MULTI-OBJECTIVE OPTIMIZATION OF THERMODYNAMIC POWER CYCLES USING AN EVOLUTIONNARY ALGORITHM

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ABSTRACT

Pressurized water nuclear power stations are characterized by thermal efficiencies of about 31 to 35% which are much lower than those that are in general obtained by fossil fuels plants. It has been demonstrated that the effect of superheating the steam before entering into a low-pressure turbine makes it possible to increase the cycle efficiency by about 16% but it can affect the overall generated power. In this work, an optimization study is applied to the secondary circuit of Gentilly-2 nuclear power station, where the resulting steam flow distribution required to obtain superheated steam, increases the available energy at the entrance of low-pressure turbine but decreases the total work produced by the high-pressure stage. Further, the Gentilly-2 secondary loop regenerates part of the thermal energy in feed-water preheaters, therefore, the problem consists of determining the best fractions of extracted steam that permit increasing cycle efficiency without decreasing the power produced by the station. The simultaneous improvement of the power and the plant efficiency constitutes a multi-objective optimization problem where two objective functions compete with each other. It is obvious that such an optimization task does not have a unique solution, but rather a set of optimal solutions that consists of a compromise among the objectives imposed to the problem. In this work, an innovative technique is presented based on a genetic algorithm that consists of finding optimal values that converge towards Pareto's optimal front.

Keywords: CANDU reactor, thermodynamic cycle, power plant, multi-objective optimization, evolutionary algorithms, Pareto's front.

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1. INTRODUCTION

Many studies have demonstrated that reengineering can permit the performance of high efficient existing installations to be improved. For instance, it has been shown (Sacco, 2002) that a small increase of 0.1% of the total thermodynamic cycle efficiency can produce enormous profits with operating economies that can reach thousands of dollars per year, essentially due to the reduction in fuel consumption. Thus, it is apparent that this reduction can help in diminishing greenhouse emissions. Even though nuclear power plants can greatly contribute in reducing emissions, they cannot achieve high thermal efficiencies.

Pressurized water nuclear power plants in particular are characterized by thermal efficiencies of about 31 to 35% which are much lower than those that are in general obtained from power plant that use fossil fuels, where efficiency of up to 45% or even better can be achieved. The principal reason of this tremendous difference is determined by the heat transfer rate from the nuclear fuel to the coolant. In fact, the maximum temperature imposed in the nuclear fuel makes it very difficult to obtain superheated steam under high-pressure conditions. In addition, the use of close to saturation steam at the entrance of a high-pressure (HP) turbine increases its humidity content (i.e., formation of liquid droplets) that tends to deteriorate both the turbine's integrity (i.e., increases the erosion of the blades) and efficiency. If a small amount of humidity is tolerated at the outlet of a HP stage, a vapor superheating is absolutely necessary before it enters into the low-pressure (LP) stage. The effect of superheating the steam before entering into a LP turbine makes it possible to increase the generated power by about 70% and the cycle efficiency by 16% (Lior, 1997). It is important to note, however, that in his analysis Lior has proposed the use of an external fossil fuel source to obtain superheated steam conditions.

In this work, a similar study is applied to the secondary loop of Gentilly-2 nuclear power station. It must be pointed out that in this system, superheated steam is obtained from a derivation of a fraction of the vapor produced at the steam generators (SG). Thus, for a given amount of produced steam, this flow redistribution may increase the available energy at the entrance of LP turbine but it can reduce the total work produced by the HP unit. Further, since the Gentilly-2 secondary loop regenerates part of the thermal energy in feedwater preheaters, the problem consists in determining the best fractions of extracted steam that will permit to increase the overall efficiency without decreasing the net power produced by the station. The simultaneous improvement of the output power and the overall plant efficiency constitutes a multi-objective optimization problem where two objective functions compete with each other. It is apparent that such an optimization task does not have a unique solution, but rather a set of optimal solutions that consists of a compromise among the objectives of the problem. In such a case, the solution space converges towards the so-called Pareto's front (Deb, 2001). It is obvious that these kinds of thermodynamic cycles lead to a rather complex optimization problem that for similar systems, some authors (Sacco et al., 2002) had solved by using genetic algorithms (Goldberg, 1989). These algorithms are very robust and make it possible to treat complex problems, usually very difficult or impossible to solve by using traditional optimization techniques (i.e., simplex).

Different approaches to solve multi-objective optimization problems based on the genetic algorithms for seeking optimal Pareto solutions have been proposed (Deb, 2001 and Coello et al., 2002). These techniques were then intensively applied in a large number of industrial applications (Lazzaretto et al., 2004). Recently, this type of algorithm has been shown to be powerful in the optimization of both the topology and the thermal power distribution of large heat exchanger networks (Dipama et al., 2008). Although most of these methods have been successfully used to solve complex systems yet unsolved by using traditional methods, they often have a very slow convergence rate. Further, they also present difficulties to explore the whole set of Pareto's optimal solutions due to the inherent complexity of Pareto's front landscape.

