Adaptive mutation probability as an efficient tool to incorporate knowledge in an Evolutionary Algorithm for multiobjective electricity planning

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ABSTRACT

Evolutionary Algorithms (EAs) belong to the set of meta-heuristic search tools presenting a behaviour similar to natural evolution. EAs are characterized by competition among individuals, in which some of them are selected based on their fitness for contributing to the next generation. Crossover and mutation operators introduce variability in the genetic material and allow for exchange of some individuals’ characteristics through recombination. Usually, an evaluation function and appropriate genetic operators that select, recombine and mutate individuals are needed to make a population of solutions evolve over generations.

This work presents a comparative analysis of the effects of the incorporation of the available information through the use of an adaptive mutation operator in the operational framework of a specific EA. The main goal of the EA is the automatic identification of a set of solutions to be presented to a decision maker, in the framework of a multiobjective model to provide decision support in the selection of the use of demand resources in the electricity sector.

1. INTRODUCTION

Evolutionary algorithms (EAs) present a behaviour similar to natural evolution, in which a population of potential solutions evolve over successive generations. The
evolution process takes place in several phases. Generally, the first one is the evaluation of individuals according to some objectives. A selection phase follows in which some potential solutions are chosen from the population, using a probability that is a function of individual performance. Usually, a higher selection probability is given to more performant individuals. Crossover and mutation operators are then applied to the selected solutions to give origin to the next generation. The process continues until some stopping condition is reached. These operations carried out in the realm of optimisation problems are inspired on natural evolution, allowing for the exploration of the search space and striving for good solutions to the problem under study.

These algorithms offer two very appealing characteristics. One is simplicity, since one does not need to deal with complex mathematical optimisation tools. The second one is flexibility, allowing them to be broadly used in very distinct problems arising in different application areas (Jones et al., 2002). On the other hand, EAs must be tailored to the specific problem under study. Namely, the parameters need to be tuned otherwise EAs may become very ineffective when compared with other approaches. An important source of the eventual lack of EAs’ efficiency arises when the available knowledge about the evolution of the optimisation process is neglected, that is, when the behaviour of the population is not taken into account in the evolution process. The incorporation of available information to guide the search is a crucial task in the operational framework of meta-heuristics. So, in order to better adapt EAs to the current search space and allowing it to evolve according to the objectives being evaluated, it is necessary to supply EAs with knowledge obtained from the results of the evolutionary process.

Unlike in single objective optimisation problems, in which it is easy to find a metric that allows the solutions to be compared and ranked, in a multiobjective (MO) environment each solution is evaluated according to its performance on multiple, conflicting and incommensurate aspects of evaluation operationalized through objective functions. Therefore, instead of a single optimal point, the decision maker (DM) has to choose, according to his/her preferences, between a set of non-dominated (Pareto optimal) solutions, the so-called Pareto front (PF). EAs, while optimisation tools, work with a set of potential solutions for the problem under study, making them suited for MO problems. When dealing with multiple conflicting objectives, some strategy must be used if every solution is to be assessed according to its performance in each objective function. Two main approaches are usually implemented. One is the aggregation of all the objectives, known as the scalarization approach. A second one
consists of making use of the non-dominance definition, in which solutions are ranked according to their degree of non-dominance. This approach, for which several different implementations can be found, has been suggested in (Goldberg, 1989) and it seems to be the most popular in the evolutionary computation community (Fonseca and Fleming, 1993; Horn and Nafpliotis, 1994; Srinivas and Deb, 1994; Zitzler and Thiele, 1998). However, Pareto-based approaches do not perform well when the search space is very large (Fonseca and Fleming, 1995), since in this situation the number of solutions that are in accordance with the Pareto non-dominance definition increases, a good compromise solution being harder to find.

The fitness of each individual is based on its performance in all the objective functions, but it may address other criteria or preferences the DM may want to include in the assessment. The fitness represents the quality of each element in the population and thus the selection of the elements that are going to contribute to the next generation is usually done according to it. Mutation and crossover operators are used as a way for discovering new solutions, that is, they contribute to focus the search into new regions of the search space. These operators give EAs the ability to go through the search space allowing, for example, to escape from local optima.

