A Combined Interactive Procedure using Preference-based Evolutionary Multiobjective Optimization. Application to the Efficiency Improvement of the Auxiliary Services of Power Plants

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Abstract

While the auxiliary services required for the operation of power plants are not the main components of the plant, their energy consumption is often significant, and it can be reduced by implementing a series of improvement strategies. However, the cost of implementing these changes can be very high, and has to be evaluated. Indeed, a further economic analysis should be considered in order to maximize the profitability of the investment. In this paper, we propose a multiobjective optimization problem to determine the most suitable strategies to maximize the energy saving, to minimize the economic investment and to maximize the Internal Rate of Return of the investment. In order to solve this multiobjective problem, we have developed a novel interactive approach. This new scheme consists of a combination of existing approaches and it has been designed in order to make use of the main advantages of each method. This allows us to build a flexible scheme that is progressively adapted to the decision maker's reactions. First, the evolutionary algorithm NSGA-II is applied to approximate the efficient set and to analyse the trade-offs among the objectives. Second, the two-slope achievement scalarizing function is used to help the decision maker to explore the efficient set and identify her/his region of interest. Finally, the preference-based evolutionary algorithm WASF-GA is used to concentrate the search for solutions into the most interesting part of the nondominated objective set. Besides, we solve, together with a real decision maker, the multiobjective problem associated to a real case study using this interactive procedure. With this case study, we show the usefulness of the interactive scheme proposed, and we highlight the importance of an understandable feedback and an adaptive process.

Keywords: Auxiliary services of power plants, Multicriteria, Decision making/process, Preference-based evolutionary algorithms, Reference point, Interactive procedure.

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1 Introduction

Nowadays, countries depend on electricity for their development, meaning that energy is, as a final term, the motor of current societies. However, energy consumption and electricity generation are themselves among the main reasons for some environmental problems, such as CO_2 emissions, global warming, pollution or depletion of the most used sources of energy. Apart from the environmental problems, other important concerns come from the economic perspective of energy, given that without a cheap and available supply of energy, the economic growth of many nations will be restricted. Therefore, one of the main challenges the whole humanity faces is to assure the energy supply taking into account the economic, social and environmental sustainability.

Most of the electricity consumed nowadays is generated in large power plants, some of which were built many years ago, without taking into account good efficiency practices. Several years ago, the priority when building a new power plant was not to create efficient and environmentally friendly energy systems, but to build reliable networks which could produce as much energy as possible [1]. Besides, the cost of energy at that moment was much cheaper than nowadays. Therefore, reducing the energy production costs was not an important issue in the design phase. Nowadays, these old power plants have to adjust to the new situation of the energy sector and, in order to improve their efficiency, some retrofits are being carried out. Mainly, these improvements are focussed on the equipment with a direct impact in the system, as is the case of the generator, the condenser or the turbine, but relatively little attention has been paid to the improvement of the auxiliary services of the power plants [1]. The auxiliary services are installed in power plants in order to satisfy certain requirements needed for the plant operation, such as fuel, water or air supply, and waste removal. Usually, the auxiliary equipment consists of several drive power components, working at medium (MV) and low (LV) voltage, such as pumps, fans and their electric motors. Also, the cables and transformers required are part of the auxiliaries.

Obviously, the plant produces energy, but it also needs to consume part of the energy produced. Despite their important role, and although their energy consumption is often significant (among $6-15\%$ of the total electricity generation in fossil-fuel power plants, and among $4-6\%$ in nuclear power plants [1]), the auxiliaries rarely attain high performance levels. Therefore, reducing the energy consumption at the auxiliary services is not a trivial issue.

Some improvement strategies can be carried out in order to raise the efficiency of the auxiliary services. For example, the use of high-efficiency electric motors to reduce power losses, the installation of variable speed drives to adjust the flow of pumps and fans to what is actually demanded at each moment, or the power factor correction by the installation of banks of capacitors that provide the required reactive power to the network. These efficiency improvements have a direct impact on the electricity consumption and losses of the auxiliary systems, what implies a reduction of the electricity required for the operation of the plant. The benefit is twofold: given that the fuel consumption required for the plant operation is reduced, on the one hand, the operation costs of the auxiliary systems are reduced, and on the other hand, the CO_2 emissions decrease, in turn, for the same final electricity production.

However, these strategies can be implemented in different parts of the auxiliaries and there is a wide range of possible combinations among them. In this paper, we study the multiobjective optimization problem that emerges when we want to implement the most adequate of the three strategies mentioned before in the auxiliary systems of a power plant. As previously said, the main motivation of the problem is to increase the efficiency of the auxiliaries. Therefore, the problem proposed maximizes the energy saving achieved when some of the previous policies are implemented. Obviously, if we were only interested in maximizing the energy saving (or minimizing the CO_2 emissions), the solution would be trivial: all the strategies should be implemented in all the elements involved. But there are other issues we should consider to determine which are the most profitable solutions among the wide range of improvement options. We cannot overlook the investment cost of implementing such strategies, which may be very high and has to be minimized. Moreover, as saving some energy implies a reduction of the electricity production cost, a further economic analysis must be considered in order to maximize the profitability of the initial investment. One of the most widely used economic indexes to analyse the profitability of an investment in a given period of time is the *Internal Rate of Return (IRR)*, which is the rate at which an initial investment is recovered by the benefits in a fix period of time. Then, apart from maximizing the energy saving and minimizing the investment cost, the IRR of the investment cost is also evaluated and maximized.

The research reported in this paper is the result of a R&D contract with the Endesa Generation S.A. company, one of the largest electrical companies in the world which holds a strong position in Latin America and in Mediterranean Europe. This company runs several power plants worldwide and they desired to carry out an optimization analysis to improve the efficiency of the auxiliaries of their power plants. In particular, our research study is based on the auxiliary systems of the Litoral Thermal Power Plant of Almería (Spain). This power plant is a coal-fired steam thermal power plant of 1,100 MW.

Many applications of multiobjective optimization to problems related to the power plant sector can be found in the literature. Some applications of *Multiple Criteria Decision Making (MCDM)* techniques to problems regarding energy modelling and planning can be found in [5, 10, 12, 24]. On the other hand, *Evolutionary Multiobjective Optimization (EMO)* algorithms have also been successfully applied to determine the optimal size of a power plant [4, 8]; to optimize the exergy, exergoeconomic and environmental impact of several combined cycle power plants [2]; to optimize the energy consumption, efficiency and environmental impact of power plants [11]; to find the optimal shape design of a generator [9]; to solve the generation expansion planning problem associated to the creation of new power plants [15]; and to simultaneously satisfy exergetic and economic objectives in thermal system design problems [21].

In this paper, we model and solve the multiobjective problem that emerges when we try to determine which are the most convenient strategies in order to maximize the energy saving (what is equivalent to minimize the CO_2 emissions), minimize the economic investment and maximize the IRR. Given that the whole auxiliary system is interconnected, each particular improvement decision on any element influences the energy consumption of the rest of the elements in the network. This fact implies that some of our objective functions are discontinuous and, moreover, they depend on the energy model of the plant, which has been simulated using a black-box. Besides, the decisions to be made are represented by both binary and continuous variables, which also complicates the solution process. Moreover, the mathematical model proposed has been designed in order to be applied to the auxiliaries of any power plant. Thus, the number of decision variables cannot be known beforehand and it may be very high, because it depends on the number of elements and on the configuration of the auxiliary services considered.

Our main purpose is to solve our problem together with a real decision maker (DM) from the Endesa Generation S.A. company. As explained in [3], in an interactive decision making process, we have to pay especial attention to how and what the DM learns about the problem itself. By learning about the problem and about one's preferences, the DM becomes more confident when making decisions during the process, and (s)he is able to foresee what may happen in the next steps. But, as the DM learns from the information given, the process must also be adapted and updated accordingly to the DM's expectations, in order to guide the search for the preferred solution.

Precisely, the main purpose of classical interactive MCDM methods is to help the DM to find his/her most preferred solution [16, 20]. To this end, they require some information about the DM's preferences during the solution process. But, in real cases, this information may be hard to provide if the DM does not have a sufficient knowledge about the problem. Besides, most of these methods provide only one solution at each step, and this makes it harder to explore in depth the regions of the nondominated set that are interesting for the DM. On the other hand, EMO algorithms are designed in order to find a set of well-distributed nondominated solutions that approximate the whole set of Pareto optimal solutions. This information can be interesting for obtaining global valuable information about the structure of the Pareto optimal set, and about the trade-offs among the nondominated solutions. But it is almost impossible for the DM to make a final decision just by choosing a solution among the (generally huge) set generated. Finally, some *preference based EMO algorithms* have been developed in order to take into account the preferential information given by the DM, and to concentrate the search on the corresponding part of the Pareto optimal set. Obviously, they can lead to wrong final solutions if the DM is not completely sure about the area of the Pareto optimal set (s)he wishes to concentrate on.

For these reasons, in this paper, we have developed a novel approach by combining several multiobjective optimization techniques. Our aim is to make use of the main advantages of each technique, and to overcome their drawbacks by integrating them in a global procedure. This procedure has two different phases: a preliminary phase and an interactive phase.

In the preliminary phase, in order to let the DM learn about the conflict degree among the objective functions, we have approximated and studied the set of Pareto optimal solutions of the problem from an overall perspective. For this aim, EMO algorithms are specially suitable, given their ability to approximate the whole set of Pareto optimal solutions, and to handle complex multiobjective problems with different types of variables and objectives [6, 23]. In our paper, we have applied the well known EMO algorithm NSGA-II [7], and we have used graphical views of the solutions obtained to extract some general conclusions.