Within the framework of the present study, a very robust and effective multi-objective optimization technique named "Boundary Exploring Search Technique" (BEST) has been developed (Dipama et al., 2007). The proposed algorithm has a simple structure based on an original approach that consists of partitioning the solution space into separate *"exploring corridors"*. Hence, the algorithm allows a rigorous control of the entire solutions space to be carried out, independently of the Pareto's front complexity. In this paper, the BEST technique is used to identify trade-off solutions of two objective optimization problem of the secondary circuit of Gentilly-2 nuclear power plant. The goal of the optimization is to handle the simulation of a sequence of Rankine cycle configurations (each configuration corresponding to a particular setting of decision variables); thus, several system configurations are first randomly generated, which provides Pareto or near Pareto optimal solutions. The results of the optimization are presented and discussed in the following sections.

2. INTRODUCTION TO A MULTI-OBJECTIVE OPTIMIZATION PROBLEM

Let $x_1, x_2, \ldots, x_k$ be decision variables for a simulation model of any energy system. Consider then $f_1(x_{1,} x_2, \ldots, x_k)$, $f_2(x_{1,} x_2, \ldots, x_k)$, $\ldots$ $f_n(x_{1,} x_2, \ldots, x_k)$ the output functions of a power plant simulation model corresponding to a set of values $X = x_1, x_2, \ldots, x_k$. Hence, the plant optimization problem can be summarized as follows:

$$\textit{minimize} \quad f_i(X) \qquad\qquad i = 1, 2, \ldots, n$$

subjected to the constraints

$$g_j(X) \geq 0 \qquad\qquad j = 1, 2, .., m \tag{1}$$

$$x_k^L \leq x_k \leq x_k^U$$

Thus, the principal idea consists of minimizing (or maximizing, depending on the type of problem to handle) the objective functions $f_i(X)$ over all possible values of vector X that satisfy the set of constraints $g_j(X)$. It is important to remark that x_k^L and x_k^U are the lower and upper bounds for variables x_k, respectively. It is obvious that if any of the components $f_i(X)$ are competing with each other, there is no a unique solution to this problem. For such a case the concept of Pareto optimal (Goldberg, 1989) must be used to properly evaluate all the objectives that control the process. The condition of Pareto optimal for a minimization task can be formulated as follows (Van Veldhuizen & Lamont, 2000):

- **Pareto dominance:**

Given a vector $\vec{F} = (f_1, f_2, \ldots, f_n)$, it is considered that dominates the vector $\vec{F}' = (f_1', f_2', \ldots, f_n')$ if and only if F is partially less than F', i.e, $\forall i \in \{1, 2, \ldots, n\}$, $f_i \leq f_i' \wedge \exists i \in \{1, 2, \ldots, n\} : f_i < f_i'$.

- **Pareto optimal:**

A solution $X^* \in \Omega$ (where Ω is a feasible region in the parameter space) is said to be Pareto optimal with respect to Ω if and only if there is no $X \in \Omega$ for which $\vec{F}' = (f_1'(X), f_2'(X), \ldots, f_n'(X))$ dominates $\vec{F} = (f_1(X^*), f_2(X^*), \ldots, f_n(X^*))$. In others terms, an optimal solution (X^*) is one for which an improvement in one of the objective functions requires a degradation of the other one. Then a Pareto optimal solution is not dominated by any other solutions, it is said "*non-dominated*". Hence, a multi-objective evolutionary algorithm seeks the achievement of the three following goals:

a) Find the best-known Pareto front that should be as close as possible to the true Pareto front. Ideally, the best-known Pareto set should be a subset of the Pareto optimal set.
b) The best-known Pareto front should capture the whole spectrum of the Pareto front. This requires investigating solutions at the extreme ends of the objective function space.
c) Solutions in the best-known Pareto set should be uniformly distributed and diversified along the Pareto front in order to provide decision-makers a true picture of trade-offs.

This paper propose an efficient and robust evolutionary algorithm (named BEST), capable of satisfying these goals for tackling a multi-objective optimization problem concerning the secondary cycle of the Gentilly-2 nuclear power plant. The main purpose of the algorithm consists of handling very complex, large-scale systems, where traditional optimization methods do not work. The robustness of BEST algorithm has already been proved in the optimization of a cogeneration system (Dipama et. al., 2007).

3. DESCRIPTION OF THE PROPOSED METHOD

Unlike classical evolutionary algorithms that promote non-dominated solutions at each population generation, the main idea of the present approach consists of emphasizing also those solutions that drive the searching operation towards the boundaries of the feasible region. To this aim, we use a "*corridors exploring*" strategy that allows both dominated and non-dominated solutions to be considered.

