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An Application of Genetic Fuzzy Systems to the Operation Planning of Hydrothermal Systems

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1. Introduction

The operation planning of hydrothermal systems aims to specify how the set of power plants should be operated so that the resources available for power generation are used efficiently. In hydrothermal systems with great participation of hydroelectric generation, as is the case of the Brazilian system, the operation planning intends to establish Reservoir Operation Rules (RORs) to replace, whenever possible, the thermoelectric generation by the hydroelectric generation (Christoforidis et al., 1996). Due to their peculiar characteristics, the operation planning of the Brazilian hydrothermal system can be classified as a problem coupled in time (dynamic) and space (not separable), nonlinear, nonconvex, stochastic and large scale (Leite et al., 2002; Oliveira & Soares, 1995; Silva & Finardi, 2001).
It is worth mentioning that the RORs are present in some stages of the operation planning of hydrothermal systems, such as:

- Obtaining the equivalent reservoir of energy(Arvanitidis & Rosing, 1970a;b);
- Breakdown of the goals of hydraulic generation of the equivalent reservoir (Soares & Carneiro, 1993) and;
- Performance evaluation of the operation of hydroelectric system (Silva & Finardi, 2003).

An operation rule widely adopted in practice, including computational models of the Brazilian electric power system, known as the rule of parallel operation (RORP) (Marques et al., 2005), determines that all the reservoirs of the hydroelectric system should keep the same percentage of their useful volume. The greatest advantage of this rule is its simplicity, however, it does not conform to the principles of optimal operation of reservoirs for the electric power generation (Lyra & Tavares, 1988; Read, 1982; Sacchi, Nazareno, Castro, Silva Filho & Carneiro, 2004; Sjelvgren et al., 1983; Soares & Carneiro, 1991; Yu et al., 1998).
In order to have RORs inspired by the optimized behavior of the reservoirs, an optimization algorithm, inspired in (Carneiro et al., 1990; Carvalho & Soares, 1987), is initially applied for the operation of the hydroelectric system. As a result of the optimization, a set of operating points is obtained, which relate the energy stored in the hydroelectric system to the storage status of each reservoir. In order to make the set of points able to be used as an indication for

obtaining a ROR for a given hydro plant, it is necessary to set mathematical functions. These sets give a function that represents the rule of operation of each hydropower plant.

It is worth mentioning that several papers, from related literature, refer to obtaining RORs, differing only in the technique used for setting the points and implementing the obtained RORs. In (Soares & Carneiro, 1993), the authors use third-degree polynomial functions to set the points. The obtained RORs were applied and compared to the RORP in simulations of the operation of hydroelectric systems. The authors in (Cruz Jr & Soares, 1996; 1999; 1995) use the method of least squares to set the polynomial, exponential and linear functions. However, the obtained RORs were applied in a computational model that adopts the representation of the equivalent reservoir and compares them with the RORP. In (Carneiro & Kadowaki, 1996), the authors do the settings of the points through an algorithm that used the method of least squares, obtaining polynomial and exponential functions to express the RORs. The obtained RORs were used to simulate the operation of hydroelectric systems and compared with the ROR-P. In (Sacchi, Carneiro & Araújo, 2004a;b), Artificial Neural Networks (ANN) are used, more specifically SONARX networks. The obtained RORs are integrated into an algorithm of operation simulation and compared with the RORP. In (Rabelo et al., 2009b) the authors present a methodology based on Takagi-Sugeno fuzzy inference systems (Takagi & Sugeno, 1985) to obtain RORs, and the application of these rules in the simulation of the operation of hydroelectric systems and compares them with the RORP. In the latter case, the representative points of the optimal operation of reservoirs are used to set the parameters of consequents of the fuzzy production rules.

Therefore, this paper intends to use some principles that govern the optimized behavior of the reservoirs in order to assist the implementation of RORs for hydroelectric systems. The proposed methodology for specifying RORs combines Mamdani fuzzy inference systems (Mamdani, 1974) and Genetic Algorithms (GAs) (Goldberg, 1989). Mamdani fuzzy inference systems are used to determine the operation rule of each reservoir, i.e., estimate the operating volume of hydroelectric power plants, using the value of the energy stored in the system as input parameter. Thus, our goal is to generate RORs through the heuristic knowledge of the relationship between the global storage status of the hydroelectric system (energy stored in the system) and the operating volume of each hydroelectric power plant. Genetic Algorithms are used to find the optimal setting of the membership functions associated with each primary term of the consequent of the fuzzy production rules. Importantly, the GAs are global optimization algorithms, based on mechanisms of natural selection and genetics, which have proven effective in a variety of problems, because they overcome many of the limitations found in the traditional methods of search/optimization (Haupt & Haupt, 1998). The systems obtained from the integration between models of fuzzy inference and Genetic Algorithms are called Fuzzy-Genetic Systems (FGSs) (Cordón et al., 2004; Cordon, Herrera, Hoffman & Magdalena, 2001; Herrera, 2005; 2008).