As previously mentioned, the set of solutions generated by NSGA-II may be too large to let the DM make a final solution. This is why we need an interactive phase. To this end, some preferences are taken into account in order to generate only those solutions that are interesting for the DM. Namely, the DM is asked to provide desirable values for each objective function, which will form a so-called reference point. But, as the DM may not be initially sure about which reference point will produce interesting solutions, we have divided the interactive phase in two stages. In the first stage, the DM learns about her/his own preferences and about their effect on the solutions obtained. This phase is based on the minimization of an achievement scalarizing function suggested in [14] over the set of solutions generated by the NSGA-II, for different reference points given by the DM. This analysis is computationally inexpensive, but still very worthy, because the DM can foresee which kind of solutions are possible and which are not from several reference points. After this stage, a reference point is chosen by the DM.

Finally, in the second stage (fine-tuning stage), we use a preference-based EMO algorithm to obtain a set with a small number of nondominated solutions which correspond to the DM's preferences expressed by the reference point. In our interactive procedure, we have used the *Weighting Achievement Scalarizing Function Genetic Algorithm* (WASF-GA) [18], because it is based on the reference point preferential scheme, and because it is able to approximate the area of the Pareto optimal set which best fits the reference point used. In this stage, we also allow the possibility to repeat the process with different reference points.

The main purpose of this paper is to present and show the potential usefulness of our novel combined interactive approach. In the case study considered, the DM reached a satisfactory solution for the problem because he gained a global understanding of the problem progressively, but also because the process considered his preferences interactively. Initially, he could learn about the trade-offs between the objectives; next, he defined his preferences being aware of what could and could not be achieved; and finally, he found the final solution by analysing the trade-offs among a set of nondominated solutions that represented his whole region of interest.

The rest of this paper is organized as follows. Section 2 introduces the main concepts and notations used in multiobjective optimization, as well as the methodologies used for solving our multiobjective problem. Thereafter, the multiobjective problem proposed is formulated in Section 3, describing the decision variables, constraints and objective functions. Section 4 describes the interactive process proposed to solve the problem. The case study considered and the decision making task carried out by the real DM are explained in Section 5. Finally, Section 6 summarizes the main contributions of this study, and points out some future research lines.

2 General Concepts of Multiobjective Optimization

In general, a *multiobjective optimization problem* can be formulated as:

$$\begin{array}{ll} \text{minimize} & \{f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x})\} \\ \text{subject to} & \mathbf{x} \in S, \end{array} \tag{1}$$

where $f_i : S \to \mathbf{R}$ $(i = 1, \ldots, k)$ are k $(k \geq 2)$ conflicting *objective functions* that must be minimized simultaneously, and $S \in \mathbf{R}^n$ is the (non-empty) *feasible set* of *decision vectors* $\mathbf{x} = (x_1, x_2, \ldots, x_n)^T$. We will refer to any $\mathbf{x} \in S$ as a *feasible solution*. The image of the feasible set is called the *feasible objective region* $Z = \mathbf{f}(S) \in \mathbf{R}^k$ and it consists of *objective vectors* $\mathbf{z} = \mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x}))^T$, for some $\mathbf{x} \in S$.

Due to the conflict degree among the criteria, a solution that simultaneously optimizes all the objectives does not exist. Instead, we can identify a set of compromise solutions, the so-called

Pareto optimal, efficient or nondominated solutions, where none of the objectives can get a better value without deteriorating, at least, one of the other objectives. We say that a decision vector $\mathbf{x} \in S$ is an *efficient* or a *Pareto optimal solution* of problem (1) if there does not exist any $\mathbf{x}' \in S$ such that $f_i(\mathbf{x}') \leq f_i(\mathbf{x})$ for all $i = 1, \ldots, k$ and $f_j(\mathbf{x}') < f_j(\mathbf{x})$ for at least one $j \in 1, \ldots, k$. The corresponding objective vector $\mathbf{z} = \mathbf{f}(\mathbf{x}) \in Z$ is called a *nondominated objective vector*. We will refer to the set of all efficient decision vectors as the *Pareto optimal set*, denoted by E, and to the set of all nondominated objective vectors as the *nondominated objective set*, denoted by $\mathbf{f}(E)$.

Because all nondominated solutions can be regarded as equally desirable in the mathematical sense, we need some information about the preferences of a DM. The Pareto optimal solution that best satisfies the DM's preferences is usually known as *the most preferred solution*. Different types of preference information can be asked to the DM (see, e.g. [16]). A natural way to express the preferences consists of specifying desirable objective function values, which constitute the components of the so-called *reference point*. A *reference point* is given by $\mathbf{q} = (q_1, \ldots, q_k)^T$, where q_i is an aspiration value for objective function f_i provided by the DM, for all $i = 1, \ldots, k$. Usually, a reference point is said to be *achievable* if the corresponding reference levels can be simultaneously achieved or improved by some feasible solution; otherwise, the reference point is said to be *unachievable*.

Given a reference point, many techniques use achievement scalarizing functions to find efficient solutions. An *achievement scalarizing function (ASF)* is a single real-valued function which combines the original objective functions of problem (1) and the preferences specified by the DM. In an ASF, the preferences can be expressed by means of a reference point. Then, problem (1) is transformed into a single-objective optimization problem consisting of the minimization of the ASF over the feasible set. For an overview about ASFs, see [17].

One of the most used ASF is the one proposed by Wierzbicki in 1980 [22]. For a given reference point $\mathbf{q}$, a vector of weights $\mu = (\mu_1, \ldots, \mu_k)$, with $\mu_i > 0$ for all $i = 1, \ldots, k$, and a parameter $\rho > 0$, this ASF is given by:

$$s(\mathbf{q}, \mathbf{f}(\mathbf{x}), \mu) = \max_{i=1,\ldots,k} \{ \mu_i (f_i(\mathbf{x}) - q_i) \} + \rho \sum_{i=1}^{k} \mu_i (f_i(\mathbf{x}) - q_i), \tag{2}$$

which must be minimized over S:

$$\begin{array}{ll} \text{minimize} & s(\mathbf{q}, \mathbf{f}(\mathbf{x}), \mu) \\ \text{subject to} & \mathbf{x} \in S. \end{array} \tag{3}$$

The weight $\mu_i > 0$ assigned to the objective function f_i can have a normalizing role or a preferential meaning [13, 19]. The small value $\rho > 0$ is the so-called *augmentation coefficient* and it is used to assure that, for any reference point, the optimal solution of problem (3) is a nondominated solution of problem (1) with bounded trade-offs between objectives (*properly efficient solution*). In general, solving (3) means to find the "best" Pareto optimal solution with respect to the reference point and to the weight vector used. This implies, in practice, to project the reference point onto the set of nondominated solutions in the direction determined by the inverse of the weights.

Obviously, not all the weights produce equally satisfactory solutions for the DM. Besides, it has been proved that the effect of a given set of weights is different for achievable and unachievable reference points (see [19] and references therein). For this reason, a new ASF, called the *two-slope achievement scalarizing function*, is proposed in [14], which enables us to work with two different weight vectors simultaneously. For a reference point $\mathbf{q}$ and two vectors of weights $\mu^U = (\mu_1^U, \ldots, \mu_k^U)$ and $\mu^A = (\mu_1^A, \ldots, \mu_k^A)$, with $\mu_i^A, \mu_i^U > 0$ for all $i = 1, \ldots, k$, the two-slope ASF is defined as follows:

$$\bar{s}(\mathbf{q}, \mathbf{f}(\mathbf{x}), \mu^U, \mu^A) = \bar{s}_0(\mathbf{q}, \mathbf{f}(\mathbf{x}), \mu^U, \mu^A) + \rho \sum_{i=1}^{k} (f_i(\mathbf{x}) - q_i), \tag{4}$$

where $\rho > 0$, and $\bar{s}_0$ is given by

$$\bar{s}_0(\mathbf{q}, \mathbf{f}(\mathbf{x}), \mu^U, \mu^A) = \max_{i=1,\ldots,k} \big\{ \max\{\mu_i^U (f_i(\mathbf{x}) - q_i), 0\} + \min\{\mu_i^A (f_i(\mathbf{x}) - q_i), 0\} \big\}. \tag{5}$$

When minimizing (4) over S, [14] proves that, in practice, μ^A is used when $\mathbf{q}$ is achievable and μ^U is used if it is unachievable. The consideration of the most appropriate weight vectors for each case allows us to reflect the DM's preferences in a better way. The main novelty of this ASF is that it is not necessary to test a priori whether the reference point is achievable or not in order to choose the most suitable weight vector. Instead, the optimization process guarantees that the most appropriate weight vector is used in each case.

One way of giving different preferential weights for achievable and unachievable reference points is described in [13]. After giving a reference point, the DM is asked to give some additional information in order to determine the vectors of weights. (S)he is asked to classify the objective functions into classes, depending on the importance of achieving the corresponding aspiration levels. This allows us to allocate the k objective functions into index sets J_r which represent the importance levels $r = 1, \ldots, s$, where $1 \leq s \leq k$. If $r < t$, then achieving the aspiration levels of objective functions in the index set J_r is less important than achieving aspiration levels of the objectives in J_t. It is noteworthy that the DM is not asked to give a global preference ranking of the objectives, but just a local importance order for achieving each of the aspiration levels. Therefore, in the procedure proposed, we use the two-slope ASF and we set μ^A and μ^U to the weight vectors given in [13] for the achievable and the unachievable cases, which are defined as follows:

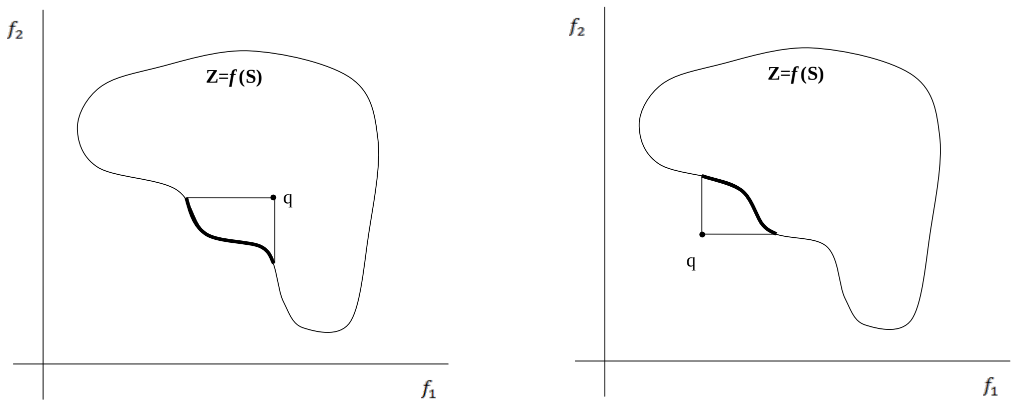
$$\mu_i^A = \frac{1}{r(\mathbf{z}^{nad} - \mathbf{z}^*)}, \qquad \mu_i^U = \frac{r}{\mathbf{z}^{nad} - \mathbf{z}^*}, \tag{6}$$

for $i \in J_r$ and $r = 1, \ldots, s$. Other schemes are also proposed in [13], but we have chosen the previously described one because it is the most intuitive and simple for the DM.