3.1 A "corridor exploring" strategy

As has been explained before, in order to catch extreme solutions a "*corridors exploring*" strategy in the search space has been implemented. It consists of a series of open corridors which are parallel to the axis of the search space (i.e., the axis correspond to the objective functions). These corridors are equally spaced according to regular steps determined by the algorithm itself. In each corridor the best individual (in genetic algorithms each individual corresponds to a possible solution of the problem) is gathered; either if it is dominated or non-dominated it becomes the "*header individual*" of the corridor. Figure 1 shows a schematic representation of several header solutions shown by black points in the feasible region of a hypothetical minimization problem governed by two objective functions. In the figure the same number of open corridors along each objective axis is shown, however, this number can be different for each axis. For example, by moving along the objective function f_2, the corridors that are parallel to the objective function f_1 be then analyzed and the best individual (solution) appearing in each corridor are selected and gathered (see Figure 1a). In the same manner, by moving along the objective function f_1 and analyzing corridors parallel to the objective function f_2 the best individuals (solutions) are also retained (Figure 1a). It must be pointed out that for this step of the searching process, it is not necessary to use non-domination sorting routine to classify the individuals. The unique requirement consists of finding header solutions at each generation step. These headers start mapping the contour of a feasible population that optimizes the multi-objective problem. Note that only two objectives are considered in the schematic representation shown in Figure 1, however, a multi-objective task may require several competing functions.

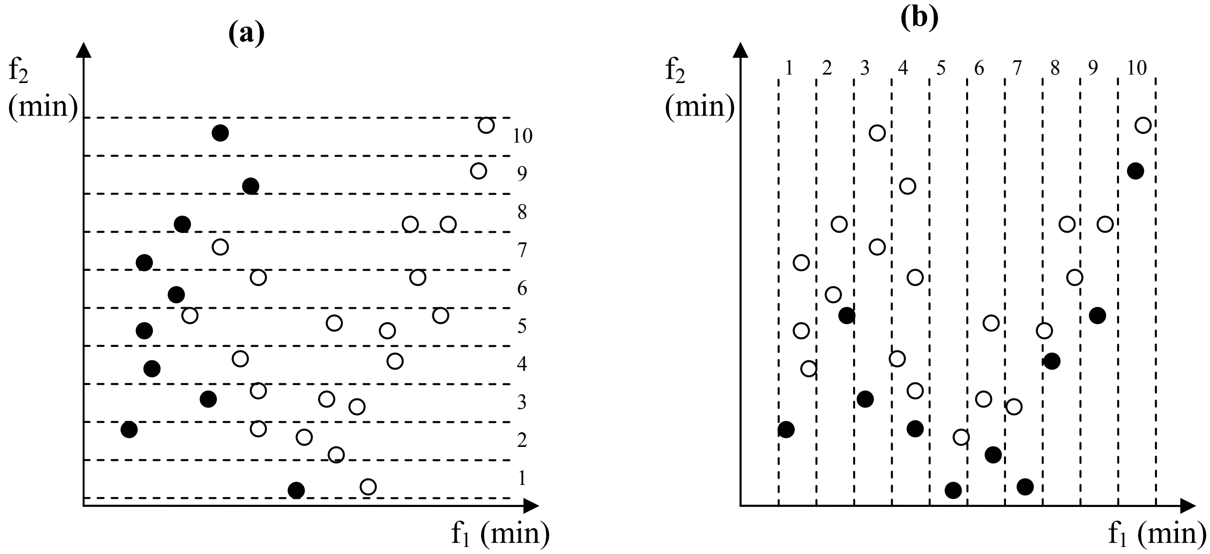

Figure 1. Schematics of best solution searching corridors;
(a) minimization of f_1, (b) minimization of f_2.

Combining the solutions of Figure 1a and 1b produces the result given in Figure 2a. This figure shows a set of best solutions that will be most likely selected as parents for the reproduction of offspring's in the next generation step. The proposed corridor header tracking technique is compared with Goldberg's ranking approach (Goldberg, 1989) in Figure 2b. It is obvious that the application of the proposed procedure permits the solutions that belong to the Pareto optimal front to be captured, which is not the case when the ranking method is used. Moreover, the completely feasible region is easily mapped by collecting header individuals from each corridor, overcoming in this way the difficulties that arise when complex Pareto's front landscapes must be treated.