Another fuzzy model broadly used is the Takagi-Sugeno fuzzy inference system. This model was proposed as an effort to develop a systematic approach to generate fuzzy production rules from a set of input and output data (Mendel, 2001). The fuzzy rules, in a Takagi-Sugeno fuzzy inference system, have linguistic variables only in their antecedents, and the definition of its consequents, usually based on the method of least squares, requires numeric data. On the other hand, the production rules in a Mamdani fuzzy inference model have linguistic variables in both their antecedent and in their consequent. Therefore, the basis of rules in the Mamdani fuzzy model can be defined solely in linguistic form, without the need for numeric input/output data. However, the need to adjust the membership functions of the linguistic variables of the consequent requires an additional effort by the designer in developing the system.

2. Operation planning of hydrothermal systems

2.1 Mathematical formulation

The operation planning of hydrothermal systems, with individualized representation of the hydroelectric plants and deterministic inflows can be formulated as the following optimization problem:

$$\min \quad \sum_{t=1}^{T} CVP_t \cdot 0,5 \cdot \Phi(D_t - H_t)^2 + V(x_T) \tag{1}$$

$$s.a. \quad D_t = E_t + H_t, \tag{2}$$

$$H_t = \sum_{i=1}^{N} k_i \cdot hl(x_{i,t}^{avg}, u_{i,t}) \cdot min[u_{i,t}, q_{i,t}^{max}], \tag{3}$$

$$x_{i,t} = x_{i,t-1} - x_{i,t}^{evap}$$

$$+(y_{i,t}^{inc} + \sum_{k \in \Omega_i} u_{k,t} - u_{i,t}) \cdot [\tfrac{\Delta t_t}{10^6}], \tag{4}$$

$$u_{i,t} = q_{i,t} + v_{i,t}, \tag{5}$$

$$x_{i,t}^{min} \leqslant x_{i,t} \leqslant x_{i,t}^{max}, \tag{6}$$

$$u_{i,t}^{min} \leqslant u_{i,t} \leqslant u_{i,t}^{max}, \tag{7}$$

$$q_{i,t}^{min} \leqslant q_{i,t} \leqslant q_{i,t}^{max}, \tag{8}$$

$$x_{i,0} \text{ given}, \tag{9}$$

onde:

- T: number of intervals of the planning horizon;
- N: number of hydroelectric plants;
- CVP_t: coefficient of present value associated with the interval t;
- E_t: complementary generation (thermal generation, imports of energy and load shortage) [MW];
- H_t: total hydroelectric generation [MW];
- D_t: demand (electricity market) [MW];
- $x_{i,t}$: volume stored in the reservoir i at the end of the interval t [hm^3];
- $x_{i,t}^{avg}$: average volume stored in the reservoir i at the interval t [hm^3];
- $x_{i,t}^{evap}$: volume evaporated in the reservoir i during the interval t[hm^3];
- $hl_{i,t}$: height of the net fall of the plant i in the interval t [m];
- $y_{i,t}^{inc}$: incremental inflow to the reservoir of the plant i in the interval t [m^3/s];
- $q_{i,t}$: water discharge (through turbines) of the plant i in the interval t [m^3/s];
- $u_{i,t}$: flow released of the plant i in the interval t [m^3/s];
- $v_{i,t}$: flow spilled from the plant i in the interval t [m^3/s];

- $x_{i,t}^{max}$, $x_{i,t}^{min}$: maximum and minimum of volume stored for the reservoir of the plant i at the end of the interval t [hm^3];
- $u_{i,t}^{max}$, $u_{i,t}^{min}$: maximum and minimum flow released of the plant i in the interval t [m^3/s];
- $q_{i,t}^{max}$, $q_{i,t}^{min}$: maximum and minimum water discharge through turbines of the plant i in the interval t [m^3/s];
- Δt_t: number of seconds in the interval t [s];
- Ω_i: set of indexes of the plants immediately upstream of the plant i.