Like other meta-heuristics, EAs are usually parameter intensive in the sense that they need several parameters, which must be tuned for the problem under study in order to make EAs work properly. Therefore, the identification and the selection of a suitable value or range of values for every parameter become a crucial step when using meta-heuristics. Two different approaches can be used for the process of identification of the parameter values. One, and perhaps the most common, consists of tuning the parameters, through experimentation based on the DM’s expertise. Several runs are executed until the parameters are calibrated, which may be considered done when the results produced are good enough according to the DM’s preferences. This is an empirical process relying on the expertise of the actors involved (the DM and the analyst who mediates the communication of the DM with the computer tools). The second approach for the parameters setting is through adaptive control. Instead of being constant over each simulation, like in the tuning process, the values of different parameters may vary with time. This variation may appear in two forms. In the simplest one the values are a function of time, generally of the number of generations. In the second form, the parameters are given the ability to evolve over generations (self-adaptive control), in which the parameter codification is made within the chromosomes of the individuals and thus are part of the evolution process. Therefore, if changes in the parameters are based on the results obtained in each generation.
rather than being a simple function of time (generally a function of the number of generations) this adaptive control can be a privileged manner of incorporating knowledge about the evolutionary process into the search, thus making the EA to work more effectively. In this paper, the influence of using such kind of adaptive control of the parameters in an EA for a MO problem is analysed. This problem deals with the identification and the selection of suitable control strategies to be applied to groups of loads, in the framework of load management in electric power systems.

2. The Problem of Selecting Load Control Strategies in Power Systems

In power systems, the use of available demand-side resources by changing the regular working cycles of loads through the implementation of appropriate power curtailment actions has revealed potential attractiveness. Several activities, encompassed by the so-called Load Management (LM), and recently renamed Demand Responsive Programs (DRP), have been implemented by some electric utilities as a way of increasing the efficiency of their electric system. Recently, this kind of programs has experienced an enormous increase in number mainly due to the economic interests related with the volatility and spikes of wholesale electricity prices and also because of reliability concerns (transmission congestion and generation shortfalls) (Heffner and Goldman, 2001; Hirst and Kirby, 2001). These programs, which include direct load control, interruptible power and voluntary load shedding, can be very attractive for a retailer dealing with volatile wholesale prices and fixed, over a certain time period, retail prices. The integrated resource management embracing DRP asks for the (design and) selection of suitable load shedding actions. Some of the objectives that a DM may consider when dealing with this kind of strategies are: minimize maximum power demand, maximize profits, minimize losses and minimize causing discomfort to customers.

The selection of adequate load shedding actions to be implemented over sets of loads, grouped according to some criteria, is therefore a multiobjective optimisation problem to be faced by load management programs. In the study reported in this paper, the demand of controlled loads results from Monte Carlo simulations through the use of Physically Based Models (PBM) that have been experimentally validated. These models reproduce the behaviour of the simulated loads with a time resolution of one minute.
The loads usually considered in LM programs are thermostatic loads, air conditioners (AC) and electric water heaters (EWH), among others.

In this work, the behavior of some AC and EWH groups are simulated. Each group contains one type of loads only. One control strategy encompasses the control actions to be applied to every group of loads during one day. Therefore, this is a hard combinatorial problem due to the potential size of the search space and number of evaluation dimensions. As already referred to above, Pareto-based approaches to MO do not usually work appropriately in these situations. Different approaches have been implemented. Two of them are based on scalarisation: weighted sum and goal programming; and two other are based on the non-dominance definition: FF (Fonseca and Fleming, 1993) and NSGA (Srinivas and Deb, 1994).

3. A MULTIOBJECTIVE MODEL FOR SELECTING LOAD CONTROL ACTIONS

In the current restructuring and liberalisation environment in the electricity sector, the increase in revenues with the inclusion of demand-side resources in planning has gained further attractiveness. Besides, the traditional goals within the energy efficiency framework, such as cost reduction (Salehfar and Patton, 1991; Chen et al., 1995), increase in power system reliability (Salehfar and Patton, 1989), reduction of air pollution (Talaq et al., 1994), or reduction of the dependence on overseas fuels, keep their intrinsic interest (Lachs et al., 1996). On the other hand, the volatility and the diversity of the electricity market structure ask for a model that should be able to deal with different possible scenarios. On one hand, the model should be adequate to the more traditional market structure, where the activities of production, transmission, distribution and selling of electricity are usually integrated in the same utility. On the other hand, should also be suited for newer scenarios where several entities – producers, retailers, costumers- appear in different branches of activity, in a setting of total unbundling of previous integrated utilities. In this setting, different entities pursue distinct goals, and therefore, multiple and conflicting objectives are at stake. The implementation of any strategy dealing with load pattern changes must be carefully assessed in order to design suitable load control actions.