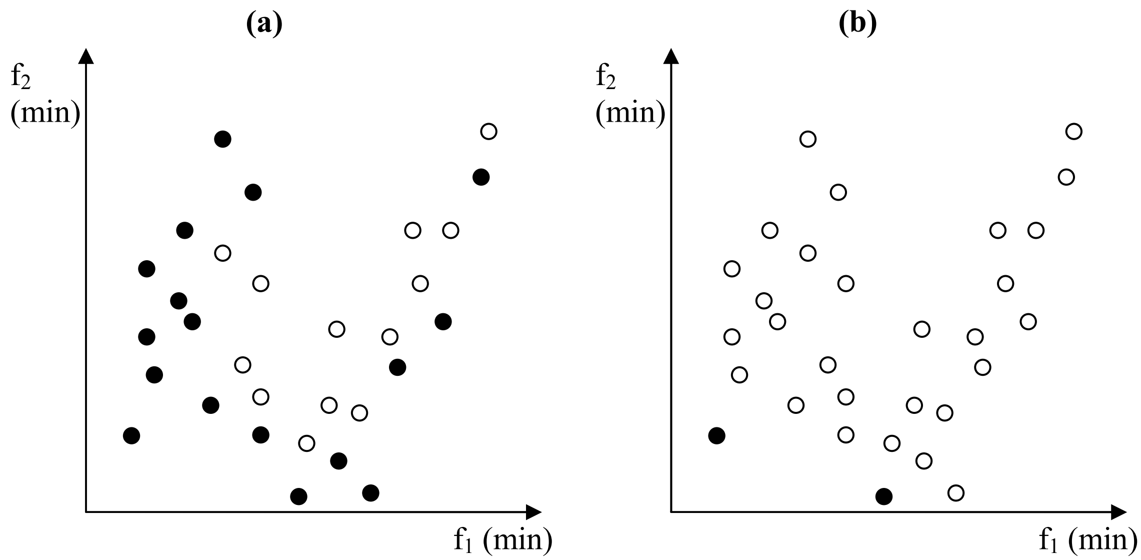

Figure 2. Best solutions; (a) *corridor* method, (b) Goldberg's ranking method.

3.2 The evolution process and description of the BEST algorithm

The evolution process is essentially based on the selection of captured solutions in the aforementioned *corridors* searching space. At each generation, the sizes of the corridors along the axis (functions) of the objective space are determined according to the lower and upper bound of the objective functions. By crossing each corridor, the best individual inside them are captured and they are then used as parents that undergo a phase of crossover and mutation operations.

To spread the characteristics of a population (i.e., a set of individuals) and in order to establish rapidly the boundaries of a feasible region, a mutation operator with a relatively initial high probability (70 to 80%) is used. Note that the mutation operation enriches the genetic diversity of the population. The mutation probability is then progressively decreased as the algorithm evolves. There are no special mechanisms for the maintenance of the diversity of the population; the corridor strategy implicitly ensures this role. The exploration of a promising solutions area (i.e., contour of the feasible region) is achieved by using a crossover operator whose intensity (crossover probability) increases while mutation is decreased. The crossover operator controls the reproduction rate of a given population. Figure 3 shows the structure of BEST evolutionary algorithm.

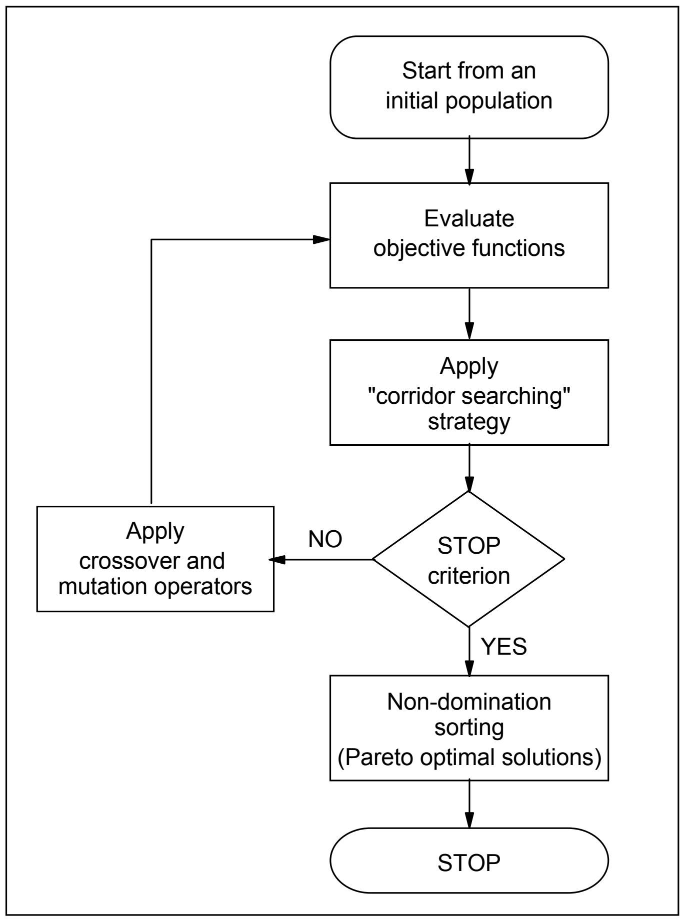

Figure 3. BEST algorithm flow chart.

