Multiobjective dispatch of hydrogenerating units using a two-step genetic algorithm method

Glauber R Colnago and Paulo B Correia

Abstract— **This paper proposes a multiobjective dispatch model to operate hydroelectric power plants. The model is composed of two algorithms that are based on Genetic Algorithms. The first algorithm is used for the static dispatch of generating units and is aimed at maximizing plant efficiency on an hourly basis. The second step is a multiobjective technique for the daily operation of generating units. The two objectives are to maximize the plant efficiency and to minimize the number of startups and shutdowns of generating units. Data from a Brazilian power plant were used in the simulation of a daily operation. A daily load curve contains 24 static problems, each one solved on average in approximately 2 minutes. The second step was executed in approximately 99 seconds. The proposed model proved suitable for the daily operation of the hydroelectric power plant studied, given the low computational time, satisfactory efficiency and low number of generating units startups and shutdowns (only 12).**

I. Introduction

Several objectives are adopted for the dispatch models of generating units in hydroelectric power plants. These objectives depend on the priorities of the generating agent and/or on the electric system. Generally, the dispatch models based on Brazilian plants are aimed at maximizing plant efficiency (minimizing energy losses) and minimizing generating unit startups and shutdowns. Each startup or shutdown of a unit implies degradation of equipment and higher maintenance requirements. Thus, there are costs associated with the startup and shutdown of generating units [1]. In contrast, high plant efficiency implies economy of water stored in the plant's reservoirs. Plant efficiency depends on its units' efficiencies; hence, the quality of the information concerning generating unit efficiencies is important for a good dispatch.

Generally, unit efficiencies are determined from reduced scale models of the turbines. The same efficiency curve is usually adopted for all the units of a plant. However, particularly in the case of hydroelectric units with long operational histories and frequent maintenance stoppages, the efficiency curves are probably not the same as those determined from the reduced model. Moreover, these efficiency curves probably differ from each other. This fact was verified through data recently measured from the units of a Brazilian hydroelectric power plant [2].

In 2007, Colnago [2] made a comparison of dispatches using data obtained from reduced scale models and the recently measured data. The monetary gains achieved through the use of the more recent data were estimated at values of US$ 2,000 to US$ 2,500 a day, considering an electrical energy price of close to $24\,\mathrm{US\$/MWh}$, which is considered low. The proposed model is a mixed integer nonlinear program (MINLP) which was solved by a global search method.

When one considers different units that are to be dispatched in the same hydroelectric plant, the number of combinations of units increases exponentially with the number of available units. That is a problem, and the solution method adopted must explore well the feasible region.

This work proposes GAs to solve the dispatch problem in hydroelectric power plants. These algorithms use the idea of natural selection, because traditionally, the best adapted individuals (solutions) have a higher probability of generating other individuals [3]. However, other kinds of selection can be used, such as the least adapted individuals, or the selection can be made randomly.

GAs have proved to be a good tool to solve many problems and have also been used in the power plant unit dispatch problem [4], [5], [6], [7], [8], [9].

Some genetic algorithms approaches are combined with other methods of optimization. Santos and Ohishi in 2004 [4] and Rodolf and Bayrleithner in 1999 [8] developed a genetic algorithm approach to choose the combination of generating units, and the generation of each unit is optimized by Lagrangean Relaxation.

The first of these approaches is not a pure GA, while the second one is at a disadvantage compares with the use of a real variable, because the binary values must be converted into real values, a larger memory is required, and there is a loss in precision when values are converted [10]. We propose to use an integer codification of variables and genetic operators appropriated.

A two-step method is proposed. The first focus on the maximum efficiency of each combination of units.

The second method uses the results obtained in the first step to find solutions for the daily operation in two objective ways, i.e., by maximizing the daily efficiency and minimizing the number of unit startups and shutdowns.

II. Physical aspects

The physical aspects of units must be more detailed in the dispatch, unlike mid- and long-term planning, where costs and goals are more important. A model with a poor representation of the plant's operational constraints can lead to undesired consequences, such as low efficiency operation point or units working under detrimental conditions as problems of cavitation in the turbines. The next section discusses the physical aspects of hydroelectric power plants

Glauber R Colnago and Paulo B. Correia are affiliated to the Faculty of Mechanical Engineering at the State University of Campinas - UNICAMP, Campinas, SP, Brazil (email: grcolnago@fem.unicamp.br and pcorreia@fem.unicamp.br).