The objective function consists of two parts: the operational cost during the planning horizon (Φ) and the future costs associated with the state of final storage of the hydroelectric reservoir (V). For our purposes, the complementary generation system is being represented by an equivalent thermoelectric plant that replaces all the non-hydraulic system (Huang, 2001). Thus, the operating cost is given by the cost of fuel used in the operation of the thermoelectric power plants, the cost of importing energy from other systems, and the cost of "deficit" (penalty associated with the lack of power supply). Therefore, the operating cost is represented by a single cost function of the non-hydraulic sources (Carvalho & Soares, 1987). The future cost is a terminal condition, used in the optimization models of the operation, to balance the water use during the planning horizon and its future use (Martinez & Soares, 2002).

Equality (2) represents the restriction of meeting the demand of electricity in the time range t. The total generation from the hydroelectric system is represented by equation (3), given by the sum of the functions of hydraulic production of each hydroelectric power plant. Equation (4) represents the equation of water balance in the reservoirs. The flow released is equal to the sum of the turbine discharge flow with the spilled flow, and is shown in equation (5). The restrictions (6) and (7) represent the limits of storage and flow released of the hydroelectric plants, respectively. These limits vary over time, as they reflect the operational constraints of the power plants and other constraints associated with the multiple uses of water such as irrigation, flood control, navigation, etc. The restriction (8) represents the minimum and maximum turbine discharge, which may be associated with physical restrictions of the plant itself or electrical constraints. The values of the initial volumes of the reservoirs are given (9).

2.2 Hydroelectric system used

Figure 1 illustrates the set of hydroelectric plants used in this chapter. The hydroelectric system is comprised of seven hydroelectric plants of the Brazilian system (Emborcação, Itumbiara, São Simão, Furnas, Marimbondo, Água Vermelha e Ilha Solteira) represented individually. The set of plants chosen forms a complex system because it contains large plants, connected in parallel and in cascade. It is worth mentioning that the representation of the hydroelectric plants is done individually. The simplification of the equivalent representation of the hydroelectric system causes the generating capacity not to be utilized as efficiently as possible, since the energy equivalent reservoir cannot represent the operating characteristics of individual plants and hence their respective hydraulic coupling (Oliveira et al., 2009; Silva & Finardi, 2001). These factors, therefore, lead to an inefficient use by the hydraulic generator park (Cruz Jr & Soares, 1995). Thus, the individualized representation of each hydroelectric power plant is important since the main objective of the operation planning is to determine the generation targets for each plant, at each interval.

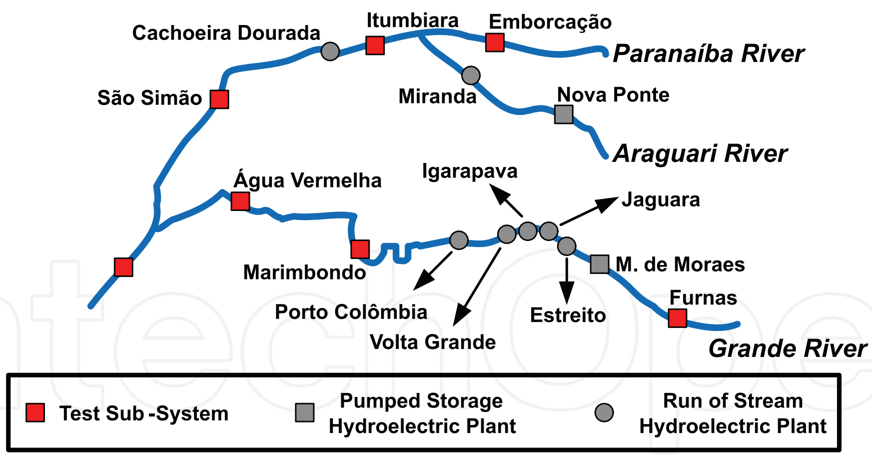

Fig. 1. Hydroelectric System Used.

2.3 Planning horizon

The complexity of the operation planning cannot be accommodated by a single mathematical model, therefore the use of models chains with different planning horizons and degrees of detail in the representation of the hydrothermal generation system is necessary (Pereira, 1985). In this chapter, the operation planning with the five-year horizons, discretized on a monthly basis, was adopted, which implies a horizon composed of 60 intervals.

2.4 Computational models of optimization and simulation

In this study, we used a computational model for optimization and simulation of the operation of hydroelectric systems. The optimization model is used to determine the optimal operation of reservoirs and is inspired by optimization algorithms specifically designed for the operation planning of hydrothermal systems (Carneiro et al., 1990; Carvalho & Soares, 1987). The simulation model includes a simulation algorithm which enables the evaluation of the performance of reservoir operation rules. The simulation algorithms aim to replicate the operating behavior of the power plants of the hydroelectric system under certain operating conditions. It is noteworthy that the computational models used are part of a computational tool that has been developed by the authors to conduct studies related to the operation planning of hydrothermal systems (Rabelo et al., 2009a). It should be stressed that the authors applied a process of development (UML Components) (Cheesman & Daniels, 2001) based on software components (Szyperski, 2002) for building the computer models mentioned above, in order to guide the development of the tool, with the possibility to add or change requirements in an orderly manner, even when the application is running.