4. OPTIMIZATION OF GENTILLY-2 SECONDARY CYCLE

Figure 4 shows a simplified schematic of the secondary circuit of Gentilly-2 nuclear power plant. It consists of a conventional reheat-regenerative Rankine thermodynamic cycle with HP and LP turbine units running in tandem. Key thermodynamic states of the cycle are shown by open circles with numbers while the most important thermal equipment are identified using the technical designation used by plant engineers. As illustrated in the figure, the HP unit uses saturated vapor (state 1) produced in the steam generators (SG) that expands to a medium pressure condition (state 7). Depending on the opening of the admission valves (AV), under some operation conditions the steam at the entrance of the HP unit can be slightly superheated (state 4). For the present study, however, it is assumed that state 4 corresponds to saturation conditions. It is obvious that the expansion in the HP unit causes both the steam temperature and pressure to decrease, which provokes a partial vapor condensation (i.e., the exit quality at state 7 is less than unit). Therefore, before the steam enters into the LP turbine unit, it is mechanically dried and superheated by a humidity-separator and superheater system (see the figure). This medium-pressure superheated vapor (state 9 or 10) expands into the LP turbine before it enters the condenser (state 15) where it is cooled at a constant pressure and temperature until the saturated liquid conditions are reached at state 16. The condensate is then pre-heated in a series of feedwater preheaters by using extractions from different stages of the turbine and the cycle. Preheaters 4312-HR11 to 4312-HR13 are shell-tube condenser type heat exchangers. These units are connected in cascade, however, to maintain the tubes in contact with the vapor alone, required to maintain very high heat transfer efficiency, the level of the condensate is rigorously controlled. Note that unit 4312-DC10 is an open waterfeed preheater system that collects the condensate from the rest of the units. In addition, heat exchanger 4315-GSC10 permits to recover heat from turbine steam-tight bulkheads collected at state 6. The relatively high pressure at state 29 permits the water to be discharged back into the condenser. Air transported by the steam at state 6 is vented while the residual steam at state 27 is also send back to the condenser. Preheated water is degassed in a deaerator unit, which under normal operation conditions uses steam from an extraction of the LP unit. Note that under some abnormal operation conditions this unit can receive vapor from the SG's, however, this case is not treated in this work. The deaerator also collects the condensate from the humidity-separator equipment as well as from the last feed-water preheater (i.e., high pressure preheater) of the system (i.e., unit 4312-HR15 in Figure 4).