978-1-4244-2959-2/09/$25.00 ©2009 IEEE

and their generation units.

A. Unit efficiencies

Generation unit efficiency depends on three variables: water head of the plant, water discharge, and electric power of the unit. The hill is a three-dimensional curve that plots efficiency as a function of the water head of the plant and the electric power of the unit (Fig. 1).

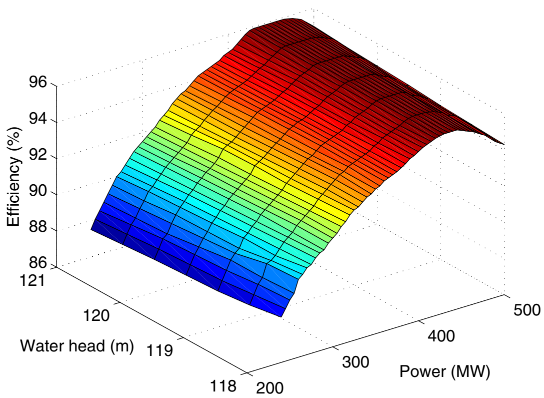

Fig. 1. Hill curve of a real hydroelectric power plant

These efficiency curves are generally determined by means of reduced scale models of the turbines before the construction of the units. However, if the efficiency curves are reasonable for new units, they may differ considerably for long-standing units. Furthermore, their efficiency curves differ one another because each unit has its own operational history.

It is possible to obtain, by measurement, a more detailed efficiency curve for installed units than for that of reduced scale models. The unit load and the plant water head can be measured with good accuracy. Thus, the accuracy of the efficiency curve depends on the accuracy of the water discharge measurement.

B. Global power plant efficiency

The power plant load can be allocated in many combinations of units and the level of generation can be allocated in several ways. What is commonly done in dispatches is to consider that all the units have equal efficiencies. The allocation of the load is obtained by dividing the load equally between generation units. However, when units are considered with different efficiency curves, an equal division among these units is not the optimal solution. In this case, each combination of units ensures different global efficiencies.

C. Forbidden operation zones

Forbidden zones are crucial to avoid phenomena such as mechanical vibrations in the turbine, cavitation, and low efficiency levels. The latter problem can directly affect the power plant's overall efficiency. In view of these factors, operation zones where cavitation occurs must be avoided. This means that the operation zone is partitioned into various disjoined zones.

D. Spinning reserve

Brazil's power system has three main operative reserves to be considered: the first is destined for the regulation of the interconnected system frequency; the second serves to control the system frequency during brief changes or momentary variations in load; and the third ensures the system's stability against unprogrammed generating unit stoppages [11]. The second and third reserves must be allocated to running generating units, considering the generation slack of those units. Thus, spinning reserves improve the system's reliability in the case of failures [12].

E. Demand

The load of the plant is determined by long- and mid-term planning. A short-term scheduling model estimates the plant's daily load curve. Fig. 2 shows a typical load curve of one day.

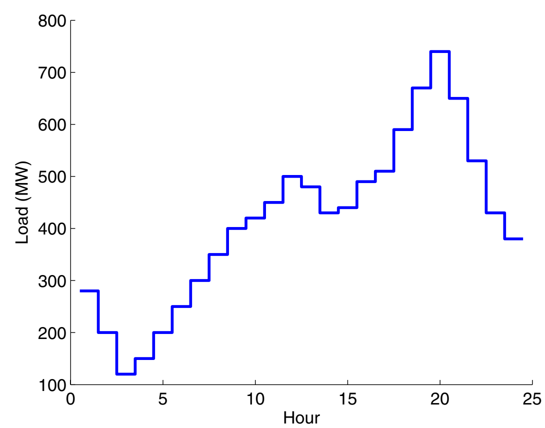

Fig. 2. Typical daily load curve

III. Genetic Algorithms

GAs were developed by Holland [13], who analyzed phenomena occurring in the genetic selection of a race. This method uses random numbers to simulate the casualties that occur in the natural selection process: the initial composition of a group of individuals; selection of individuals for reproduction; the choice of characteristics that will be transmitted to the next generation; the occurrence of mutation and in what gene the mutation will occur. Thus, GAs are not a deterministic but a probabilistic method. Simulating a GA more than once using the same parameters may lead to different results.

The advantages of GAs are that they do not need differentiable functions and they are evenly applied to problems with discontinuities, which are very common in dispatch problems.