The objective functions considered in the proposed model are:
• Minimization of peak power demand. A usual objective when implementing load management programs is the reduction of maximum demand. From a distribution utility perspective, the reasons behind this objective are capacity constraints (substations, distribution transformers, feeders, etc) or efficiency improvement through loss reduction. Also, peak reduction enables both the distribution utility and the retailer to have a better capability of continuously exploring the differences between purchasing and selling prices. The reduction of power demand is evaluated in the model at three different demand aggregation levels.

• Profit maximization. Profits of electricity sales are generally influenced by the amount of electricity sold, according to the time of day/season/year. In the presence of demand and wholesale price forecasts, the distribution utility / retailer can design adequate load shedding actions in order to maximize profits once retail prices are fixed.

• Loss factor minimization. This objective function is related with both operational and economic goals. Losses are a function of some physical network parameters. In the absence of a detailed knowledge on the network characteristics that would allow evaluating the losses imposed at a specific power demand, an estimate is usually used through loss factor. Loss factor is the ratio between the sum of losses and the maximum losses value. Since loss reduction is directly proportional to loss factor reduction, this has been considered in the model.

• Minimize discomfort caused to customers. The electricity service provided by loads under control is changed, possibly postponed or even not provided at all, when load management actions are implemented. These changes can eventually cause some discomfort to customers that must be minimized, in such a way that those actions become also attractive from the customers’ point of view (with eventual reduction in their electricity bill) and/or at least not decrease their willingness to accept them. Discomfort is evaluated through two objective functions related with the time some state variable (controlled by loads) is over or under a pre-specified threshold level. The objective functions to be minimized are the maximum continuous time interval in which this situation has occurred and the total time it has occurred.

The mathematical formulation of the model is developed in the appendix.
4. An EA-Based Approach

The main purpose of the study is to identify sets of load curtailment actions to be applied to the different groups of loads under control. This is an iterative process encompassing the simulation of loads using the PBM and the run of the EA, as described in the following. The EA identifies a set of potential solutions (individuals in the population), which are then decoded into load control strategies (one strategy for each individual). PBM use these strategies and simulate the demand of the loads under control. The results obtained with PBM, using a specific set of strategies corresponding to the actual population in the EA, are then used by the EA to evaluate every individual in the population. The EA proceeds with its normal functioning: selection, crossover and mutation until a new population (generation) is obtained. The cycle repeats until the stop condition in the EA is verified. In figure 1 this iterative process is schematically described.

![Figure 1 - Iterative process for the identification of load control strategies](image)

The phenotype space is the set of all possible load-shedding strategies that can be used and can be mapped into the objective space by using PBM. As described in section 3 (see also the appendix), it is a seven-dimension space whose structure depends on the control strategies applicable to loads. The codification of each control strategy in the genotype space is done through the use of binary matrices each one representing a control strategy applicable to all groups of loads. Each column in the
matrix represents the control strategies applied to a group of loads. For $ng$ groups of loads a control strategy is set up with $ng$ columns in the matrix. So, each individual in the EA’s population is a matrix whose size is $1440 \times ng$ (1440 rows and $ng$ columns). 1440 is the number of minutes in a day, in accordance with the time resolution used in PBM, once these models simulate the demand of groups of loads on a daily basis with a time resolution of one minute, for a more detailed representation of load behaviour. In these matrices a “1” means that the load is shut-off during the corresponding period of time and a “0” means that the load is operating as usual, i.e. without any external control action. If the size of the population in the EA is $N$, the genotype space is set up with $N$ matrices (individuals) and its size is $N \times (ng \times 1440)$. That is, each element of the population (potential solution) represents a control strategy for all groups under control. In the following figure the structure of the genotype space as well the structure of each individual in the population are shown.