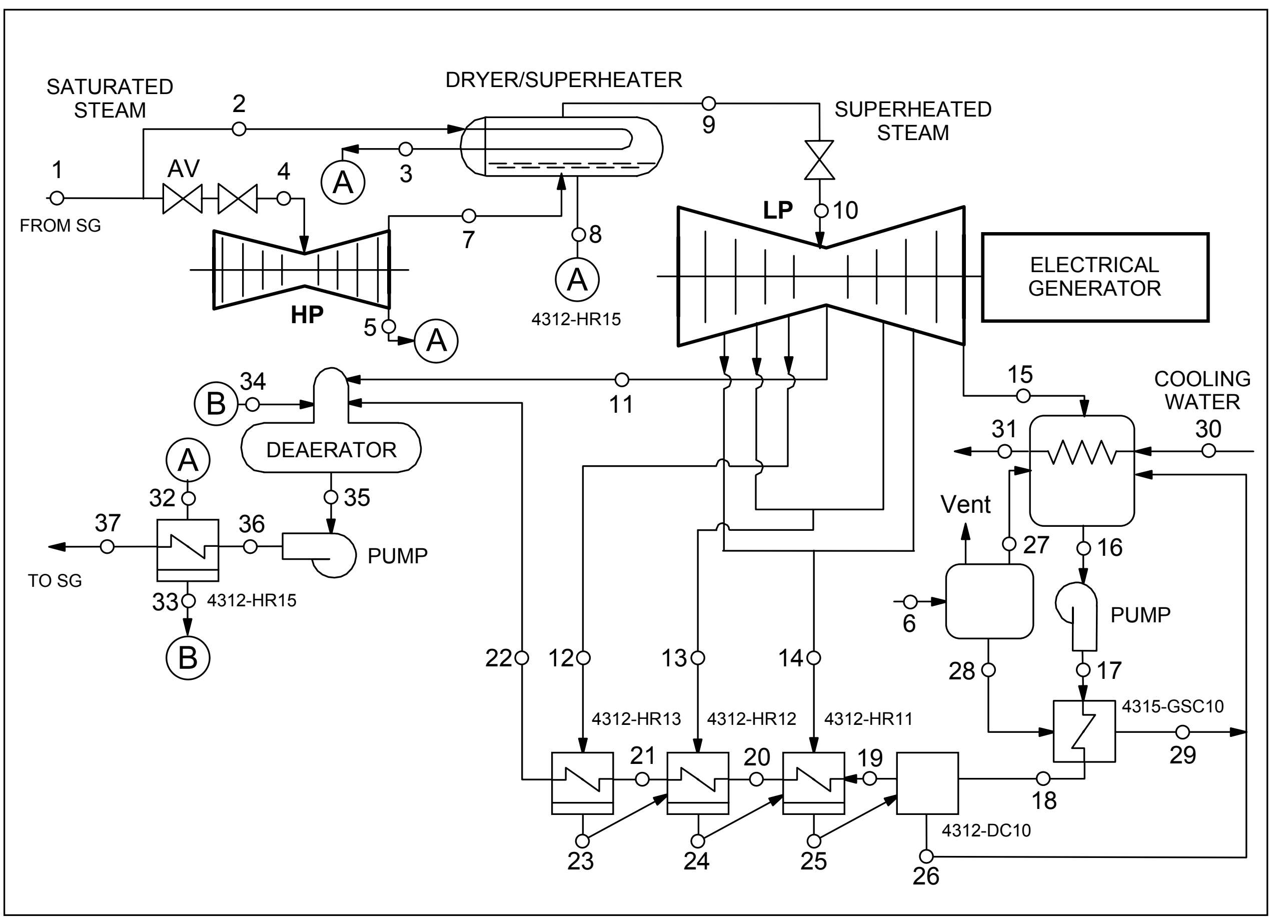

Figure 4. Simplified schematic of Gentilly-2 secondary circuit.

4.1 Objective functions and decision variables

Two objective functions, i.e., the net work W and the thermodynamic efficiency η_{th}, are considered for the performing the optimization of the present problem. The flexibility of the proposed algorithm, however, should permit us to handle other objectives, for instance environmental and economic aspects can be easily treated. The objectives used in the present case are:

a) Maximize $W = w_{HP} + w_{BP}$, (2)

b) Maximize $\eta_{th} = \frac{W}{Q}$, (3)

where w_{HP} and w_{BP} are the net power of the HP and LP turbine units, respectively and Q is the heat transferred from the reactor to the light water in the steam generators. The main decision variables used to optimize the thermodynamic cycle shown in Figure 4 are Y_2, Y_{12}, Y_{13}, Y_{14}, Y_{15} with:

- Y_2 is the fraction of vapor used to superheat the steam before it enters into the LP unit.
- Y_{12} is the fraction of vapor extracted from the LP turbine and supplied to the deaerator system.
- Y_{13}, Y_{14} and Y_{15} are three vapor extractions from different stages of the LP turbine.

It is important to remark that such a multi-objective optimization problem can also be solved using the weighted sum method or by using penalty functions (Dipama et. al., 2008). These methods, however, transform multiple objectives into an aggregated objective function by multiplying each objective by a weighting factor and then summing them up. It is apparent that a reduced single-objective optimization procedure provides only one particular optimal solution point on the Pareto front. Therefore, a major drawback of this method consists of the impossibility to obtain points on nonconvex portions of a Pareto optimal set. Moreover, a priori selection of the weights doesn't necessarily guarantee that the final solution will be the appropriate one. Usually, this situation necessitates recurrent solutions to be carried out by selecting new weights. Further, the major advantage of using evolutionary algorithms over the deterministic techniques like the steepest descent method is that, they do not require a mathematical formulation of objective functions instead, the values obtained from plant simulators can be used for optimization purposes. It is obvious that in the case of a thermal power station the formal representation of all engineering aspects that determine the optimal operation of the plant must be given under the form of several coupled equations. Therefore, it is very difficult if not impossible to treat this kind of problems using a deterministic approach.

4.2 Constraints and modeling assumptions

The thermodynamic states identified in Figure 4 in conjunction with the thermo-physical properties of the different fluids (i.e., steam, mixture or liquid) encountered in the cycle are used to write energy and mass conservation equations for the thermal equipment that constitute the entire system. Hence, a model formed by a system of equations was written using the Engineering Equation Solver (EES) software (Klein, 2007). It must be pointed out that this piece of software already contains libraries required for calculating the thermo-physical properties of the coolant. In particular, to perform the simulations of the actual system the IAPWS library is used. The secondary circuit model was run several times by randomly changing the decision variables within given (realistic) limits. Thus, each solution corresponds to a set of thermodynamic states that are then send to the BEST algorithm for performing optimization calculations. However, due to the high complexity of the Gentilly-2 secondary circuit, some simplifying assumptions were required; the most important ones are:

a) The pressure and temperature in the condenser model were considered constants (i.e., we do not take into account possible effects due to the presence of non-condensable gases).
b) The pressure drops in pipes, flanges, unions and tees junctions are neglected; thus, the pressure drops in the vapor extraction lines are neglected.
c) The pressure drop in all feed-water preheaters are supposed to be the same.
d) A unique value of the isentropic efficiency for both the HP and LP turbine units is assumed. This value was previously determined from experimental data obtained from the plant.