2.5 Optimized operation of the reservoirs for the power generation

Figures 2, 3 and 4 show representative points of the optimized operation of some plants of the hydroelectric system.

Despite the dispersion in the points, we can see a different behavior of the hydroelectric plants in the optimal operation. It appears that the volume of the reservoirs upstream is reduced when the energy stored in the system decreases. The plants further downstream aim to keep their reservoirs full, and only reduce the volume when the energy stored in the system is critical. On the other hand, intermediate plants have variations not as severe as in reservoirs upstream, or as soft as in downstream reservoirs. Thus, the relative location

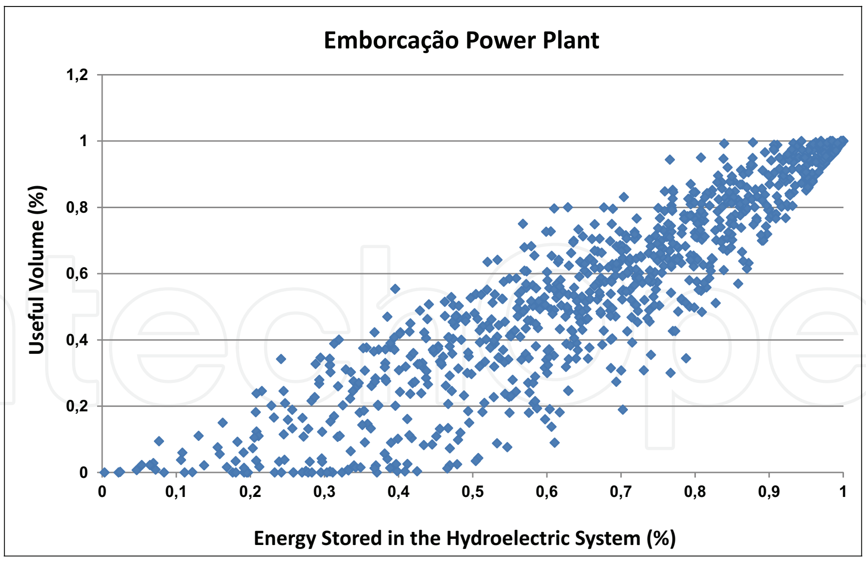

Fig. 2. Representative Points of the Optimized Operation of Emborcação Power Plant.

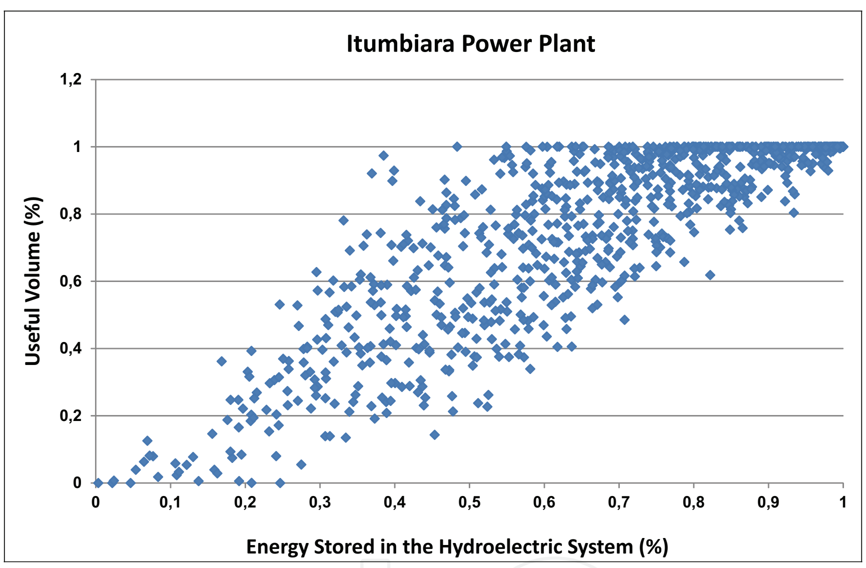

Fig. 3. Representative Points of the Optimized Operation of Itumbiara Power Plant.

of the hydroelectric plants influences the optimized operating behavior of the reservoirs. (Soares & Carneiro, 1991).