IV. Units dispatch (first-step algorithm)

A. Mathematical formulation

The dispatch formulation is shown in Equations 1 to 7

$$\max N \quad (1)$$

$$\text{s.t.} \quad N = \frac{D}{\sum_{i=1}^{n} B_i} \quad (2)$$

$$\sum_{i=1}^{n} P_i = D \quad (3)$$

$$y_i \underline{P_i} \leq P_i \leq y_i \overline{P_i} \quad (4)$$

$$\eta_i(P_i) = \frac{P_i}{B_i} \quad (5)$$

$$\sum_{i=1}^{n} \left(y_i \overline{P_i} \right) - D \geq R \quad (6)$$

$$y_i \in \{0, 1\} \quad (7)$$

for $i = 1, ..., n$, where

N	Hydroelectric power plant global efficiency
i	Generating unit index
P_i	Power generated by unit i (MW)
B_i	Gross power in unit i (MW)
$\eta_i(P_i)$	Unit i efficiency curve as a function of P_i
y_i	Dispatch of the unit i
n	Number of available units in the plant
D	Plant load demand (MW)
R	Spinning reserve (MW)
$\overline{P_i}$	Upper limit for unit i (MW)
$\underline{P_i}$	Lower limit for unit i when dispatched (MW)

The problem 1–7 is the static dispatch problem (solved for a constant load D) and it is formulated as a Mixed Integer Nonlinear programming problem. The variables of the problem are P_i, B_i and y_i. The nonlinearity is in the variables P_i and B_i in Equations 2 and 5. $\eta(P_i)$ is a fourth degree polynomial as a function of P_i. N is the plant's global efficiency, which is the efficiency in the conversion of $\sum_{i=1}^{n} B_i$ in D (Equation 2). B_i is the gross efficiency in unit i, that is, for a generating unit to generate P_i, it uses the B_i energy; and the waste energy in that unit is $B_i - P_i$. B_i is computed by Equation 5, with the efficiency curve $\eta_i(P_i)$. The curve $\eta_i(P_i)$ is a fourth degree polynomial as a function of P_i. This is the reason the problem is nonlinear in P_i.

The variable y_i indicate whether unit i is dispatched ($y_i = 1$) or not dispatched ($y_i = 0$). The prohibited zone for unit i is the interval $]0, \underline{P_i}[$, so Equation 4 ensures that unit i is either not generating (in this case, $P_i = 0$ because $y_i = 0$) or, if it is generating, its power is between $\underline{P_i}$ and $\overline{P_i}$. Equation 3 ensures the demand D is met and Equation 7 allocates the spinning reserve. The generating units that contribute to the spinning reserve have y_i equal to 1.

B. Proposed algorithm

The problem 1–7 was implemented using the GAs. This section explains the details of the proposed GAs model.

1) Variables representation: The formulation 1–7 shows that there are three variables for each unit, i.e., P_i, B_i and y_i. Thus, for n units, the number of variables is $3n$. For the proposed algorithm, only one variable (P_i) was used for each unit. Therefore, for n units, the number of variables is n. The variables B_i were eliminated by substituting B_i from Equation 5 in Equation 2 and substituting N from Equation 2 in the objective function (1). This way, the objective function is

$$\frac{D}{\sum_{i=1}^{n} \frac{P_i}{\eta(P_i)}}, \quad (8)$$

and Equations 2 and 5 were eliminated.

Complete enumeration was used to list all the possible dispatched generating unit combinations, this way, fixing variables y_i. Complete enumeration was proposed because the number of generating units of the study case is only six. For each load, all the feasible combinations are computed using the limits $\underline{P_i}$ and $\overline{P_i}$. For example, if $D = 280$, $n = 6$, $\underline{P_i} = 50$ and $\overline{P_i} = 140$ for $i = 1, ..., n$, it is feasible to activate 2,3,4 or 5 units. Thus, the algorithm is used in each of the combinations of 6 units chosing 2, 3, 4 and 5 units. The total number of combinations in this case is $k = 51$.

For each dispatched combination of units, the variables y_i are eliminated and the remaining variables are P_i with their real representation. For example, if the combination of generating units is $[\ 1\ 0\ 0\ 1\ 1\ 0\ ]$, i.e., units 1, 4 and 5 are chosen to be dispatched, then an individual can be $[\ 110\ \ 0\ \ 0\ \ 80\ \ 90\ \ 0\ ]$. All the individuals generated for that combination of units must have zero in the positions 2, 3 and 6. Furthermore, all the descendants generated have the same property. The GA is used only in the P_i variables.