![Figure 2 – Structure of the genotype space (G1: group #1; Gng: group #ng)](image)

The minimum period of time in which loads are cut-off has a duration of 5 minutes and each period of normal operation lasts at least for 5 minutes. When crossover or mutation occurs, chromosomes are checked and eventually repaired in order to maintain these two minimum periods of time in which a load is shut-off or powered on. This time resolution demands for some computational effort but the corresponding load switching maximum frequency (1/10 minutes) is not too high for loads of this size and type and, moreover, it also allows a more effective dispatch of the load under control to be achieved.

The decision support tool we have developed based on the model presented in section 3 (see also the appendix) allows for the automatic identification of a set of solutions that will be presented to the DM, enabling him/her to go through the search space and find good compromise solutions for the problem. The population of potential
solutions evolves over successive generations until a stop condition is reached, usually a maximum number of generations. Eventually before this, the DM finds a satisfactory compromise solution, which a final decision can be based on. In the results shown in section 6, 10000 generations have been simulated, which seems to be a sufficiently high value for experiments and validation of results.

5. Knowledge Incorporation by Using an Adaptive Mutation Probability

In order to improve the efficacy of EAs and, to some extent, to avoid them to become a random walk through the search space, EAs must be supplied with the available information about the environment and the performance of the individuals in the population. One way to do this is through genetic operators, in this case resorting to the mutation operator. This operator becomes a function of time within each simulation and also changes from one simulation to another, in such a way that it allows for a more effective dynamic incorporation of available information into the search process. The information is collected by analyzing the results obtained by every individual present in the population in the phenotype space. The dynamic behavior of this operator, changing from one individual to another and from one generation to another, allows the search to be effectively guided towards regions of the search space in which more interesting compromise solutions can be found.

As mutation occurs in the genotype space and the alphabet used in the construction of the chromosomes is a binary one, two kinds of mutation are considered in this problem: “normal operation” can mutate to “no operation” and a period of shut-off can become a “normal operation” period. The two probability values are:

\[ pm_{1\_0} \]: probability that a load curtailment stops (in the genotype space, a “1” gene mutates to “0”)

\[ pm_{0\_1} \]: probability that a load curtailment is applied to a load “operating as usual” (in the genotype space, a “0” gene mutates to “1”).

The probabilities of these two mutations can vary in different ways during the simulation, in the sense that when changes occur it may be interesting to increase the mutation rate in one direction but not in the other. For example, in a scenario in
which simulation is going on in time interval \( n \) and in interval \( n+1 \) profits increase, from the profit maximization perspective \( pm_{1,0} \) may increase and \( pm_{0,1} \) may decrease in interval \( n+1 \) with respect to their values in interval \( n \). If the maximum aggregate power demand decreases in interval \( n+1 \) when compared with demand in interval \( n \) then \( pm_{1,0} \) may decrease and \( pm_{0,1} \) may increase with respect to their values in interval \( n \). These are simplified examples, in the sense that each time interval must not be taken separately, as the effects of changing power demand in one interval last for several subsequent intervals, depending on the amount of power controlled and other parameters that influence loads operation.

Besides the split of the mutation operator into two different values of probability, according to which action is occurring (\textit{load curtailment} mutates to \textit{no load curtailment} and \textit{no load curtailment} mutates to \textit{load curtailment}), each of these two values is computed individually for different levels of demand aggregation. The reason is that each LM action can produce opposite effects in each load diagram and, to improve the EA’s efficiency, it must be supplied with qualified knowledge. Also, with the purpose of contributing to increase the efficiency of the EA, each of the individual values of the mutation probability is built up according to each objective function. That is, as every objective function can be diversely influenced by the information obtained from the evolution process, then each individual contribution to mutation probability values changes accordingly. In order to increase the flexibility of such approach, the DM is given the capability to set weights for each objective, which are taken into account to compute the contribution of all objectives to the mutation probability.

One question that this methodology arises is how and where the information needed for constructing the knowledge about the evolutionary process can be obtained. This information is collected in the phenotype space by using the PBM, meaning that each simulation cycle encompasses one run of PBM, resulting in one point belonging to the phenotype space, and one generation of the population of the EA, resulting in one point in the genotype space. In summary, the probability associated with the mutation operator can have two different values according to what mutation is occurring (0 to 1 or 1 to 0) and each one of the values can receive different and independent contributions from each objective function. Such an approach is aimed at increasing the effectiveness of the EA. It should be noted that weights are used herein only as an operational means to aggregate the contribution of all objective function values and not as a way of eliciting the DM’s preferences.
The overall weighted sum (by using the individual objective function weights) to compute $pm_0_1$ and $pm_1_0$ is obtained as in the following. The objectives presenting a time varying behaviour (within each simulation and from one simulation to another) have a contribution that is also time dependent, in a way closely related to the variation in time of the objective, and limited by a maximum threshold specified by the analyst: $pm_{up}$. The way each contribution varies in time is a function of the distance between the current value of the objective function and a percentage of the maximum value (90% is the current value used in the experiments).