2.6 Reservoirs operation rules

The operation rules are functions that determine the operating volume of each reservoir to establish a coupled behavior between the hydroelectric power plants. To implement the coupling on the operation of the hydroelectric plants set, a global parameter called coupling factor of the operation of the hydroelectric system is defined, denoted by λ_t. The coupling factor represents the storage percentage of the system in a given interval t, and is calculated (Equation 10) as the ratio between the energy stored in the system (ESS_t) and maximum energy that can be stored in the system (ESS^{max}), resulting in values in the interval $0 \leq \lambda_t \leq 1$.

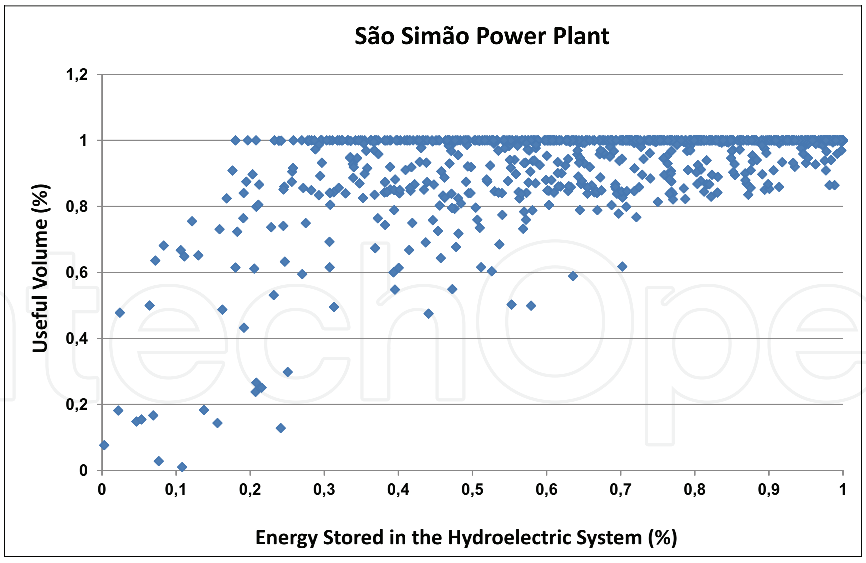

Fig. 4. Representative Points of the Optimized Operation of São Simão Power Plant.

$$\lambda_t = \frac{ESS_t}{ESS^{max}} \tag{10}$$

With the value of λ, the volume of each plant reservoir can be defined by the following equation:

$$x_{i,t}(\lambda_t) = x_{i,t}^{min} + f_i(\lambda_t) \cdot (x_{i,t}^{max} - x_{i,t}^{min}) \tag{11}$$

where:

- $f_i(\lambda_t)$: reservoir operation rule of the plant *i* in relation to the parameter λ_t. It expresses the operating behavior (emptying/filling) of the reservoir together with the other reservoirs of the hydroelectric system.

3. Fuzzy-genetic systems

3.1 Fuzzy inference systems

The fuzzy inference systems are based on linguistic production rules like "if ... then" in which the fuzzy set theory (Zadeh, 1965) and the fuzzy logic (Zadeh, 1996) provide the mathematical foundations needed for dealing with very complex processes, based on inaccurate, uncertain and qualitative information. These rule-based systems are more suitable for complex problems where it is very difficult to describe the problem (behavior of the process) quantitatively. Additionally, fuzzy rule-based systems are able to yield good results with reasonably simple mathematical operations (Ross, 2004).

The fuzzy inference systems are based on three steps: fuzzification, inference procedures and defuzzification. The fuzzification is a mapping from the domain of the input variable to the fuzzy domain, representing the allocation of primary terms (linguistic or qualitative values), defined by membership functions, to the input variables. The fuzzy inference procedure is responsible for assessing the primary terms of the input variables by applying the production rules in order to obtain the fuzzy output value of the inference system. The defuzzification is used to associate a numeric value to the fuzzy output set, which is obtained from the fuzzy inference procedure.