2) Population: Section VI discusses the number of individuals. Because of the constraints of prohibited zones and load meeting, the following algorithm was used to generate an initial population: when a combination of dispatched generating units is determined, e.g., $[\ 1\ 0\ 0\ 1\ 1\ 0\ ]$, the load is shared equally among all the dispatched units. Thus, an individual in the initial population would be $[\ 280/3\ \ 0\ \ 0\ \ 280/3\ \ 280/3\ \ 0\ ]$ for $D = 280$. Two positions are randomly chosen (e.g., 1 and 5) and the unit whose load will be increased or decreased is also chosen randomly. For example, the power in unit 1 will be increased and the power in unit 5 will be decreased. Two constants are then computed, namely, $k_1 = \overline{P_1} - 280/3$ and $k_2 = 280/3 - \underline{P_5}$. A number k between 0 and $\max\{k_1, k_2\}$ is generated. The individual is then changed to $I_j = [\ 280/3 + k\ \ 0\ \ 0\ \ 280/3\ \ 280/3 - k\ \ 0\ ]$. If the number of dispatched units is four, the procedure is executed twice, and so on. With this procedure, the individuals of the initial population ensure the load is met and the power in the units lies within the permitted zone.

3) Crossover: The crossover operator used is the arithmetic crossover [5]. This operator defines a linear combination of two individuals. Two individuals are selected randomly, I_j and I_k, and a number α between 0 and 1 is generated randomly to generate two descendants, as follows:

$$A_t = \alpha I_j + (1-\alpha) I_k \text{ and} \tag{9}$$

$$A_q = (1-\alpha) I_j + \alpha I_k. \tag{10}$$

Individuals that have zeros in certain positions will have descendants with zeros in the same positions. Another good characteristic of this crossover for this problem is that the load is met and the prohibited zones are avoided by the descendants if they are met by the ascendants.

4) Mutation: The mutation rate adopted here was divided by the number of individuals in the populations. This was done because, when the rate is constant, the larger the population is the higher the probability that the mutation to occur. Thus, by making the rate of mutation inversely proportional to the population size, the chance of an individual mutating is greater when the population is smaller and smaller when the population is larger.

The mutation operator adopted is the swapping mutation, which swaps the values of two positions chosen randomly. For example, before the mutation an individual is [125 0 0 90 65 0] and after the mutation it is [90 0 0 125 65 0], i.e., the values of positions 1 and 4 were inverted.

5) Iterations: The number of iterations differs depending on the number of dispatched units. The higher the number of dispatched units the higher the number of iterations. That was adopted because the higher the number of dispatched units the larger is the feasible region. The number of iterations is given by $act^2 c$, where act is the number of dispatched units and c is a constant. For example, for $D =$ 280 MW, the feasible numbers of units to be dispatched are 2, 3, 4 and 5. Hence, if $c = 1000$, for act equal to 2, 3, 4 and 5, the number of iterations are 4000, 9000, 16000 and 25000, respectively.

6) Evaluation function: The objective function for the formulation 1–7 is the plant's global efficiency N, but for this algorithm, the variables B_i were eliminated and the curves $\eta_i(P_i)$ were brought to the objective function. Therefore, the evaluation function is

$$\frac{D}{\sum_{i=1}^{n} \frac{P_i}{\eta_i(P_i)}}. \tag{11}$$

7) Constraints: Two operational constraints, Equations 3 and 4, were eliminated in the algorithm, because of the population creation procedure and the genetic operators adopted. The constraint of Equation 7, which is for the spinning reserve, was not eliminated. The procedure is as follows: given a certain spinning reserve, the algorithm is executed for the combinations of generating units which allocate this reserve. For example, for $D = 280$ for the unit numbers 2, 3, 4 and 5, the margins of reserve are $2\overline{P_i} - D = 2 \times 140 - 280 = 0$, 140, 280 and 420 MW, respectively. Then, if $R =$ 150 MW, units 2 and 3 cannot meet the spinning reserve constraint, so the algorithm is not executed for them.

