Expert Systems with Applications 42 (2015) 7466–7482

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A combined interactive procedure using preference-based evolutionary multiobjective optimization. Application to the efficiency improvement of the auxiliary services of power plants

Ana B. Ruiz [a,*], Mariano Luque [a], Francisco Ruiz [a], Rubén Saborido [b]

[a] Universidad de Málaga, Department of Applied Economics (Mathematics), Calle Ejido 6, 29071 Málaga, Spain
[b] Polytechnique Montréal Researchers in Software Engineering, École Polytechnique de Montréal, Canada

ARTICLE INFO

Article history:
Available online 9 June 2015

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

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. Solving this real-life multiobjective optimization problem with a decision maker presents several challenges and difficulties and we have developed a novel interactive procedure which combines three different approaches in order to make use of the main advantages of each method. The idea is to start with the approximation of the Pareto optimal set, in order to gain a global understanding of the trade-offs among the objectives, using evolutionary multiobjective optimization; next step is aiding the decision maker to explore the efficient set and to identify the subset of solutions which fits her/his preferences, for which interactive multiple criteria decision making methodologies are used; and finally we concentrate the search for new solutions into the most interesting part of the efficient set with the help of a preference-based evolutionary algorithm. This allows us to build a flexible scheme that is progressively adapted to the decision maker's reactions until (s)he finds the most preferred solution. The interactive combined procedure proposed is applied in practice for solving the problem of the auxiliary services with a real decision maker, extracting interesting insights about the efficiency improvement of the auxiliary services. With this practical application, we show the usefulness of the interactive procedure proposed, and we highlight the importance of an understandable feedback and an adaptive process.

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 (ABB Ltd. Switzerland, 2009). 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.

* Corresponding author.
E-mail addresses: abruiz@uma.es (A.B. Ruiz), mluque@uma.es (M. Luque), rua@uma.es (F. Ruiz), ruben.saborido-infantes@polymtl.ca (R. Saborido).

http://dx.doi.org/10.1016/j.eswa.2015.05.036
0957-4174/

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 (ABB Ltd. Switzerland, 2009). 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 (ABB Ltd. Switzerland, 2009)), the auxiliaries rarely attain high performance levels. Hence, 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 1100 MW.

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 minimizing 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.

Once the problem is modeled, our main purpose is to solve it together with a real decision maker (DM) from the Endesa Generation S.A. company. As explained in Belton et al. (2008), in an interactive decision making process, we have to pay special 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 interactive *Multiple Criteria Decision Making* (MCDM) methods is to help the DM to find his/her most preferred solution (Miettinen, 1999; Steuer, 1986). 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, *Evolutionary Multiobjective Optimization* (EMO) algorithms (Coello, Lamont, & Veldhuizen, 2007; Deb, 2001) are designed in order to find a set of well-distributed nondominated solutions that approximate the whole set of Pareto optimal solutions of complex problems where traditional multiobjective programming techniques cannot be used. 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.

When applying multiobjective optimization techniques to real-life problems, in most of the cases, it is not possible for the DM to express her/his preferences if (s)he does not know the interdependencies among the objectives and analyse what can or cannot be obtained beforehand. But most of the real applications either stop when an approximation of the Pareto optimal set is