3.2 Genetic algorithms

Genetic Algorithms (GAs) are search/optimization algorithms based on the mechanisms of genetics and natural selection. Its operation follows the biological inspiration, which implies that in a given population, individuals with "good" genetic characteristics are more likely to survive and to generate individuals increasingly stronger (able), while the less fit individuals tend to disappear during the evolutionary process. When using GAs, each individual in the population, called chromosome, represents a potential solution to the problem to be solved.
The basic operation of GA is to generate an initial population formed by a set of individuals. During the evolutionary process, an evaluation function is applied for each individual, to assign it an ability (fitness) index that characterizes the quality of the individual as solution of the problem. Based on the ability index, a part of the individuals is selected randomly, while others are discarded. Individuals chosen by the selection process are subject to form descendants for the next generation through changes in their genetic characteristics by applying the genetic operators of mutation and crossover (recombination). This iterative process continues until a satisfactory solution to the problem is found. Each of the iterations of the process is denominated a generation of GA. To prevent the most capable individuals to disappear from the population by applying genetic operators, an elitist strategy can be applied (Goldberg, 1989), which is to automatically put the best individuals in the next generation.
Seemingly simple, due, in part, to its bio inspired nature, GAs are capable of solving complex problems in a very elegant manner. Moreover, they are not affected by assumptions about differentiability or continuity of the objective function of the problem. This implies that the GAs can be very appropriate for dealing with problems with non-differentiable and discontinuous functions. Additionally, GAs operate on a population of individuals in order to explore different points of the search space in parallel.

3.3 Aspects of the implementation of genetic fuzzy system

The implemented fuzzy inference systems have a linguistic input variable, the energy stored in the system (ESS_L), defined on the set of linguistic terms (Very Low, Low, Medium, High and Very High) (Figure 5) and a output linguistic variable, the useful volume, also defined in the set of linguistic terms (Very Low, Low, Medium, High and Very High).
In this paper, a Mamdani fuzzy inference system, consisting of a rule base with 5 disjunctive rules of inference was specialized for each hydroelectric plant (Figure 1). The syntax of the rule base of the implemented fuzzy systems is represented by the following linguistic conditional statements:

- Rule 1: If (ESS_L *is Very Low*) Then (*Useful Volume is Very Low*), or
- Rule 2: If (ESS_L *is Low*) Then (*Useful Volume is Low*), or
- Rule 3: If (ESS_L *is Medium*) Then (*Useful Volume is Medium*), or
- Rule 4: If (ESS_L *is High*) Then (*Useful Volume is High*), or
- Rule 5: If (ESS_L *is Very High*) Then (*Useful Volume is Very High*)

GAs were used to set (adjust) the membership functions associated with the linguistic variable Useful Volume in each of the seven fuzzy systems. The differentiated setting in the linguistic output variable is made to represent the different behavior of each reservoir in optimal operation of the system. After setting all fuzzy systems, they can make inferences from numerical values of the input variable, to obtain the value of the output variable, the operating volume of the reservoirs in the interval t. For this, the rules are inferred in parallel. The inference of each rule consists in evaluating the antecedent, then the application of the

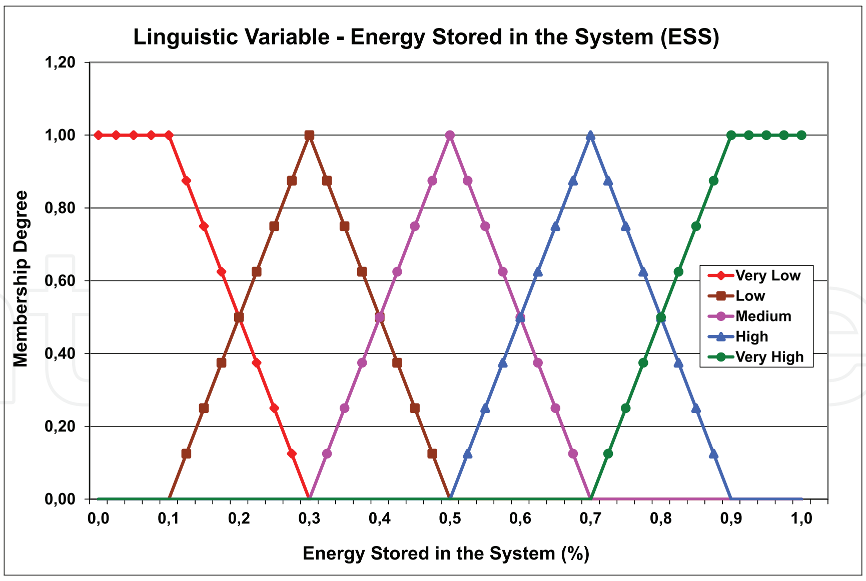

Fig. 5. Linguistic Variable representing the Energy Stored in the System.

implication operator to determine the implication of the fuzzy set of the consequent. The aggregation of the consequent consists of aggregating, or combining, the consequent obtained by the inference of each rule. The defuzzification procedure gets the numeric value of the useful operating volume of each of the plants of the hydroelectric system. The implication operator used was the minimum operator of Mamdani, the aggregation of the consequent was performed by the maximum operator, and the defuzzification method used was the method of center of area (Ross, 2004; Zimmermann, 2001).