8) Selection: The process of selection adopted here was the Roulette Wheel [14] used in the classic GA. In this method, each individual has a probability proportional to its fitness in relation to the total sum of the fitness. Suppose that f_j is the value of the objective function of an individual. All the f_j values are divided by $\sum_{j=1}^{pop} f_j$, generating the number d_i, where *pop* is the number of individuals in the population. In this way, the interval $[0, 1]$ is divided into various intervals $[0, d_1]$ for individual 1, $]d_1, d_1 + d_2]$ for individual 2, $]d_1 + d_2, d_1 + d_2 + d_3]$ for individual 3, and so on, until $]\sum_{j=1}^{pop-1} d_j, 1]$ for individual *pop*. *pop* numbers between 0 and 1 are then generated and the corresponding individuals are selected. The individuals that have a higher objective function have a greater chance of being selected. In this process, individuals may be selected more than once, while other individuals may not be selected to generate the new population of descendants.

9) Results filed: The results of this technique are filed in a database and are used by the multiobjective genetic algorithm. Given a demand D, all k feasible unit combinations are computed, as explained in Subsection IV-B.1. The technique is applied to each combination and its best solution is stored. The filed data are the binary vector of combination C_i for ($i = 1, ..., k$) (e.g. [1 0 0 1 1 0]), the units dispatch X_h^i (e.g. [110 0 0 80 90 0]), and the efficiency associated N_i.

10) Algorithm: The proposed algorithm is shown in lines 1 to 13.

```
1:  Data insertion
2:  Computing of all the feasible combinations k for demand D
3:  For combination 1 to k
4:      Creation of initial population
5:      For iteration 1 to end
6:          Evaluation of the objective function of the individuals
7:          Population selection
8:          Crossover
9:          Mutation
10:         New population
11:     End
12: Filing of the solutions
13: End
```

In line 1, data such as the load D, spinning reserve R, limits $\underline{P_i}$ and $\overline{P_i}$, and the efficiency curve coefficients are inserted. In line 2, all the feasible combinations of units are computed using D, R, $\underline{P_i}$ and $\overline{P_i}$. For each combination, the proposed is executed (lines 4 to 11). The details of the proposed GA have already been explained in the previous subsections. The population that generates the

$$
\begin{array}{ll}
[\,1\;0\;0\;1\;1\;0\,] & \text{Gene 1: 38} \\
[\,0\;0\;1\;0\;1\;0\,] & \text{Gene 2: 10} \\
[\,1\;0\;1\;1\;0\;1\,] & \text{Gene 3: 45} \\
[\,1\;1\;0\;1\;1\;0\,] & \text{Gene 4: 54} \\
\vdots & \quad\vdots
\end{array}
$$

Fig. 3. Integer representation of the combinations

new descendant population is chosen by Roulette Wheel, after which the new population is computed by executing crossovers and mutations in the ascendant population.

V. Daily operation of units (second-step algorithm)

A. Mathematical formulation

The multiobjective problem of generating units is shown in Equations 12 to 15

$$\max\ F_1 \tag{12}$$

$$\min\ F_2 \tag{13}$$

$$\text{s.t.}\quad F_1 = \frac{\sum_{h=1}^{24} D^h}{\sum_{h=1}^{2} 4\frac{D^h}{N_j^h}} \tag{14}$$

$$F_2 = \sum_{h=1}^{23} \left\| \vec{C}_j^{h+1} - \vec{C}_m^h \right\| \tag{15}$$

for $j, m \in \{1, ..., k_h\}$ with the norm defined as $\|\vec{w}\| = \sum |w_i|$, where

F_1	Daily plant's global efficiency
F_2	Number of startups and shutdowns of generating units in the day
D^h	Plant load demand at hour h (MW)
N_j^h	Plant global efficiency at hour h for combination j
$\vec{C}_j^h$	Binary vector that indicates dispatched units at hour h (refers to combination j)
k_h	Number of feasible combinations for D^h

B. Proposed algorithm

1) Population: For each demand, D^h, and a feasible combination of units, C_j^h, the best efficiency, N_j^h, obtained with the dispatch technique is filed as explained in Subsection IV-B.1. In the daily unit operation technique, an individual is a set of 24 feasible combinations. Gene h is a feasible combination that refers to D^h (hour h). However, each gene is not a vector like [1 0 0 1 1 0], but the decimal number referring to the binary number. The gene that refers to combination [1 0 0 1 1 0] is 38. Fig. 3 shows 4 genes of an individual.