\[
pm_{*0_1}[n] = \frac{\max(0; D[n] - 0.9*MD)}{\max(D[n] - 0.9*MD)} \times pm_{up} \times weight_{of\_objective}
\]

\[
pm_{*1_0}[n] = \left[1 - \frac{\max(0; D[n] - 0.9*MD)}{\max(D[n] - 0.9*MD)}\right] \times pm_{up} \times weight_{of\_objective}
\]

In the first expression, the numerator gives the maximum difference between the current demand and the referred level (90%) of the maximum demand (in each level of aggregation), at time interval $n$. The denominator is the maximum value of that difference when all the time intervals are accounted for. $D[n]$ is the power demand at interval $n$ and $MD$ is the original maximum peak demand. $pm_{*0_1}$ ($pm_{*1_0}$) is the contribution of this objective to $pm_0_1$ ($pm_1_0$) mutation probability. When the difference is negative (the actual demand is below the threshold level) the value 0 is considered for $pm_{*0_1}$ meaning that, from this dimension point of view, there is no interest in a mutation 0 to 1. For $pm_{*1_0}$, the value $pm_{up}* weight_{of\_objective}$ is considered. That is, when power demand is low there is no interest in having load curtailments. When the current demand is over the threshold value, higher differences mean bigger mutation probability from “non load curtailment” to “load curtailment” situation (from 0 to 1 in the genotype space). That is, the probability of occurring a load shedding rises when power demand increases. When the difference reaches its highest value $pm_{*0_1}$ is given the value $pm_{up}* weight_{of\_objective}$ and $pm_{*1_0}$ is given the value 0. The contribution of this dimension for the mutation operator, within one generation and for one of the individuals, is depicted in figure 3. The load demand diagram is also presented and it can be seen that mutation from 0 to 1 increases substantially during higher demand periods. Moreover, once $pm_0_1$ and $pm_1_0$ are function of the values of the corresponding variable (being, for this reason, function of time), the objectives related with consumers’ comfort, minimisation of peak power demand and losses depend on the control strategy applied to each group of loads. This
means that the different components used to build up \( pm_{0\_1} \) and \( pm_{1\_0} \) are different from one individual to another individual and must be evaluated in each simulation.

\[
\text{pm}^*_{\_0\_1} - \text{full}; \quad \text{pm}^*_{\_1\_0} - \text{dotted}
\]

Figure 3 – The contribution of objective “minimize maximum value of aggregate demand” for the mutation probability.

Figures 4 and 5 show the contribution of the objectives related with power demand at the less aggregate levels for the mutation operator. The rational is the same used for the more aggregate level: to increase the probability of occurring load curtailments when power demand is above the threshold level and simultaneously increase the probability of not occurring load control actions when the power demand is below the threshold level.

\[
\text{pm}^*_{\_0\_1} - \text{full}; \quad \text{pm}^*_{\_1\_0} - \text{dotted}
\]

Figure 4 – Contribution of power demand at less aggregate level 1 (PD1) for the mutation probability.
The aspects related with consumers’ comfort participate in the construction of the mutation operator with fixed values during the simulation. Their contribution is based on the rationale that to minimize the discomfort of consumers the number of load curtailments should be reduced. The analyst is asked to specify the maximum and minimum values desired for the mutation probability \( pm_{\text{maximum}} \) and \( pm_{\text{minimum}} \). The values of the individual contribution of each objective \( (pm^{*}_{0\_1} \) and \( pm^{*}_{1\_0} \)) are computed by:

\[
pm^{*}_{0\_1} = pm_{\text{minimum}}\times \text{weight of objective}
\]

\[
pm^{*}_{1\_0} = pm_{\text{maximum}}\times \text{weight of objective}
\]