With respect to EMO approaches, the *Non-dominated Sorting Genetic Algorithm (NSGA-II)* [7] has been used to obtain an approximation of the whole nondominated objective set of our problem. In general, at each generation of NSGA-II, the populations of parents and offsprings are joined and the population to be used in the next generation is formed by the best solutions of both populations, which are selected in the following way. From the resulting population, the individuals which are not dominated by any solution constitute the so-called first nondominated front. These individuals are temporarily discarded from the population and, subsequently, the second nondominated front is formed by the next individuals which are not dominated by any solution. This process continues until every individual has been included in some front. Afterwards, the solutions in the lower level nondominated fronts are passed to the new population. If there are more solutions in the last allowed front than the remaining space in the new population, the individuals in that front are sorted according to a crowding distance, which, somehow, measures the objective space around each solution which is not occupied by any other solution in the population. Then, the individuals with the least crowding distance complete the new population. This algorithm has stood out by its fast nondominated sorting procedure for ranking solutions in the selection procedure and its diversity preserving mechanism. Besides, it has provided well-distributed sets of nondominated solutions for different types of real-life problems [6, 23]. For these reasons, we decided to include it in our combined procedure.

Finally, we have also approximated the region of interest of the DM using the preference-based EMO algorithm called the *Weighting Achievement Scalarizing Function Genetic Algorithm (WASF-GA)* [18]. The main purpose of WASF-GA is to approximate the area of the nondominated objective set that is "reachable" from a reference point $\mathbf{q}$ given by the DM.

The *reachable area of the nondominated objective set from* $\mathbf{q}$ is defined as follows. If $\mathbf{q}$ is achievable, the reachable area is the set of Pareto optimal solutions which dominate $\mathbf{q}$, that is, the solutions $\mathbf{x} \in E$ which verify that $f_i(\mathbf{x}) \leq q_i$, for every $i = 1, \ldots, k$. When $\mathbf{q}$ is unachievable, the reachable area is formed by the Pareto optimal solutions which are closer to $\mathbf{q}$ regarding to the minmax distance, for different sets of weights. This implies that, in many cases, the reachable area of unachievable reference points is formed by the solutions $\mathbf{x} \in E$ which verify that $f_i(\mathbf{x}) \geq q_i$, for every $i = 1, \ldots, k$, but this is not true for all the cases. Figure 1 gives a graphical idea of the reachable area for an achievable and an unachievable reference point in a biobjective optimization problem. The reachable area has been highlighted with a bold line in both cases. In the achievable case, the Pareto optimal solutions lying in the reachable area are the most interesting solutions for the DM, given that these solutions improve all the aspiration values at the same time, without having to impair any of them. When $\mathbf{q}$ is unachievable, no Pareto optimal solution dominates it.



(a) Achievable reference point. (b) Unachievable reference point.

Figure 1: Reachable area of the nondominated objective set from a reference point.

In that case, although the Pareto optimal solutions lying inside the reachable area do not improve any aspiration value, they deteriorate them as little as possible. It can be seen that the efficient solutions outside the reachable area may improve some of the aspiration values, but at the expense of a sacrifice of other(s).

For a given reference point $\mathbf{q}$, any Pareto optimal solution in the reachable area of $\mathbf{q}$ can be found by minimizing (2) over S for $\mathbf{q}$, using an appropriate vector of weights (see [16]). Then, using a sample of weight vectors, WASF-GA approximates the reachable area by minimizing the ASF given in (2) for the reference point given by the DM. If the weight vectors are as evenly scattered as possible in the weight vector space, the solutions generated by WASF-GA will be as evenly distributed as possible in the desired area.

WASF-GA works as follows. At each generation, the individuals of the population of parents and offsprings (we will refer to the combined population as P) are classified into different fronts, according to the values that each solution takes for the ASF given in (2), for the given reference point $\mathbf{q}$, and for the sample of weight vectors mentioned before. Let N_μ be the number of weight vectors in the sample. The classification is done as follows: the first front is formed by the individuals in P with the lowest values of (2) for each one of the N_μ weight vectors; the individuals in P with the next lowest values of (2) for each one of the N_μ weight vectors form the second front; and so on until every individual in P has been included into some front. Finally, the population for the next generation is formed by the individuals in the lowest level fronts. If there are more solutions in the last front considered than the remaining space in the new population, the solutions in that front with the lowest values of (2) are selected. The individuals in the first front of the last generation represent the outcome of WASF-GA. Consequently, N_μ solutions are shown to the DM, so the DM can indicate how many solutions (s)he would like to revise in the final population of WASF-GA just by giving a desirable value for N_μ.

3 The Multiobjective Optimization Model

Next, we will describe the main features of the multiobjective model proposed to solve the real problem described in Section 1. Given the aim of this study, we will not go deep into many technical details. The technical and economic parameters used in the model have been provided by the Endesa Generation S.A. company and we do not specify them here. Further details are available upon request to the authors.

3.1 Main assumptions

We have considered three strategies for the improvement of the efficiency of the auxiliary services (for more details, see [1]):

Strategy 1: *Replacement of current motors by high efficiency ones.* Nowadays, most of the motors used in the auxiliaries reach only standard efficiency levels. The use of high efficiency motors assures, on the one hand, less motor energy losses due to the high performance, and, on the other hand, less transmission lines energy losses, as the current flow throughout the network is reduced. Although the cost of these high efficiency motors may be high, the investment is usually recovered in a very short time because of the resulting energy saving.

Strategy 2: *Installation of variable speed drives.* It is desirable to control the shaft speed or torque of electric motors, by varying the electrical supply at their terminals. This feature is exploited by a separate piece of power electronic hardware known as the *variable speed drive (VSD)*, which provides the necessary speed control. Compared with other flow control methods, such as control valves (throttling or bypassing) or dampers (inlet or outlet), VSDs are generally more efficient, have better power factor[1] and offer more precise speed control. They automatically adjust the flow of pumps and fans to what is actually demanded at each moment, according to the plant requirements.

Strategy 3: *Power factor correction or compensation for reactive power.* The capacity of the power system to deliver active power (the only kind of energy which can produce real work) is fully related to the power factor (PF). The necessity of reactive power in large inductive loads, such as induction motors, causes the electric load to have a PF lower than 1. The higher the reactive power which an electric load draws from the power source, the lower the PF is. A low PF decreases the overall efficiency of the system due to the reactive power distribution through transmission lines, distributors and transformers, and reduces the capacity of the equipment to carry real power. However, the PF can be increased (i.e., the reactive power can be decreased) by installing capacitors, which work as reactive current generators, providing the required reactive power to the power supply.

Due to some technical limitations, and in agreement with the experts participating in this study, the following assumptions have been made about the component systems of the auxiliaries and their operation.

Our mathematical model has been designed in order to study the implementation of these strategies in a *single line diagram* as the one shown in Figure 2. As it can be seen, the network of the auxiliary loads consists of several transformers, with their corresponding busbars, from which several drives working at MV or LV may hold. We will suppose that each single line diagram has just one MV busbar (that is, one HV-MV transformer), from which several LV busbars (that is, several MV-LV transformers) may be holding. It is important to say that the drives, either fans or pumps, do not work independently from each other. They operate in parallel with other drives with the same role and which are technically equal. They form what we will refer to as a *group of drives*. Besides, there is always a backup drive in each group which is ready to replace any drive in case of a failure.

Industrial systems do not usually operate under the same conditions at all times due to cyclical production demands, environmental conditions, changes in customer requirements, and so on. This variation is described by the the *plant operating profile*, which describes the amount of hours per year that the plant operates at various percentages of full load. Our mathematical model will evaluate the energy consumption of the auxiliaries for load rates of 50%, 60%, 70%, 80%, 90% and 100% of full load, taking into account the hours per year that the plant is operating at each load[2].

Regarding the PF correction strategy, we have assumed that we can compensate for some reactive power either directly at the motors of the drives, or centrally at busbars, or as a mix of these two options. Although the benefits of PF correction are enjoyed by all the equipment above the location of the capacitors, correction at the source generally avoids problems with over compensation and greatly reduces the current flowing through the network. However, the economic criterion plays an important role to decide whether to correct the PF individually at each motor, centrally at each busbar or as a combination of both. In addition, we are not forced to compensate

[1] The *power factor (PF)* is a dimensionless number between 0 and 1, frequently expressed as a percentage, which represents the percentage of apparent power that is transformed into real work (active power).

[2] The minimum operating load is usually 50% because of some technical constraints.

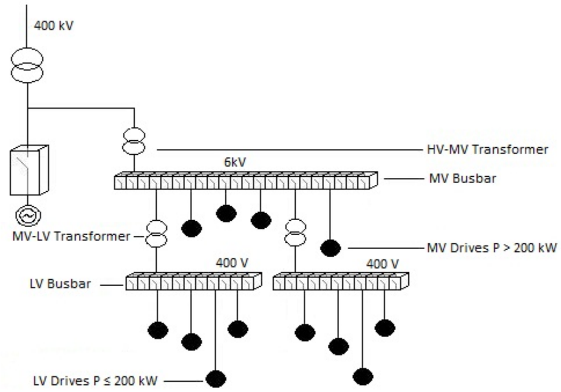


Figure 2: Single line diagram.