2) Genetic operators: The crossover operator adopted is the one-point crossover introduced by Holland in 1975 [13]. This crossover is applied to two individuals. One location is chosen (crossover point), determining the gene segments to be exchanged. Fig. 4 shows how the exchange of gene segments takes place.

Individual 1 [**38 10 45** | **54 32 05 27 42**]
Individual 2 [42 15 22 | 60 21 12 47 31]

Crossover point

New Individual 1 [**38 10 45** 60 21 12 47 31]
New Individual 2 [42 15 22 **54 32 05 27 42**]

Fig. 4. One-point crossover

The mutation operator used here is based on the mutation of binary individuals. That operator consists of changing the gene from 0 to 1 and vice versa. The operator adopted changes a gene that is a integer number corresponding to a feasible combination of generating units to another number corresponding to another feasible combination of units. For each demand D^h, there is a list of feasible solutions. A solution is then chosen randomly to replace that gene that will be mutated.

3) Objective function: One objective of the problem is to maximize the plant's global efficiency. The objective function is

$$F_1 = \frac{\sum_{h=1}^{24} D^h}{\sum_{h=1}^{H} \frac{D^h}{N_j^h}},$$

where $\sum_{h=1}^{24} D^h$ is the total energy generated during the day, and $\sum_{h=1}^{H} \frac{D^h}{N_j^h}$ is the gross energy used. The second objective is to minimize the number of startups and shutdowns of units. In this case, the objective function is

$$F_2 = \sum_{h=1}^{23} \left\| \vec{C}_j^{h+1} - \vec{C}_m^h \right\|$$

where $\vec{C}_j^h$ is a binary vector that indicates the dispatched units at hour h. Thus, using the Weighted Sum multi-objective method, the objective function is

$$F = \alpha F_1 - (1 - \alpha) F_2$$

to be maximized.

4) Algorithm: The proposed algorithm for the problem of daily unit operation is shown in lines 1 to 10.

```
1:  Data insertion
2:  Reading the data filed in algorithm 1
3:  Initial population creation
4:  For iteration 1 to end
5:      Evaluation of the objective function of the individuals
6:      Population selection
7:      Crossover
8:      Mutation
9:      New population
10: End
```

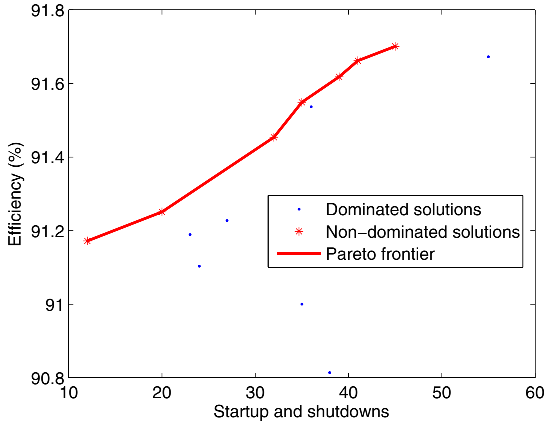

Fig. 5. Dominated and nondominated solutions for α from 0 to 1

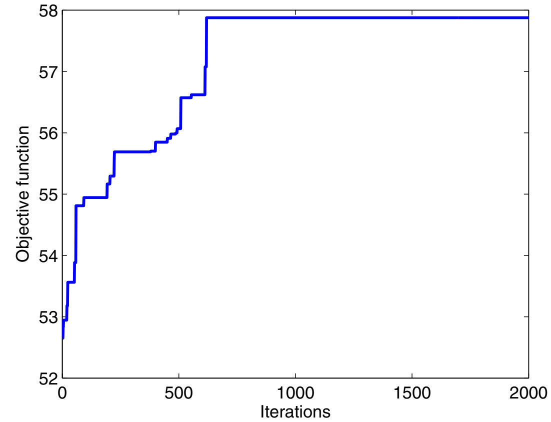

Fig. 6. Convergence of objective function with $\alpha = 0,7$

VI. Simulation Results

Data from a Brazilian hydroelectric power plant were used. The generating units' efficiency data were recently obtained by the Winter Kennedy water discharge measurement method. It was found that each unit behaves differently. The plant in question has six generating units, and the possible operating region for each unit is between 50 and 140 MW.

For the simulations, a spinning reserve of 50 MW and a water head of 24.8 m were adopted. The dispatch was made for one day using the load curve shown in Fig. 2.

In the first step, we used $c = 400$ (a constant related with the number of iterations), a population of 240 individuals, and a mutation rate of $1/240$.

