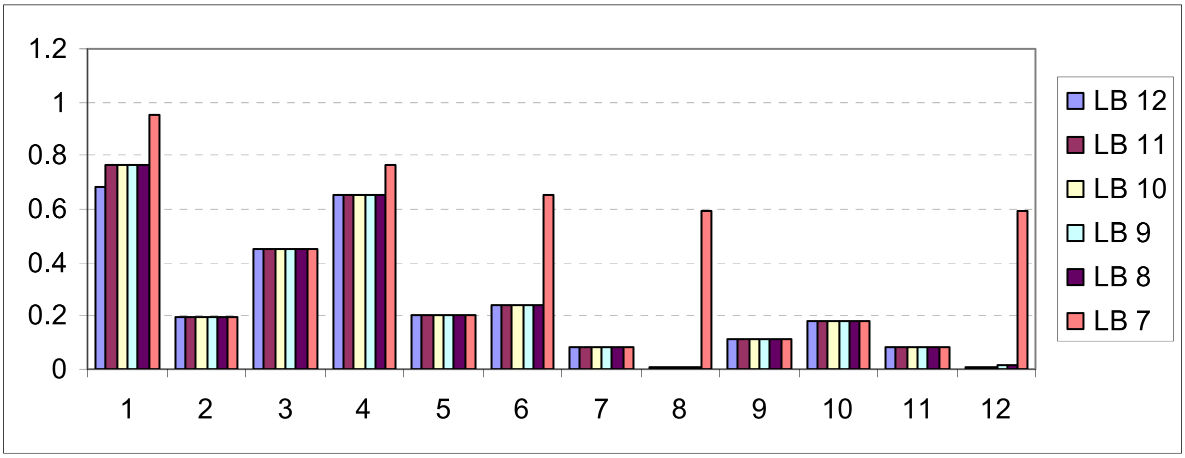


Figure 5. Lower bound (LB).

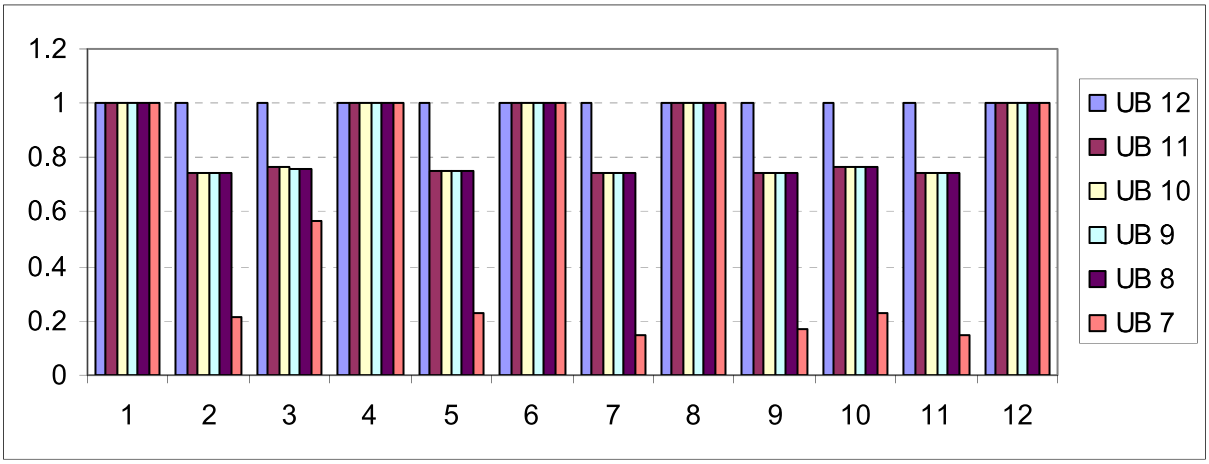


Figure 6. Upper bound (UB).