The first aspect to be considered in the use of GAs for solving a problem is the chromosome representation, that is, map the information of the parameters of the problem in a way viable to be handled by the GA. When designing a fuzzy system using a GA, the fuzzy system within a chromosome must be mapped. A fuzzy system is specified only when the rule base and the definition of membership functions of each linguistic variable are specified (Shi et al., 1999). In this paper, as the rule base has been previously defined, based on the authors' experience regarding the optimal behavior of the reservoirs, the chromosomes contain only information about the distribution of the membership functions of the linguistic output variable (useful volume) against to universe of discourse, to reflect the specialized behavior of each reservoir in the coupled operation of the system. It is noteworthy that some studies have shown that the performance of the fuzzy inference system is much more sensitive to the choice of fuzzy database (fuzzy sets, membership functions) than to the composition of the fuzzy production rule base (Bonissone et al., 1996; Cordón et al., 2000; Cordón, Herrera & Villar, 2001; Zheng, 1992). Since the problem has continuous parameters that need high precision, the chromosome representation was done by using real numbers (Srikanth & kamala, 2008) instead of binary representation (Holland, 1975) traditionally used. The membership functions used for the linguistic variables are triangular and trapezoidal. The output linguistic variables of each of the seven fuzzy systems have five membership functions, two trapezoidal representing the very low and very high fuzzy sets, and three triangular representing low, medium and high sets. Due to the distribution adopted by the fuzzy sets, each trapezoidal membership function requires two parameters to represent it, and each triangular membership function needs 3, so 13 genes are used for each fuzzy inference

system, which implies a chromosome with 91 genes, due to the fact that each chromosome stores information from all seven plants of the hydroelectric system. The values of the genes are real numbers ranging between 0 and 1 and the population is composed of 80 individuals.
After defining the chromosome representation, the design of GA focuses on the specification of an evaluation function. The evaluation function assigns a numerical value (fitness, ability index) that reflects how well the parameters represented in the chromosome adapt and thus it is the way used to determine the quality of an individual as a solution to the problem. As the availability of water in a given interval depends on the degree of its former use, this study used as evaluation function the difference between the maximum stored energy that can be achieved in the system (ESS^{MAX}) and the energy stored in the system regarding the last interval of the planning horizon (ESS_{60}). Since the decisions taken at interval of the planning depends on the decisions taken in the past and determine the future development of the hydroelectric system, the use of stored energy in the last interval of the horizon is feasible because it takes the link between operational decisions in time into account, commonly known as temporal coupling (problem coupled in time). Numerically, the evaluation function is represented by (12), where 60 indicates the index of the last interval of the planning horizon:

$$\text{Evaluation Function} = ESS^{MAX} - ESS_{60} \tag{12}$$

Therefore, there is a minimization problem, whose goal is to find a value ESS_{60}, so as to minimize the difference from ESS^{MAX}.
After calculating the evaluation function for every individual of the chromosomes population, the selection process chooses a subset of individuals of the current population, to compose an intermediate population in order to apply the genetic operators. The selection method adopted in this study was the method of the tournament (Eiben et al., 1999). It is worth mentioning that the tournament size adopted was equal to 2. In combination with the selection module, an elitist strategy was used, keeping the best individual from one generation to another.
Genetic operators are applied to make the population go through an evolution. The genetic, crossover and mutation operators are used to transform the population through successive generations in order to extend the search/optimization to a satisfactory result. The crossover is the operator responsible by the genetic recombination of the parents, in order to enable the next generation to inherit these characteristics. In this study we used the discrete crossover (Herrera et al., 2003; 2005). This operator includes the main crossover operators for the binary representation, which are directly applicable to the real representation. The mutation genetic operator (Hinterding et al., 1995) is necessary to introduce and maintain genetic diversity of the population through random change of genes within the chromosomes, which provides a means to incorporate new genetic characteristics in the population. Therefore, the mutation ensures the possibility of reaching any point in the search space, and helps overcome the problem of local minima. However, the mutation is applied less frequently than the crossover, in order to preserve the relationship exploration-exploitation (Herrera et al., 1998). In this study, the random mutation was used (Michalewicz, 2011).
Table 1 sumarizes the values of the parameters used in the implementation of the Fuzzy System. The Table 2 sumarizes the values of the parameters used in the implementation of the Genetic Algorithm responsible by the adjustment of the Fuzzy System.
Several criteria can be applied to finalize the implementation of a GA. In this paper, a maximum limit of 100 generations was set. The stop criterion was set for this value

Parameters of Fuzzy System	
Membership Functions	Trapezoidal and Triangular
Implication Operator	Minimum of Mamdani
Agregation Operator	Maximum
Defuzzification	Center of Area

Table 1. Main Parameters used in the Fuzzy System.