Decision variable	Description	Indexes
XML_i	Binary. 1 if motors of LV group i are of high efficiency, 0 if not	$i = 1, \ldots, NG_{LV}$
XMM_k	Binary. 1 if motors of MV group k are of high efficiency, 0 if not	$k = 1, \ldots, NG_{MV}$
XVL_i	Binary. 1 if VSDs are installed on LV group i, 0 if not	$i = 1, \ldots, NG_{LV}$
XVM_k	Binary. 1 if VSDs are installed on MV group k, 0 if not	$k = 1, \ldots, NG_{MV}$
XQL_i	Continue. Reactive power (in kVAR) to be compensated for on drives of LV group i	$i = 1, \ldots, NG_{LV}$
XQM_k	Continue. Reactive power (in kVAR) to be compensated for on drives of MV group k	$k = 1, \ldots, NG_{MV}$
$XQBL_j$	Continue. Reactive power (in kVAR) to be compensated for on busbar of the MV-LV transformer j	$j = 1, \ldots, N_T$
$XQBM$	Continue. Reactive power (in kVAR) to be compensated for on busbar of the HV-MV transformer	-

Table 1: Decision variables of the problem.

for all the reactive power with capacitors, given that compensating part of the reactive power also reduces the transmission losses proportionally.

If a VSD is installed in a drive, there is no reactive power to compensate for in this drive. Then, the model has been built in order to discard the PF correction strategy if the optimization process determines to install a VSD in a drive, or if the flow is initially controlled by a VSD.

The multiobjective problem has been mathematically modelled in such a way that it can be applied to the auxiliaries of any power plant. Consequently, the problem will not be completely defined until the DM has provided some technical and economic information about the auxiliary services. Furthermore, the whole auxiliary system is interconnected, so each particular improvement decision on any element influences the energy consumption of the rest of the elements in the network.

3.2 Decision variables

The three improvement strategies considered may be implemented in any drive, while the third strategy of reactive power compensation may also be carried out in the busbar of any transformer. However, if a drive is modified in some way, all the drives in the same group should be modified as well, including the backup one, in order to preserve the same technical features. Therefore, the convenience of any of the strategies will be decided per group of drives, and not per individual drives.

Our multiobjective problem involves binary (0–1) and continuous variables. These decision variables are described in Table 1, where NG_{LV} denotes the number of LV groups of drives, NG_{MV} is the number of MV groups of drives and N_T is the number of MV-LV transformers.

The binary decision variables (related to strategies 1 and 2) reflect the final situation of the drives after applying the most suitable strategies, taking into account their initial situation with respect to the corresponding strategy (what will be controlled by the constraints). After solving the problem, we will really know which strategies must be implemented by comparing the initial situation of the drives regarding the strategies with the final values of the decision variables.

According to Table 1, the number of decision variables of the problem depends on the number of groups of drives and on the number of transformers of each single line diagram. In general, our multiobjective problem has:

- 3 (2 binary and 1 continue) decision variables per LV group of drives.
- 3 (2 binary and 1 continue) decision variables per MV group of drives.
- 1 (continue) decision variable per MV-LV transformer.
- 1 (continue) decision variable for the only HV-LV transformer.

Therefore, the number of decision variables we will manage is $n = 3 \cdot NG_{LV} + 3 \cdot NG_{MV} + N_T + 1$. Depending on the system network, this number can vary significantly.

3.3 Constraints

Taking into account the meaning of the binary variables associated to strategies 1 and 2, some simple bound constraints have been introduced in the model in order to ensure that the final situation of the auxiliaries regarding these strategies is never worse than their initial situation. In practice, these constraints control that the binary variables are properly upper and lower bounded by 0 or 1. For example, if a VSD cannot be installed in a group of drives due to some technical limitations, the corresponding variable is upper bounded by 0, forcing it to be 0. On the other hand, if the drives of a group already have high efficiency motors, it is clear the strategy 1 cannot be implemented in this group, but the corresponding variable must be 1 in order to reflect that these drives have high efficiency motors after solving the problem. Then, this variable will be lower bounded by 1, forcing it to be 1.

Finally, regarding strategy 3, some constraints control that the reactive power to be compensated for, on either the drives of a group or on the busbar of a transformer, is never higher than the reactive power needed on the element.

3.4 Objective functions

The criteria of our problem are the maximization of the energy savings, the minimization of the investment cost and the maximization of the IRR of the investment, denoted by f_1, f_2 and f_3, respectively:

$$f_i : D \subset \mathbb{R}^n \longrightarrow \mathbb{R} \text{ where } n = 3 \cdot NG_{LV} + 3 \cdot NG_{MV} + N_T + 1, \text{ for every } i = 1, 2, 3.$$

Due to lack of space and taking into account that some of our objectives are black-box functions[3], we just briefly describe the objective functions of our problem. From now on, we have skipped the decision variables in the notation for simplicity:

Yearly energy savings, f_1 (in kWh). The energy saving achieved for given values of the decision variables is the difference between the initial and the new energy consumptions of the single line diagram. Then, for every $p = 50, 60, 70, 80, 90, 100$, we first calculate the initial power required by the single line diagram at $p\%$ of the operating load, denoted by P_p^0. Secondly, we obtain the power required by the single line diagram at $p\%$ of the operating load for the given values of the decision variables, denoted by P_p. Once we have P_p^0 and P_p for every $p = 50, 60, 70, 80, 90, 100$, the yearly energy saving achieved is obtained as follows:

$$f_1 = \sum_{p=50,60,70,80,90,100} (P_p^0 - P_p) \cdot h_p, \tag{7}$$

[3] A *black-box function* is an expensive to compute function, for which, given a decision vector, the value of the function is returned and no further information is provided. Usually, black-box functions appear in engineering problems and try to reflect complicated relationships between several variables which cannot be explicitly expressed.

where h_p is the average amount of hours per year that the plant is operating at $p\%$ of full load.

However, calculating P_p is not a trivial issue. The simulation of the performance of the auxiliaries by means of the engineering models, considering the binary and continuous decision variables, involves several difficulties. Internally, the implementation of any of the strategies may alter either the active and reactive power needed by the drives of each group, or the reactive power accumulated up to the transformers. So these powers must be recalculated for every $p = 50, 60, 70, 80, 90, 100$, using the values of the decision variables. Furthermore, as the whole system is interconnected, the improvement of one element by some strategy not only modifies its powers, but it also changes the power required by the components of the single line diagram above it. Therefore, the powers required by the rest of the components must be recalculated as well, from the bottom to the top of the single line diagram, which makes the overall process quite complex.

Therefore, the complicated engineering formulas, the energy consumption dependencies between the auxiliary components, and the fact that a particular decision on any element modifies the energy consumption of the whole system, make it impossible to give an explicit mathematical expression of the energy saving objective function. Instead, a black-box function is used to model the energy consumption model of the auxiliary services.

Investment cost, f_2 (in €). The investment cost objective function has an explicit mathematical expression which calculates the overall cost by adding the investment required by each strategy. The investment needed to carry out each strategy has been obtained by adding the current prices of the equipment required and the installation costs. Besides, the cost of improving the backup drive of every group has been also included. Additionally, we have considered a commissioning cost for every strategy, which is charged only once if the strategy is carried out in any element, and not every time that it is implemented in some element. This can be controlled by means of a binary auxiliary variable.

When the power factor correction strategy is implemented, the cost of installing a capacitor depends not only on the amount of reactive power to be compensated for, but also on whether the compensation is made individually or centrally. If the capacitor is installed in a drive (individual compensation), then the equipment consists of a capacitor as well as a box. However, if the capacitor is installed in a busbar (central compensation), we have to consider the price of a switch apart from the price of the capacitor.

Therefore, a number of binary auxiliary variables would be required to get an explicit formulation of the cost objective function, which would increase the complexity of the model. On the other hand, the black box has to be built anyway for the other two objective functions. For this reason, we have decided to use the black box also to evaluate the investment cost, given that this does not imply a higher computational cost.

IRR of the investment, f_3 (in %). The IRR is the discount rate, r, that makes the net present value of costs equal to the net present values of the benefits in a given period of time, N (in years). In our problem, the initial investment is given by $C_0 = -f_2$ (negative cash flows) and the annual benefits, which are constant for all years, are $C_i = P_E \cdot f_1$ (positive cash flows), for $i = 1, \ldots, N$, where P_E is the current price of the electrical energy. We have estimated the IRR for a 10 years planning period ($N = 10$). Then, r is implicitly defined by the following formula:

$$C_0 + \sum_{i=1}^{N} \frac{C_i}{(1+r)^i} = 0 \Longleftrightarrow -f_2 + \sum_{i=1}^{10} \frac{P_E \cdot f_1}{(1+r)^i} = 0 \qquad (8)$$

Then, the objective function f_3 is defined by the IRR, r, that solves equation (8). In practice, r has been approximated by the bisection method[4].

[4]The bisection method is a practical method used to find roots of equations. It is based on the statement of the *Intermediate Value Theorem*.