Profits are in an intermediate situation, that is, the information varies within each simulation but it is constant from one simulation to another one since 24 hours price forecasts are considered and its contribution for the \( pm \) values is based on that forecasts only. Profits are in the range \([\text{minimum profit}, \text{maximum profit}]\) according to the forecasts and, in each time interval \( n \), the contribution for \( pm \) is given by

\[
pm^{*}_{0\_1}[n]= \frac{\text{Profits}[n] - \text{Maximum profit}}{\text{Minimum profit} - \text{Maximum profit}} \times pm_{\text{maximum}}\times \text{weight of objective}
\]

\[
pm^{*}_{1\_0}[n]= \left[1 - \frac{\text{Profits}[n] - \text{Maximum profit}}{\text{Minimum profit} - \text{Maximum profit}} \right] \times pm_{\text{maximum}}\times \text{weight of objective}
\]

where \( \text{Profits}[n] \) is the forecasted value for profits in interval \( n \).
That is, in a very similar way to the contribution of dimensions related with power demand, \( pm \) varies according to the distance of current profits to their maximum value. When profits raise, their contribution to \( pm_{0\_1} \) approaches 0 and their contribution to \( pm_{1\_0} \) approaches \( pm_{maximum} \). When profits reduce, the contribution for \( pm_{0\_1} \) (\( pm_{1\_0} \)) approaches \( pm_{maximum} \) (0). The rationale is to stimulate the occurrence of “operating as usual” rather than load curtailments in periods of time in which profits are higher. This behaviour is displayed in figure 6.

![Figure 6 - Contribution of profits to mutation probability.](image)

The loss factor (\( L \)) changes only from one simulation to another, and its contribution is computed as follows. Let \( ML, AL, \) and \( mL \) be the maximum, average and minimum values of the loss factor, respectively.

If \( L > AL \) then

\[
pm^{*}_{0\_1}[n] = \frac{L - AL}{ML - AL} \times pm_{maximum} \times weight_{of\_objective}
\]

\[
pm^{*}_{1\_0}[n] = \frac{ML - L}{ML - AL} \times pm_{maximum} \times weight_{of\_objective}
\]

else

\[
pm^{*}_{0\_1}[n] = \frac{AL - L}{AL - mL} \times pm_{maximum} \times weight_{of\_objective}
\]

\[
pm^{*}_{1\_0}[n] = \frac{L - mL}{AL - mL} \times pm_{maximum} \times weight_{of\_objective}
\]

The contribution of the loss factor to the mutation probability is displayed in figure 7.
Figure 7 – Contribution of loss factor to the mutation probability

Figure 8 shows an example of the total mutation probability taking into consideration all contributions.

Figure 8 – Final values for mutation probability along a day simulation for one individual

Having in mind that mutation is an essential step in the evolution process, bringing new potential solutions for the search, there is a minimum value for the probabilities associated with it that is pre-specified by the DM/analyst, \( pm_{\text{minimum}} \). Thus, if the contribution of all objectives for mutation operator is below that threshold level, then \( pm_{\text{minimum}} \) is attributed to \( pm_{0.1} \) or \( pm_{1.0} \).
6. **ILLUSTRATIVE RESULTS**

The following results illustrate the effects of incorporating different amounts of available information in EA through adaptive mutation probability. Some characteristics of the EA used in the simulations are:

- Population size: 20
- Maximum number of generations: 10000 (this number was used to allow the comparison of the evolution of the different algorithms. As shown in figure 11 a lower number of generations may be used as a stop condition.)
- Crossover probability: 0.01
- Minimum value for mutation probability: 0.0001
- Maximum value for mutation probability: 0.0005
- One run (PBM + one EA generation): 7.9 seconds (Pentium III, 1 GHz)

A key issue in MO optimisation is how to compare two different Pareto fronts resulting from two different algorithms or from the same algorithm with two different sets of parameters. Some criteria can be used, such as the number of non-dominated solutions, the distance from the Pareto front resulting from one run to the Pareto optimal front, the diversity and the spread of solutions throughout the Pareto front (Zitzler and Thiele, 1999). In the problem under study in this work, as in many real-world problems, the Pareto optimal front is unknown and the diversity and the spreading of solutions are not to be taken for granted. Several procedures have been implemented to deal with these issues. In order to deal with the eventual lack of diversity, a fitness sharing process has been implemented. For the comparison and ranking of solutions two alternative references have been used. One of them is a so-called floating optimum point (FOP) whose coordinates are the best value obtained in each dimension when all the solutions are accounted for. These coordinates may change when the set of solutions under comparison changes, making the point float through the search space. The other reference is a meta optimum point (MOP). Its coordinates are the best achievable values in each dimension and can be changed by the DM according to his/her preferences and expertise regarding the evaluation aspect in each dimension. The DM can provide this reference point by specifying the aspiration levels he/she would like to attain in each objective function.