As described above, thermodynamic variables are randomly generated; therefore, some additional constraints must still be necessary to satisfy realistic and physical acceptable solutions (for instance, each solution must satisfy the second law of thermodynamics). These additional constrains are: *i)* the total fraction of vapor extracted from the LP turbine (sum_y) must be lower than 45% and *ii)* under normal operation conditions the pressure prevailing in the deaerator determines a minimum acceptable saturation temperature.

5. RESULTS AND ANALYSIS

The thermodynamic model was used to generate iteratively a solution space containing at least 100 individuals. The population obtained from the plant model is used as input values for running the BEST algorithm. To solve the problem presented in this paper the following algorithm settings are used:

a) population size: 100
b) number of searching corridors per objective function: 60
c) Maximum number of runs: 50

Figure 5 shows BEST results, i.e., the overall cycle efficiency as a function of the net power produced by the plant. Square dots in the figure represent the Pareto optimal front for the two objective functions given by Equations 2 and 3. It must be pointed out that only the final values of the optimization process are shown in the figure. It is obvious that the optimal searching methodology introduced in the present work, makes the Pareto front to evolve towards the set of optimal values represented by square symbols. Thus, these values represent the Pareto front that includes all compromise solutions for the aforementioned objective functions. Further, measured data taken from the power plant are used to calculate the actual plant operation state, i.e., efficiency and net work. The triangular point in Figure 5 corresponds to the simulation of the actual operating condition of the installation. It is important to mention that this calculation is also performed using the same thermodynamic model described above. However, instead of changing the decision variables Y_i and Y_{ij} their values were fixed accordingly to actual operation figures furnished by Gentilly-2 plant engineers. From the figure, it is obvious that Pareto's front provides a clear indication that there are still plenty of possibilities for increasing both the cycle efficiency as well as the net power produced by the station. However, such an optimization procedure requires changing the vapor extraction rate from the turbine and from the SG's.

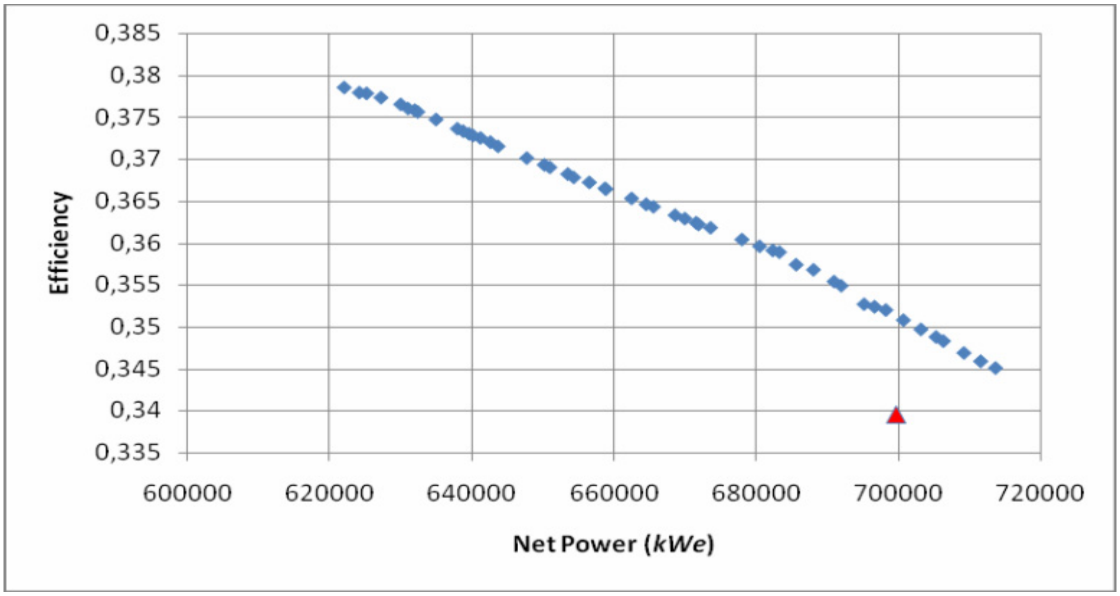

Figure 5. Set of Pareto's front optimized values.

Some points of Pareto optimal solutions as a function of the fractions of extracted steam (for their identification see Figure 4), jointly with the actual values of the power plant (boldface numbers) are given in Table 1. Note that in the net electrical power the consumption of the secondary circuit pumps has been taken into account, however, it does not include the consumption of primary circuit pumps as well as other auxiliaries.