Finally, if the vector of the decision variables introduced in Table 1 is denoted by:

$$
\begin{aligned}
\overrightarrow{\mathbf{X}} &= \{XMM_1, \ldots, XMM_{NG_{MV}}, XML_1, \ldots, XML_{NG_{LV}}, \\
&= XVM_1, \ldots, XVM_{NG_{MV}}, XVL_1, \ldots, XVL_{NG_{LV}}, \\
&= XQBM, XQBL_1, \ldots, XQBL_{N_T}, XQM_1, \ldots, XQM_{NG_{MV}}, \\
&= XQL_1, \ldots, XQL_{NG_{LV}}\},
\end{aligned} \tag{9}
$$

and if S denotes the set of feasible solutions that satisfy the constraints of the problem, our multiobjective problem is the following:

$$
\begin{array}{ll}
\text{minimize} & \{-f_1(\overrightarrow{\mathbf{X}}), f_2(\overrightarrow{\mathbf{X}}), -f_3(\overrightarrow{\mathbf{X}})\} \\
\text{subject to} & \overrightarrow{\mathbf{X}} \in S.
\end{array} \tag{10}
$$

As previously mentioned, since our objective functions are represented by black-box functions and do not have an explicit expression, we have designed an evaluation subroutine in C# language which is compiled together with the solver used. This subroutine is based on the engineering models which simulate the energy consumption of the auxiliary elements, and takes into account all the interconnections existing among them and the possible improvements introduced by the values of decision variables considered. During the solution process, the evaluation subroutine is called each time the solver needs to obtain the values of the objective functions. That is, for given values of the decision variables (inputs), this subroutine does all the required calculations and retrieves the values of the objective functions and the constraints violations (outputs). The software developed for the evaluation subroutine is available upon request.

4 Description of the Interactive Combined Procedure

In order to find the DM's most preferred solution for the problem, we have designed a combined interactive scheme, which progressively adapts itself to the results obtained and to the reactions and expectations of the DM. During this process, we let the DM learn step-by-step about the problem itself, getting to know the interrelationships among the objective functions. Our main purpose is that the DM gains a realistic perspective about the problem, what will help her/him to make up her/his mind about which kind of solutions are of her/his interest, and to find a satisfactory solution.

The combined procedure we suggest has two phases, and each of them divided in two stages:

1. Preliminary Phase. This non-interactive part of the process is devoted to the definition of the model, and to the overall study of the efficient set of the problem.

Stage 1.1: Problem definition. Firstly, the DM has to describe the single line diagram (s)he desires to analyse in order to formulate the problem (10) associated to the given case study. For this task, we have developed a windows application in C# language where (s)he can introduce all the technical and economic information required, and which generates the internal data needed to completely define the problem (10) to be solved.

Stage 1.2: Approximation and study of the nondominated objective set. Once problem (10) has been formulated, we obtain an approximation of the whole Pareto optimal set in order to have a global understanding of the trade-offs among the objectives. Because of the presence of binary and continuous variables, and black-box objective functions, we have used the EMO algorithm NSGA-II [7] for this purpose[5].

2. Interactive Phase. The interactive phase is designed to aid the DM in making the final decision.

[5] The parameter setting used in the NSGA-II are described next. The crossover and mutation operators used are: (a) the simulated binary crossover (SBX) operator and a polynomial distribution as the mutation operator for the continuous variables; and (b) the binary crossover and the binary mutation for the integer variables [6]. We have used a population size of 2,000 individuals and 650 generations. The crossover and mutation distribution indexes have been set to 25 and 2, respectively. For both the binary and the continuous variables, the crossover probability has been set to 0.9 and the mutation probability to $1/n$, where n is the number of variables on each case.

Stage 2.1: Learning about preferences. Although very valuable information can be extracted from the solutions generated by NSGA-II, it is hard for the DM to compare the trade-offs among so many solutions. Furthermore, the DM will likely not be interested in all kind of compromise solutions, but (s)he will rather prefer to deeply analyse only a part of the nondominated objective set. Therefore, at this point, the DM is asked to provide some information about her/his preferences, in order to delimit the desired area of the efficient set. In our model, this information takes the form of a reference point $\mathbf{q}$, containing desirable values for the energy saving, the investment cost and the IRR of the investment. However, (s)he may have no idea about which reference point properly expresses her/his preferences (in terms of generating interesting nondominated solutions from it). Thus, we have designed a procedure which lets her/him study several reference points before selecting the final one.

The procedure proposed consists of the minimization of the two-slope ASF given in (4), over the set of solutions generated by NSGA-II (let us refer to this set as P). Initially, the DM indicates a reference point $\mathbf{q}$, based on the information obtained in Phase 1. Then, we find the solution in P that better fits $\mathbf{q}$ using the two-slope ASF. We use this ASF because it allows to project $\mathbf{q}$ onto the nondominated objective set, using different weight vectors for achievable and unachievable reference points. Therefore, in the procedure proposed, some additional information is also asked to the DM following the scheme suggested in [13], which was described in Section 2. The vectors of weights μ^A and μ^U to be used in (4) are calculated according to (6).

Finally, we minimize the two-slope ASF given in (4) over the set P of solutions found by NSGA-II, using the reference point $\mathbf{q}$ and the preferential weights μ^A and μ^U defined by (6). That is, we find the solution $\overrightarrow{\mathbf{X}}_P \in P$ which has the lowest value of (4). Thereafter, the objective values at $\overrightarrow{\mathbf{X}}_P$, $\mathbf{f}(\overrightarrow{\mathbf{X}}_P) = (f_1(\overrightarrow{\mathbf{X}}_P), f_2(\overrightarrow{\mathbf{X}}_P), f_3(\overrightarrow{\mathbf{X}}_P))$, are calculated and shown to the DM.

It is important to keep in mind that the main purpose of this stage is to guide the DM in the selection of the reference point, by showing some information about which kind of objective functions values could be achieved from the reference points analysed. This interactive procedure provides enough information about which kind of compromise solutions could be obtained, and, at the same time, the computational effort required is very low, given that the minimal solution is found over the finite set P.

For the interaction with the DM, we have developed a windows application in C# language, where the DM indicates the reference point (s)he wants to analyse and gives the preferential information required. Then, the objective function values at the solution in P which minimizes (4) are shown to the DM. At this moment, the DM decides either to stop if the current reference point is good enough, or to update the current information, in order to deeply analyse the current reference point or to explore a new one.

Stage 2.2: Fine tuning. Once a reference point is selected, we apply the preference-based EMO approach WASF-GA [18] in order to show the DM a reduced number of solutions approximating the area of the Pareto optimal set which best fits the selected reference point. At this moment, the DM is asked about the number of solutions (s)he wants to revise in the outcome of WASF-GA, and the value of N_μ is set accordingly in all runs of WASF-GA[6].

Once WASF-GA has been applied to narrow down the search of solutions, the DM analyses the solutions obtained. At this point, (s)he can either choose one of the solutions shown as the final one, or to repeat the search for another reference point until a satisfactory solution is found.

In Figure 3, a flowchart gives an idea of the overall interactive procedure proposed.

Regarding the computational cost of the overall process, Table 2 shows the computational complexity of each stage depending on the methodology used. Here, N_1 denotes the population

[6] In WASF-GA, we have used a population size of 200 individuals and 300 generations. The values of the rest of parameters have been set as indicated for the NSGA-II.

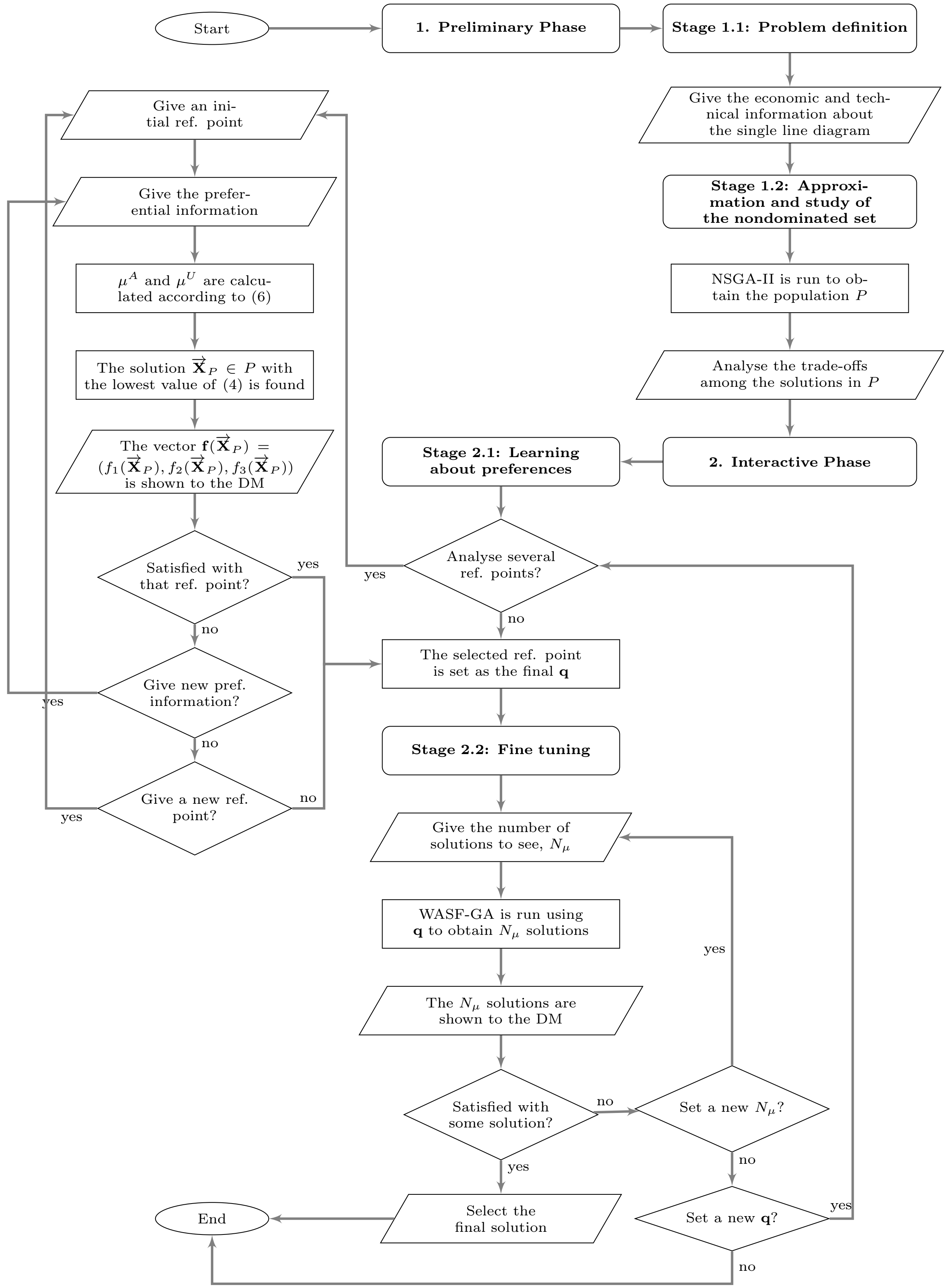


Figure 3: Flowchart of the interaction with the DM.

size used in NSGA-II and N_2 is the population size used in WASF-GA. The computational cost required by the evaluation subroutine, each time the solver needs to evaluate a solution, depends on the number of components of the single line diagram. Let us remind that the number of decision variables of the model is $n = 3 \cdot NG_{LV} + 3 \cdot NG_{MV} + N_T + 1$, and thus, it increases if there are more LV and/or MV groups and/or more MV-LV transformers in the single line diagram. Nevertheless, given that the energy saving objective function is of black-box type, it is not possible to calculate the precise computational complexity of the evaluation subroutine. Anyway, it is important to notice that:

- The NSGA-II algorithm is applied at the preliminary phase, and thus, it can be run before the DM is actually present.
- The minimizations carried out at stage 2.1 are done over the finite set P, and thus, they are computationally inexpensive.
- The most time consuming process of the interactive phase takes place in stage 2.2. But after finding an appropriate reference point at the previous stage 2.1, not many iterations will be required at this one.