In order to allow for a broader comparative analysis of the effects of using available information, different approaches to multiobjective evolutionary algorithms have been
implemented. Two of them are based on scalarisation approaches: weighted sum and goal programming; and two other are based on the non-dominance definition: FF (Fonseca and Fleming, 1993) and NSGA (Srinivas and Deb, 1994). For each of these implementations, two versions have been tested. In the first one, called “with knowledge”, the use of available information is done through adaptive control of mutation probability. In the second one, called “without knowledge”, a constant value for mutation probability is used.

The goals used in the goal programming approach were determined based on previous knowledge about the power system characteristics. The goal values for the different objectives were:

- Peak power demand (PA): 29458 kW;
- Power demand at less aggregate level 1 (PD1): 489 kW;
- Power demand at less aggregate level 2 (PD2): 479 kW;
- Total time in which the temperature is beyond the threshold level (t): 5000 minutes;
- Maximum interval in which temperature is beyond the threshold level (m): 15 minutes;
- Loss factor (l): 0.52;
- Annual profits (g): 8000 k Euros.

The performance of each approach assessed by using the average distance of the respective Pareto front to the MOP and to the FOP is shown in figures 9-10 (Euclidean distances normalized by the MOP).
It can be concluded that algorithms using knowledge information through adaptive mutation probability present a better performance and this occurs in both metrics (distance to the MOP and to the FOP). The effect of using the available information about the evolution process has also been evaluated by comparing the number of non-dominated solutions for each situation. The incorporation of knowledge produces much better results when compared with the implementations without it.

Figures 11-12 show the distance of the nearest individual to the MOP in each generation for the NSGA algorithm (figure 11) and for the WS algorithm (figure 12).
According to these figures, algorithms making use of available knowledge present in every generation the individual closest to the MOP.

Figure 13 display the minimum, average and maximum value in each objective function found in the population (in one scalarisation approach – weighted sum), which can be used as an implicit indicator of the diversity of solutions in each generation. A remarkable difference shown in these figures concerns the diversity in each generation, which is much higher when knowledge is provided to EAs (see also table 1).
Figure 13 – The evolution of minimum, average and maximum value in each objective function.

a, c, e, g, i – with incorporation of knowledge; b, d, f, h, j – without incorporation of knowledge.
7. CONCLUSIONS

In this paper, it has been shown, in the framework of a case study, that providing EAs with relevant available information is an important step for an effective and consistent behaviour of the algorithm, namely whenever multiple objective functions are at stake. In this study, the mutation operator presents an adaptive dynamic behaviour, changing according to the values achieved for the several objectives under analysis. The mutation operator has several characteristics that make the EA to work more efficiently. For example, it has been computed diversely according to the mutation which is occurring: from load curtailment to no load curtailment or from no load curtailment to load curtailment. The operator has been split up into several parts, one for each dimension, making possible to consider distinct contributions from each objective for the global values of the operator. Finally, as it is possible to evaluate the effects of each LM action through the use of PBM, in each dimension in the phenotype space, this operator changes in time and from one solution to another solution in the population. According to the results obtained, this methodology implemented to make use of available information through an adaptive mutation probability results in an EA presenting a better performance and simultaneously the diversity of the population in each generation has increased substantially.

References


APPENDIX

Notation:

\[ w \] – index related with demand type at the less aggregate level
\[ i \] – time period under consideration
\[ j \] – group of loads
\[ k \] – index for load curtailment strategies
\[ N \] - number of intervals in which the load diagram is discretized
\[ a_{ijk} \] – power demand increase/decrease at aggregate level in time interval \( i \), when strategy \( k \) is applied to group \( j \)
\[ d_{wijk} \] – power demand increase/decrease at less aggregate level, type \( w \), at interval \( i \), when strategy \( k \) is applied to group \( j \)
\[ x_{jk} \] – binary decision variable denoting whether load shedding strategy \( k \) is applied to group \( j \)
\[ D_{wi} \] – power at disaggregate level of type \( w \) at time interval \( i \), without load curtailment
\[ A_i \] – power at aggregate level at time interval \( i \), without load curtailment
\[ g_{jk} \] – profit when strategy \( k \) is applied to group \( j \)
\[ l_{jk} \] – loss factor when strategy \( k \) is applied to group \( j \)
\[ t_{jk} \] – total time in which temperature is beyond the threshold of discomfort when strategy \( k \) is applied to group \( j \)
\[ m_{jk} \] – maximum interval of time, number of minutes, in which temperature is beyond the discomfort threshold when strategy \( k \) is applied to group \( j \)
\[ e_i \] – energy profits at interval \( i \)
\[ p_i \] – power profits at interval \( i \)

Minimizing peak power at the more aggregate level corresponds to minimizing the maximum of \( A_i + \sum_j \sum_k a_{ijk} x_{jk} \). By introducing the auxiliary variable \( v \), the min-max problem can be transformed into:

\[
\min v \\
\text{s.t. } A_i + \sum_j \sum_k a_{ijk} x_{jk} - v \leq 0.
\]

In a similar way, for each power demand objective at less aggregate level (\( w=1 \) and \( w=2 \)) one obtains

\[
\min v l \\
\text{s.t. } D_{wi} + \sum_j \sum_k d_{wijk} x_{jk} - vl \leq 0
\]

and
\[
\min \ v2 : \\
\text{s.t. } D_{21} + \sum_j \sum_k d_{2jk} x_{jk} - v2 \leq 0.
\]

Profits are related with power and the amount of energy sold. Variations related with energy are given by \( a_{jk} e_i x_{jk} \) and variations related with power are given by \( (A_i + a_{ijk}) p_i x_{jk} \). These values are used on a daily basis and are evaluated according to variations on profits caused when strategy \( k \) is applied to group \( j \).

\[
g_{jk} = \sum_i a_{ijk} e_i x_{jk} + \sum_i (A_i + a_{ijk}) p_i x_{jk}.
\]

Thus the profit objective function is

\[
\max \sum_j \sum_k g_{jk} x_{jk}.
\]

The loss factor, \( l \), is given by

\[
l = \frac{1}{T} \int_0^T \text{Losses}(t) dt,
\]

where \( \text{Losses}(t) \) is the loss function, \( \max[\text{Losses}(t)] \) are the maximum losses value within the time interval considered. Usually, data about demand and losses is available in a discrete way and therefore \( l \) is given by

\[
l = \frac{1}{N} \sum_{i=1}^N \text{Losses}[i] \max[\text{Losses}[i]].
\]

Using the per unit system representation \( l = \frac{1}{N} \sum_{i=1}^N \text{Losses}[i] \), the objective function is

\[
\min \sum_j \sum_k l_{jk} x_{jk}.
\]

The minimization of discomfort is given by

\[
\min \sum_j \sum_k t_{jk} x_{jk}, \text{ and }
\]

\[
\min \sum_j \sum_k m_{jk} x_{jk}.
\]
The mathematical model is thus

\[
\begin{align*}
\min & \quad v \\
\min & \quad v1 \\
\min & \quad v2 \\
\max & \quad \sum_j \sum_k g_{jk} x_{jk} \\
\min & \quad \sum_j \sum_k l_{jk} x_{jk} \\
\min & \quad \sum_j \sum_k t_{jk} x_{jk} \\
\min & \quad \sum_j \sum_k m_{jk} x_{jk} \\
\text{s.t.} & \\
A_i + \sum_j \sum_k a_{jk} x_{jk} - v & \leq 0 \\
D_{i1} + \sum_j \sum_k d_{1jk} x_{jk} - v1 & \leq 0 \\
D_{i2} + \sum_j \sum_k d_{2jk} x_{jk} - v2 & \leq 0 \\
x_{jk} & \in \{0,1\} \quad \forall j,k
\end{align*}
\]

Other constraints can be incorporated into the model. For example, the DM may impose further constraints on the acceptable values for the objective functions (reservation levels). EAs are unconstrained search tools and, in spite of the several approaches that can be implemented in order to deal with non-feasible solutions, in this work that task is carried out by the evaluation function. In the experiments already carried out this approach has shown to be sufficient to deal with infeasibility.