In the second step, we used a population of 200 individuals, and a mutation rate of 15%. The number of iterations was 2000. Different values of α were used, from 0 (minimizing only the number of unit startups and shutdowns - F_2) to 1 (maximizing only the daily efficiency - F_1). The solutions obtained with each α are shown in Fig. 5. Some of the solutions are dominated by others. The nondominated solutions are shown in Table I.

The convergence of the method is illustrated in Fig. 6. The y-axis corresponds to the objective function $F = \alpha F_1 + (1-\alpha)F_2$ with α equal to 0.7. Fig. 7 shows the convergence of F_1 and F_2. In this case, the search converged in iteration 618. At other values of α, it converged between 200 and 1600 iterations (for 9 different values of α, the convergence occurred in fewer than 1000 iterations, and for 5 different values it required more than 1000 iterations).

The computational time for simulation with 14 different values of α was 23 minutes, with an average of 99.50 seconds for each α.

The extreme solutions are 1 and 7. Solution 1 has 12 startups and shutdowns of units and a daily efficiency of 91.17%. Solution 7 has 45 startups and shutdowns of units, and an efficiency of 91.70%.

The cost of each startup or shutdown of a unit is evaluated at 3 US$ multiplied by the effective power of the unit [1]. Thus, for the plant in question, this cost is US$ 525, implying

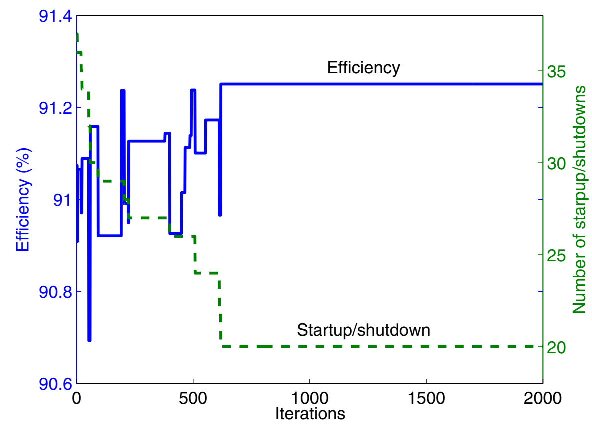

Fig. 7. Convergence of efficiency and unit startup/shutdown with $\alpha = 0,7$

a cost of US$ 6,300 for Solution 1 and US$ 23,625 for Solution 7. Solution 1 represents savings of US$ 17,325 in relation to Solution 7.

In addition, it is possible to compute energy gains. The total generated energy is $9.960\,\mathrm{MWh}$. Considering an efficiency of 91.17%, the total gross energy used to generate $9.960\,\mathrm{MWh}$ is 10,925 MWh. Therefore, the loss is $965\,\mathrm{MWh}$. At an efficiency of 91.70%, the total gross energy used in one day is 10,862 MWh, implying a loss of $902\,\mathrm{MWh}$. Solution 7 saves $63\,\mathrm{MWh}$ in comparison to Solution 1.

According to the Electric Power Commercialization Chamber (CCEE)[1], the price of electric energy in 2007 was, on average, $61.39\,\mathrm{US\$/MWh}$[2]. Thus, it is possible to compute the price of the lost energy. Considering the aforementioned costs and prices, the costs are shown in Table II, including the total cost. As can be seen, Solution 1 has the lowest cost.

The total costs for different prices of electrical energy were

[1] Site:www.ccee.org.br

[2] Considering an exchange rate of $1.58\,\mathrm{US\$/R\$}$

TABLE I
NONDOMINATED SOLUTIONS

Solution	Number of startups or shutdowns of generating units	Efficiency in the day (%)
1	12	91.17
2	20	91.25
3	32	91.45
4	35	91.55
5	39	91.62
6	41	91.66
7	45	91.70

TABLE II
TOTAL COST (US$)

Solution	Lost energy cost (US$)	Startups/shutdowns total cost (US$)	Total cost (US$)
1	59,205	6,300	65,505
2	58,624	10,500	69,124
3	57,137	16,800	73,937
4	56,443	18,375	74,818
5	55,940	20,475	76,415
6	55,620	21,525	77,145
7	55,336	23,625	78,961

computed. For an energy price below $260.71\,\mathrm{US\$/MWh}$, Solution 1 has the lowest price and for a price higher than that, the best cost is provided by Solution 6. These results were obtained according to aforementioned the costs. Depending on the kind of hydro units and the electricity market, it may be more advantageous to prioritize the efficiency over the unit startups and shutdowns, or vice versa.