Table 1. Optimized values.

y_2	y_{15}	y_{14}	y_{13}	y_{12}	W_{net} (kWe)	η
0,08	0,15	0,14	0,02	0,14	622042	0,38
0,05	0,15	0,07	0,02	0,02	713582	0,35
0,07	**0,10**	**0,06**	**0,06**	**0,03**	**699614**	**0,34**
0,05	0,15	0,15	0,02	0,10	641196	0,37
0,05	0,15	0,08	0,02	0,02	709132	0,35
0,05	0,15	0,15	0,02	0,10	640130	0,37
0,05	0,15	0,13	0,02	0,02	691885	0,35
0,07	0,15	0,11	0,02	0,02	695106	0,35
0,08	0,15	0,15	0,03	0,12	624172	0,38
0,05	0,15	0,11	0,02	0,02	696572	0,35
0,05	0,15	0,09	0,02	0,02	705214	0,35

The proposed methodology can offer, to decision makers, a realistic and valuable engineering support. Presently we are improving the thermodynamic model; it will include a series of independent thermal equipment modules developed in Matlab. This approach will permit us to better characterize local operation conditions that are controlled by mechanisms other than thermodynamic principles, i.e., heat transfer, pressure drop, effect of non-condensable gases, irreversibility, etc.

It must be pointed out that the present study is devoted to search all possible optimal operation conditions of the power plant and compare them with the actual status of the installation. Hence, each point presented in Figure 5 corresponds to particular plant steady state conditions. In other words, a sensitivity study of the system besides possible variations of the decision variables was not carried out. However, the construction of Pareto's front is followed on the screen during the whole optimization process. In any case studied, the solution space has shown neither steep nor shallow valley behaviors. In turn, evolutionary algorithms are very robust for handling this type of problems. In particular, the use of a mutation operator strongly contributes to deal with such a difficult task. Once an optimal solution is selected, it should be interesting, however, to carry out a sensitivity analysis of the system by perturbing the decision variables. This study has not yet been carried out.

6. CONCLUSIONS

A thermodynamic model of the Gentilly-2 nuclear power plant is developed. The model is used to generate a large number of plant states associated to random variations of some decision variables. The BEST evolutionary algorithm is then applied for finding the optimal operation conditions of the power plant. This algorithm has demonstrated a very high robustness and effectiveness in handling quite complex optimization problems. It uses a *corridors searching* strategy that partitions the objective space to capture solutions that contribute to explore very efficiently the feasible solution region. Thus, the proposed technique helps solutions uniformly distributed over Pareto's front to be found. Therefore, it is not necessary to use less performing methods such as *fitness sharing* or other distance-based techniques for the maintenance of the genetic diversity within a population. The proposed technique once applied to the Gentilly-2 power plant is able to show that there is plenty of possibility for increasing the overall performance of the plant. It is obvious that increasing the thermal efficiency of any power plant contributes to decreasing pollution of the environment. Work is underway to improve the modeling approach that will be able to take into account inherent characteristics of the principal power plant equipment.

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REFERENCES

COELLO C. A. C, VELDHUIZEN D. V., and LAMONT, G. B. (2002) "Evolutionary Algorithms for Solving Multi-objective Problems", Kluwer Academic Publishers, Boston.

DEB, K. (2001) "Multi-objective Optimization using Evolutionary Algorithms", John Willey & Sons, Chichester

DIPAMA, J. TEYSSEDOU, A. & M. SORIN (2008) "Synthesis of Heat Exchanger Networks Using Genetic Algorithms," *In Press:* Applied Thermal Engineering (Available online DOI: 10.1016/j.applthermaleng.2007.aa.014).

DIPAMA, J., AUBÉ, F. & A. TEYSSEDOU « Optimisation multi-objectif d'un système de cogénération à l'aide de l'algorithme évolutif BEST», VIII^{ème} Colloque Interuniversitaire Franco-Québécois sur la Thermique des Systèmes, Montréal, (mai 2007).

GOLDBERG, D. E. (1989) "Genetic Algorithms for Search, Optimization, and Learning Machine," Reading, MA. Addison-Wesley.

KLEIN, S.A. (2007) "Engineering Equation Solver," Version 7.936-3D, Ca., USA.

LAZZARETTO A. & A. TOFFOLO (2004) "Energy, Economy and Environment have Objective in Multi-criterion Optimization Thermal Systems Design," *Energy*, vol. 29, No. 8, pp. 1139-1157.

LIOR, N.R. (1997) "Energy, Exergy, and Thermoeconomic Analysis of the Effects of Superheating Fossil-fuel in Nuclear Power Plants," *Energy Conversion and Management*, vol. 38, pp. 1585-1593.

SACCO, W.F., PEREIRA, C.M.N.A., SOARES, P.P.M. & R. SCHIRRU (2002) "Genetic Algorithms Applied to Turbine Extraction Optimization of a Pressurized-Water Reactor," *Applied Energy*, vol. 73, No.3, pp. 217–222.

VAN VELDHUIZEN, D.A. & G.B. LAMONT (2000) "Multiobjective Optimization with Messy Genetic Algorithms," ACM Symposium on Applied Computing, V. 1, Como, Italy, pp. 470-476.