Stage	**Methodology**	**Computational Complexity**
1.1 - Problem definition	-	-
1.2 - Approximation and study of the nondominated objective set	NSGA-II	$O(k \cdot N_1^2)$
2.1 - Learning about preferences	Minimization of the two-slope ASF over P	$O(N_1 \cdot \log N_1)$
2.2 - Fine tuning	WASF-GA	$O(k \cdot N_2 \cdot N_\mu)$

Table 2: Computational complexity of the combined procedure.

5 Illustrative Example: a Real Case Study

In this section, we show the solution process of the problem associated to the improvement of the auxiliary services of a real power plant, following the interactive procedure described in Section 4. The power plant considered is a coal-fired steam thermal power plant of 1,100 MW and the DM was an engineer from the Endesa Generation S.A. company. The price of energy considered is 0.05 €/kWh (that is, $P_E = 0.05$ in equation (8)).

1. Preliminary Phase

Stage 1.1: Problem definition

The multiobjective problem solved in this paper is based on a single line diagram formed by the elements described in Table 3. This single line diagram is constituted by one HV-MV transformer, two MV-LV transformers, eight MV groups with several drives each one, and two LV groups of drives, with one drive hanging from each one of the two LV busbars. According to Table 1, the multiobjective problem associated to this case study has 13 continuous decision variables and 20 binary decision variables, i.e., a total of 33 decision variables.

Stage 1.2: Approximation and study of the nondominated objective set

Figure 4 shows a three-dimensional representation of the set P of nondominated solutions found by NSGA-II. Also, each pair of functions are represented in bi-dimensional images (which show the values of the two corresponding functions for all the elements of P). It can be observed that this approximation of the nondominated objective set is formed by several discontinuous regions. These discontinuities are due, on the one hand, to several jumps of the energy saving objective function which take place when some binary variable is set to 1, and, on the other hand, to the discontinuity of the investment cost objective function when a continuous variable jumps from 0

Name	Description
TMV-1	HV-MV transformer
TLV-1	MV-LV transformer
TLV-2	MV-LV transformer
GMV-1	MV group of primary air fans (2 drives)
GMV-2	MV group of condensate pumps (2 drives)
GMV-3	MV group of boiler recirculating pumps (3 drives)
GMV-4	MV group of circulating water pumps (1 drive)
GMV-5	MV group of circulating water pumps (1 drive)
GMV-6	MV group of coal mills (5 drives)
GMV-7	MV group of induced draft fans (2 drives)
GMV-8	MV group of forced draft fans (2 drives)
GLV-1	LV group of service water pumps (2 drives)
GLV-2	LV group of cooling water pumps (2 drives)

Table 3: Elements of the single line diagram of the case study.

to a strictly positive value. Let us remind that the continuous variables indicate the amount of reactive power to be compensated for at each element. When the model calculates the investment required, some commissioning costs are charged whenever some reactive power is compensated for. Then, a small variation of these variables, implies a great variation of the investment, what makes the cost be discontinuous at those solutions.

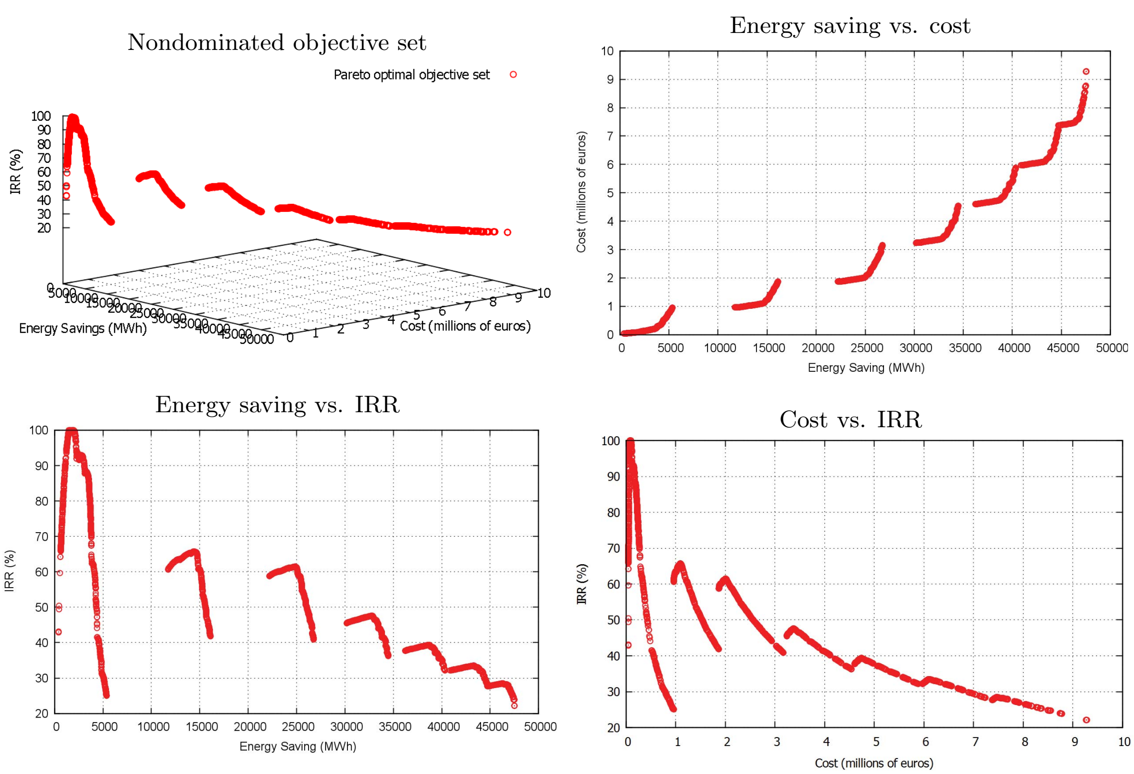


Figure 4: Solutions of the case study.

The extreme objective functions values reached by the solutions in P can be seen in Table 4. It is noteworthy that the ranges of the objective functions in the solutions obtained are very wide.

Objective	Minimum value reached	Maximum value reached
Max f_1 (kWh)	408,485.46	47,526,366.60
Min f_2 (€)	46,004.22	9,283,091.64
Max f_3 (%)	22.13	99.99

Table 4: Ranges of the objectives for the case study.

As expected, the energy saving and cost investment objective functions are directly proportional, as shown in the energy saving vs. cost graphic of Figure 4. It can be observed that each discontinuous part of the graphic has two parts with different slopes. In the first part, the energy saving is increased without a significant increase of the cost, while in the second part the cost increases rapidly. This behaviour is also reflected in the energy saving vs. IRR graphic of figure 4. Again, there are two parts in each portion. In the first part, the IRR increases as the energy saving increases, while in the second part the IRR is decreasing. However, from an overall perspective, we can say that the IRR decreases as the energy saving increases. Due to the proportionality between the energy saving and the cost, the relationship among the cost and the IRR is very similar to that of the energy saving and the IRR.

Taking into account the previous analysis and the extreme values of Table 4, we can conclude that the highest values of the IRR, which are near 100%, are reached in solutions where the energy savings and the investment costs are not very high in comparison to the rest of solutions. In contrast, solutions with higher energy savings and costs have lower IRR values, although these IRR values are still economically very profitable taking into account that the lowest IRR attained is 22.13%.

Although we managed to analyse the interdependencies among the objectives with the solutions generated by NSGA-II, as expected, the DM could not carry out a fair comparison of all the solutions because of the large size of P (2,000 individuals). Moreover, during this analysis, the DM said that not all the solutions generated were of his interest, and he desired to further study some of the solutions obtained.

2. Interactive Phase

Stage 2.1: Learning about preferences

In order to find a suitable reference point, the DM had to give initial desirable values for the energy saving, the investment cost and the IRR. For that, he made use of the trade-off information obtained in the previous stage. He decided to explore a zone with intermediate values of the investment cost and the IRR function, given that higher investment costs do not increase the energy savings accordingly, and thus, they make the IRR decrease.

After three iterations, the DM could find a reference point from which an interesting part of the Pareto optimal set could be approximated. This reference point can be seen figure 5 and it was $\mathbf{q} = (30,000,000.00 \text{ kWh}, 4,000,000.00\text{ €}, 60.00\%)$. Since in the next section we will show closer views of the region of interest approximated by WASF-GA, we have rounded that region in Figure 5 in order to place it in the nondominated objective set. From that reference point, we could obtain energy saving values ranged between 20-40 MWh, the cost can vary between 2 to 4 million €, and IRR can move between 40% and 60%.