It should be noted that the interaction between the two steps of the algorithm is important. The two-step algorithm uses only good solutions obtained in the one-step algorithm. For all the combinations of units, the two-step uses only the best solutions obtained.

VII. CONCLUSIONS

A two-step method based on genetic algorithms was proposed for the operation of hydroelectric power plants. The first step focuses on the maximum efficiency of each combination of units. The second step uses the results obtained in the first part to find solutions for the daily operation in a biobjective way: maximizing daily efficiency and minimizing the number of unit startups and shutdowns.

Step 1 files the best solutions for each load and each combination of units. Thus, in optimization step 2, only loads that have never been used in the program are simulated and then filed. Our simulations showed that, after filing the results of step 1 for each parameter α, the computational time of step 2 was, on average, 99.50 seconds.

A set of nondominated solutions is presented and, depending on the importance of each objective, the best solution changes. For the cost of startups and shutdowns of generating units of US$ 3 multiplied by the effective power of the unit, the results show that Solution 1 involves the lowest total cost, since the price of electric energy is lower than US$ 260.71, while Solution 6 is the most advantageous for higher energy prices.

ACKNOWLEDGMENT

The authors would like to thank CNPq (National Council for Scientific and Technological Development) for financial support in the development of this work.

REFERENCES

[1] O. Nilsson and D. Sjelvgren, “Hydro unit start-up costs and their impact on the short term scheduling strategies of swedish power producers,” *IEEE Transactions on Power Systems*, vol. 12, pp. 38 – 43, 1997.

[2] G. R. Colnago, “Modelo de despacho ótimo com tratamento individual de unidades geradoras em usinas hidrelétricas,” Master’s thesis, Mechanical Engineering Faculty, State University of Campinas, 2007.

[3] T. S. Hussain, “An introduction to evolutionary computation,” in *1998 CITO Researcher Retreat*, Hamilton, Ontario, 12 – 14 de May 1998.

[4] E. F. Santos and T. Ohishi, “A hydro unit commitment model using genetic algorithm,” in *Congress on Evolutionary Computation*, vol. 2, June 2004, pp. 1368–1374.

[5] T. Yalcinoz and H. Altun, “Power economic dispatch using a hybrid genetic algorithm,” *IEEE Power Engineering Letters, IEEE Power Engineering Review*, vol. 21, no. 3, pp. 59–60, 2001.

[6] M. A. Abido, “Multiobjective evolutionary algorithms for electric power dispatch problem,” *IEEE Transactions on Evolutionary Computation*, vol. 10, no. 3, pp. 315–329, 2006.

[7] G. B. Sheble and K. Brittig, “Refined genetic algorithm - economic dispatch example,” *IEEE Transactions on Power Systems*, vol. 10, no. 1, pp. 117–124, 1995.

[8] A. Rudolf and R. Bayrleithner, “A genetic algorithm for solving the unit commitment problem of a hydro-thermal power system,” *IEEE Transactions on Power Systems*, vol. 14, no. 4, pp. 1460–1468, 1999.

[9] J. R. Gomes and . R. Saavedra, “Optimal reactive power dispatch using evolutionary computation: Extended algorithms,” *IEEE Proc.-Gener. Transm. Distrib.*, vol. 146, no. 6, pp. 586–592, 1999.

[10] Z. Michalewicz, *Genetic Algorithms + Data Structures = Evolution Programs*, Springer-Verlag, Ed., Berlin, 1994.

[11] ONS, “Norma de operação - controle da geração em operação normal - submódulo 10.8,” National Operator of Electrical System, Brazil, Tech. Rep., 2003, available at: www.ons.org.br. Access in october 2006.

[12] O. Nilsson, L. Söder, and D. Sjelvgren, “Integer modelling of spinning reserve requirements in short term scheduling hydro systems,” *IEEE Transactions on Power Systems*, vol. 13, no. 3, pp. 959 – 964, 1998.

[13] J. H. Holland, *Adaptation in Natural and Artificial SystemAdaptation in Natural and Artificial System*. USA: The University of Michigan Press, 1975.

[14] D. E. Goldberg, *Genetic Algorithms in Search, Optimization and Machine Learning*. Boston, MA: Kluwer Academic Publishers, 1989.