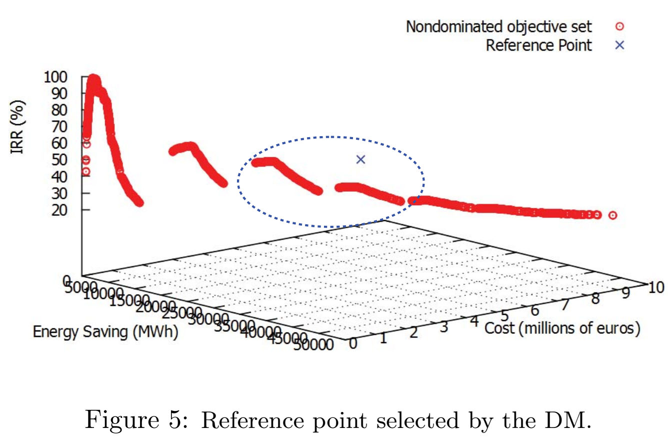


Figure 5: Reference point selected by the DM.

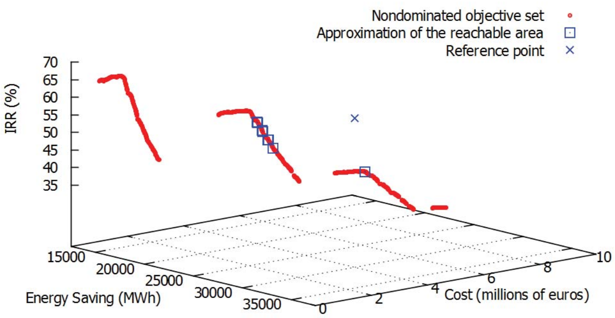
Stage 2.2: Fine tuning

Finally, the WASF-GA algorithm was run in order to approximate the region of interest that could be reached from $\mathbf{q}$. At this moment, the DM decided that he wanted to generate 10 solutions with

WASF-GA, so we set $N_\mu = 10$ in all runs of WASF-GA.

Our DM required several runs of WASF-GA until finding his most preferred solution. From now on, at each iteration h, we will refer to the reference point used as $\mathbf{q}^h$ and to the solution selected by the DM among the solutions generated by WASF-GA as $\mathbf{z}^h$.

Let us set $h = 1$ and $\mathbf{q}^1 = \mathbf{q} = (30,000,000.00 \text{ kWh}, 4,000,000.00 \text{ €}, 60.00\%)$. Figure 6 shows a representation of the solutions generated by WASF-GA for $\mathbf{q}^1$ and a table with the objective solution vectors obtained.



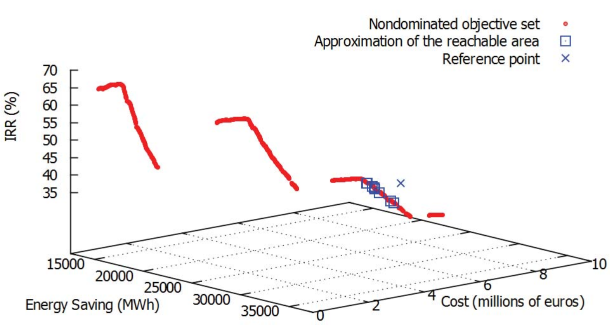
Sol.	Energy Saving (kWh)	Cost (€)	IRR (%)
1	25,395,345.26	2,154,522.33	58.34
2	25,560,070.81	2,268,726.54	55.66
3	25,371,727.90	2,147,382.65	58.49
4	25,555,978.11	2,256,269.86	55.97
5	25,795,613.05	2,388,995.31	53.23
6	32,812,546.66	3,387,268.69	47.44
7	25,950,130.92	2,510,637.64	50.83
8	25,792,674.88	2,384,238.21	53.34
9	32,812,546.66	3,387,268.69	47.44
10	32,812,546.66	3,387,268.69	47.44

Figure 6: Solutions obtained by WASF-GA for $\mathbf{q}^1$.

It is interesting to note that all the solutions generated require an investment lower than the maximum investment desired (4 million €). Furthermore, we have obtained solutions in two separated regions. On the one hand, solutions in the leftmost region sacrifice the energy saving in order to achieve the highest IRR values, although the desired IRR value (60.00%) is never reached. On the other hand, the solution in the rightmost region improves the energy saving aspiration value but at the expense of the IRR.

Once the DM analysed these solutions, he decided that the solution he liked most was the one in the rightmost region, since he was interested in reaching the highest energy saving according to $\mathbf{q}^1$. Then, we set $\mathbf{z}^1 = (32,812,546.66 \text{ kWh}, 3,387,268.69 \text{ €}, 47.44\%)$.

However, he wanted to know if it was possible to find solutions with higher energy savings in the region where $\mathbf{z}^1$ lies, by relaxing a bit the IRR aspiration value. Then, he repeated the process for another reference point closer to that region in order to narrow down the search. We set $h = 2$ and the DM gave $\mathbf{q}^2 = (35,000,000 \text{ kWh}, 4,000,000 \text{ €}, 47\%)$ as the new reference point. The solutions generated by WASF-GA at this iteration are plotted in Figure 7, where the table contains the objective solution vectors obtained.



Sol.	Energy Saving (kWh)	Cost (€)	IRR (%)
1	33,021,982.01	3,487,594.80	46.29
2	33,389,435.21	3,607,770.72	45.16
3	33,003,196.40	3,481,483.27	46.35
4	33,324,209.80	3,572,211.70	45.55
5	33,430,260.20	3,634,682.00	44.86
6	33,961,832.56	3,998,373.81	41.11
7	33,562,305.18	3,745,288.76	43.61
8	33,430,260.20	3,634,682.00	44.86
9	34,126,429.42	4,068,882.27	40.54
10	34,101,792.85	4,064,417.49	40.56

Figure 7: Solutions obtained by WASF-GA for $\mathbf{q}^2$.

As can be observed, all the solutions generated by WASF-GA for $\mathbf{q}^2$ lie in the region which the DM was interested in. We can see that no solution reaches the desired energy saving (35,000,000.00 kWh), although all of them have improved the energy saving values obtained in the previous run. Also, the IRR achieves values close to the reference level (47.00%), but no solution reaches it. Regarding the economic investments, it can be said that solutions 9 and 10 need a higher investment cost than the desired one, which is the sacrifice required to achieve the highest energy saving values of the 10 solutions. Besides, the IRR is also slightly worsened in these two solutions.

At light of these solutions, the DM selected solution 6 as his most preferred solution because it was the solution with the highest energy saving and which did not require to spend more than 4 million €. Then, $\mathbf{z}^2 = (33,961,832.56 \text{ kWh}, 3,998,373.81 \text{ €}, 41.11\%)$. Although the IRR reached at $\mathbf{z}^2$ was not the highest one, it was satisfactory enough for the DM, given that any investment with an IRR equal to 41.11% is indeed a very profitable investment. Figure 8 contains the continuous and binary decision variables values at $\mathbf{z}^2$.

Continuous variables	**Values**
$XQBM$	13,969.38 kVAR
$XQBL_1$	299.45 kVAR
$XQBL_2$	299.99 kVAR
XQM_1	41.99 kVAR
XQM_2	0.00 kVAR
XQM_3	0.46 kVAR
XQM_4	0.00 kVAR
XQM_5	0.00 kVAR
XQM_6	0.48 kVAR
XQM_7	6.59 kVAR
XQM_8	0.10 kVAR
XQL_1	0.00 kVAR
XQL_2	0.00 kVAR

Binary variables	**Values**
XMM_1	1
XMM_2	0
XMM_3	0
XMM_4	0
XMM_5	0
XMM_6	1
XMM_7	0
XMM_8	1
XML_1	1
XML_2	0
XVM_1	0
XVM_2	1
XVM_3	0
XVM_4	1
XVM_5	1
XVM_6	0
XVM_7	0
XVM_8	0
XVL_1	1
XVL_2	1

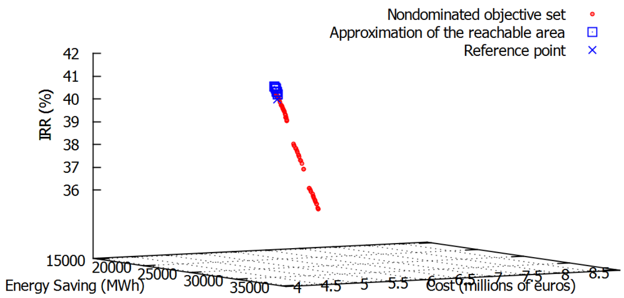
Figure 8: Decision variables values at solution $\mathbf{z}^2$.

When we analysed these decision variable values, we realized that there were some continuous variables which reached very low values (namely XQM_3, XQM_6, XQM_7 and XQM_8). Given that these variables indicate the amount of reactive power to be compensated for, we thought that compensating for such small quantities of reactive power might have implied a small improvement of the energy saving, at the expense of a high increase in the investment. Indeed, the DM expressed that it had no sense to install capacitors to compensate for such small quantities of reactive power.

It should be said that WASF-GA has generated these solutions with such small continuous variables values because of the discontinuity of the cost objective function at solutions with the continuous variables equal to 0. In practice, WASF-GA tried to find the solutions in the approximated area with XQM_3, XQM_6, XQM_7 and XQM_8 equal to 0, but it did not hit these particular values. Of course, we could have introduced some constraints to assure that a minimum amount of reactive power is compensated for, whenever this value is not 0. However, when we modelled the problem with the DM, he did not initially consider this fact as a constraint. This shows that, in practice, the DM learnt about the problem itself, and realized about how the process behaved, during the solution process.

Being aware of this situation, we believed that there may be other solutions close to $\mathbf{z}^2$ which may have these variables equal to 0 and, thus, for which the investment may decrease considerably, at the expense of a small decrease of the energy saving, which, in turn, may imply an improvement of the IRR value. Then, we decided to study the solutions that could be generated by WASF-GA if we set $\mathbf{z}^2$ as the new reference point. Subsequently, we set $h = 3$ and $\mathbf{q}^3 = \mathbf{z}^2 = (33,961,832.56 \text{ kWh}, 3,998,373.81 \text{ €}, 41.11\%)$. In this case, in order to assure that the continuous variables XQM_3, XQM_6, XQM_7 and XQM_8 were exactly 0, we upper bounded them by 0. The solutions generated by WASF-GA for $\mathbf{q}^3$ and the objective function values obtained can be seen in Figure 9.

It is important to note that the 10 solutions obtained dominate $\mathbf{q}^3$, what means that WASF-GA was able to find solutions which improve all the objective values at $\mathbf{z}^2$. In general, the final solutions obtained by any evolutionary approach are feasible solutions which may not be true Pareto optimal solutions, they are just approximations of the true Pareto optimal set. In this case, solution $\mathbf{z}^2$, which was previously generated by WASF-GA, is very close to the nondominated



Sol.	Energy Saving (kWh)	Cost (€)	IRR (%)
1	34,091,288.92	3,991,998.23	41.36
2	34,091,288.92	3,991,998.23	41.36
3	34,067,687.24	3,978,642.04	41.48
4	34,066,192.90	3,978,165.94	41.48
5	34,076,520.00	3,981,709.92	41.46
6	34,054,604.25	3,967,871.48	41.59
7	34,052,670.40	3,966,712.99	41.60
8	34,005,763.39	3,952,852.24	41.70
9	34,036,235.74	3,960,095.97	41.65
10	34,004,546.12	3,952,642.75	41.70

Figure 9: Solutions obtained by WASF-GA for $\mathbf{q}^3$.

objective set, but it is not a true efficient solution of the problem because the new generated solutions dominate it. This fact means that the new generated solutions are better approximations of the true Pareto optimal set (or are closer to the Pareto optimal set) than $\mathbf{z}^2$. It also shows that WASF-GA was able to improve the approximation of the region of interest when the search space was narrowed. Furthermore, we checked the dominance between the solutions generated by NSGA-II in the approximated area and the ones obtained by WASF-GA at this iteration and it is noteworthy that the WASF-GA solutions are not dominated by any of the NSGA-II solutions, and they even dominate some of the NSGA-II solutions. This implies that the results obtained by WASF-GA outrank those obtained by NSGA-II in that region of interest.

At this point, the DM decided that, since no solution required to spend more than 4 million €, he preferred the solution with the highest energy saving value, so he selected solution 1. Then, $\mathbf{z}^3 = (34,091,288.92 \text{ kWh}, 3,991,998.23 \text{ €}, 41.36\%)$. In comparison to $\mathbf{z}^2$, $\mathbf{z}^3$ saves 129,456.92 kWh more and needs 6,375.5 € less, so $\mathbf{z}^3$ represents a more profitable solution than $\mathbf{z}^2$. The decision variables at $\mathbf{z}^3$ are indicated in the tables of Figure 10. It can be seen that, now, all the continuous variables reach more realistic values.

Continuous variables	Values
$XQBM$	20,205.92 kVAR
$XQBL_1$	442.07 kVAR
$XQBL_2$	442.05 kVAR
XQM_1	479.22 kVAR
XQM_2	0.00 kVAR
XQM_3	0.00 kVAR
XQM_4	0.00 kVAR
XQM_5	0.00 kVAR
XQM_6	0.00 kVAR
XQM_7	0.00 kVAR
XQM_8	0.00 kVAR
XQL_1	0.00 kVAR
XQL_2	0.00 kVAR

Binary variables	Values
XMM_1	1
XMM_2	0
XMM_3	0
XMM_4	0
XMM_5	0
XMM_6	1
XMM_7	0
XMM_8	1
XML_1	1
XML_2	1
XVM_1	0
XVM_2	1
XVM_3	0
XVM_4	1
XVM_5	1
XVM_6	0
XVM_7	0
XVM_8	0
XVL_1	1
XVL_2	1

Figure 10: Decision variables values at solution $\mathbf{z}^3$.

The practical interpretation of solution $\mathbf{z}^3$ is that, if the DM wants to save 34,091,288.92 kWh every year, he has to spend 3,991,998.23 €. The IRR of the investment at 10 years will raise to 41.36%. To achieve this, the strategies to be implemented are the following ones: 20,205.92 kVAR must be compensated for in the busbar of transformer TMV-1, 442.07 kVAR in the busbar of transformer TLV-1, 442.05 kVAR in that of transformer TLV-2 and 479.22 kVAR in the drives of group GMV-1. Besides, the motors of the drives of groups GMV-1, GMV-6, GLV-1 and GLV-2 should be replaced by high efficiency ones, and a VSD has to be installed on each of the drives of groups GMV-2, GMV-4, GMV-5, GLV-1 and GLV-2. Figure 11 shows a visual interpretation of this solution, where the groups of drives where the current motors should be replaced have been plotted in green color, and the ones where VSDs should be installed in red color. Besides, we have coloured in blue wherever some reactive power must be compensated for.

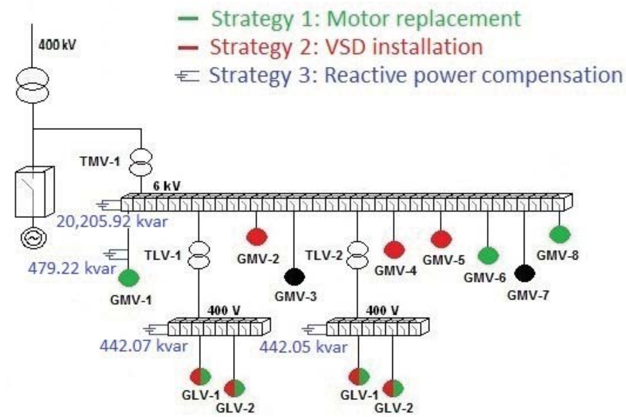


Figure 11: Single line diagram of the case study - Interpretation of solution $\mathbf{z}^3$.

6 Conclusions

In this paper, we have addressed the multiobjective problem associated to the efficiency improvement of the auxiliary systems of power plants. This improvement can be achieved by the implementation of several strategies, such as motor replacement, installation of VSDs and PF correction. Our multiobjective problem simultaneously maximizes the energy saving achieved, minimizes the investment required and maximizes the IRR of the investment. This multiobjective optimization problem grew out of a R&D contract with the Endesa Generation S.A. company, one of the largest electrical companies in the world.

The problem has been mathematically modelled in such a way that it can be applied to the auxiliary services of any plant. It manages both binary and continuous decision variables, and the objective functions are discontinuous. Due to the complex nature of the system and to the complicated engineering formulas behind it, we need a black box to simulate the energy model of the auxiliary services.

For solving the problem, we have proposed a novel combined interactive process, where we have progressively adjusted the solution procedure according to the results obtained and depending on the DM's preferences. In the case study considered, an engineer from the Endesa Generation S.A. company first described the auxiliary services considered and the problem was completely formulated. Next, in the preliminary phase, we approximate the whole Pareto optimal set using NSGA-II, in order to have a good idea of the trade-offs among the objective functions. In our case study, we could distinguish two kinds of compromise solutions among the solutions generated by NSGA-II: solutions with high energy savings, which required high investment costs and reached low IRR values, and solutions with high IRR values, achieving low costs and energy savings.

In order to study in depth only the most interesting area of the nondominated objective set for the DM, next, the interactive phase makes use of information about the DM's preferences, which are expressed by means of a reference point. Since the DM may be initially doubtful about which reference point really expresses her/his preferences and properly represents her/his region of interest, we have designed a process to learn about the preferences by analysing several reference points before selecting the final one. This process is based on the minimization of a two-slope ASF over the set of solutions generated by NSGA-II. In our case study, after several iterations, the DM could find an interesting reference point. Despite the low computational effort required, this stage was really useful in practice, since the DM could select a reference point being aware of what could and could not be achieved.

Finally, using the reference point selected, the preference-based EMO algorithm WASF-GA is run in order to approximate the region of interest. The solutions obtained in the case study enabled the DM to realize that different trade-off solutions could be achieved according to his preferences. He needed to narrow down the search space several times until finding an interesting final solution. To this end, WASF-GA was run several times using new reference points. Although the reference points used were quite close to the nondominated objective set, WASF-GA not only was able to generate solutions in the desired region, but it also generated solutions which improved the previously obtained solutions.

Solving this multiobjective problem has highlighted the usefulness of interactive multiobjective optimization to solve real-life decision making problems. The proposed methodology not only adapts the model to the auxiliaries of any thermal power plant, but has also helped the DM to gain a progressive understanding of the problem itself until reaching a satisfactory final solution. Moreover, several difficulties found during the solution process were overcome thanks to the knowledge we gradually got about the problem.

The novelty of our scheme lies on the combination of several methods, to build a global interactive scheme. This scheme makes use of the best features of each individual technique, and overcomes their potential drawbacks. The solution process would have been more difficult if we had just approximated the whole Pareto optimal set using the EMO approach. Probably, the DM wouldn't have been able to analyse the trade-offs among all the solutions presented, and to choose a single one. But, on the other hand, if we had approximated his region of interest directly, he might have given the preferential information without having a good knowledge of the problem. This might have led to the selection of a wrong final solution which would not completely satisfy the DM. Besides, the process designed for the selection of the reference point really helped the DM to make up his mind about the kind of solutions that were of his interest. Therefore, what is gained from an approach is not obtained from the others, and, in practice, the combination of these multiobjective optimization methodologies has been decisive to reach a satisfactory solution of the problem.

In the future, a possible way to enrich this study may be the introduction of new efficiency improvement practices in the problem, as well as the consideration of new economic or environmental criteria. Besides, another possible improvement would be to readjust the model so as to consider single line diagrams with several HV-MV transformers, what will open the application of our problem to a wider range of auxiliary services. Finally, in order to overcome the difficulties found because of the discontinuities of some of the objective functions, we could consider other heuristic methodologies to solve the problem, or we could introduce new variables and constraint to avoid these discontinuities.

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