Parameters of Genetic Algorithm	
Representation	Real
Selection	Tournament
Crossover	Discrete
Probability of Crossover	100%
Mutation	Random
Probability of Mutation	10%

Table 2. Main Parameters used in the Genetic Algorithm.

of generations, so there is a balance between computational effort and the result of the optimization.

As a result of the GAs operation in setting the fuzzy systems, Figures 6, 7 e 8 show the membership functions associated with the linguistic variable useful volume of plants Furnas, Água Vermelha and Ilha Solteira. One can observe a different distribution of fuzzy sets (Very Low, Low, Medium, High and Very High) for each reservoir, where the positioning of the membership functions is done according to the Genetic Algorithm.

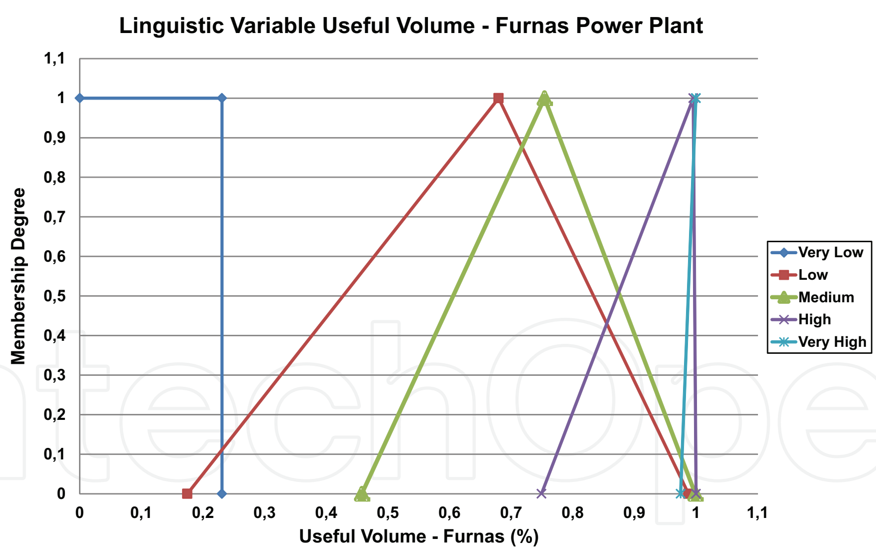

Fig. 6. Linguistic Variable Representing the Useful Volume of Furnas Power Plant.

4. Results and discussions

The simulation of the operation aims to verify the operating behavior of a hydroelectric system subject to certain operating conditions (electric power market, operating rules, water inflow, operational constraints, initial volume, etc.). So to make the comparison between the proposed Reservoir Operation Rules, based on Genetic Fuzzy Systems (RORGFS), the

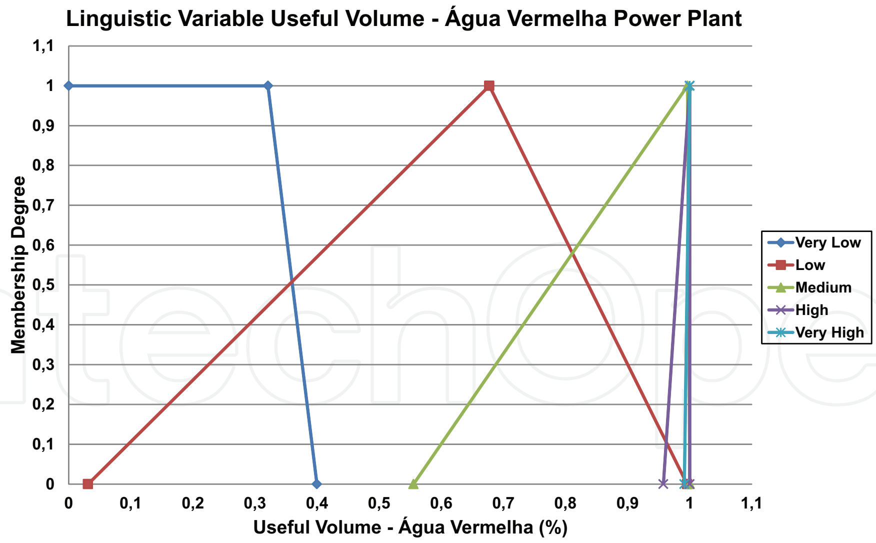

Fig. 7. Linguistic Variable Representing the Useful Volume of Água Vermelha Power Plant.

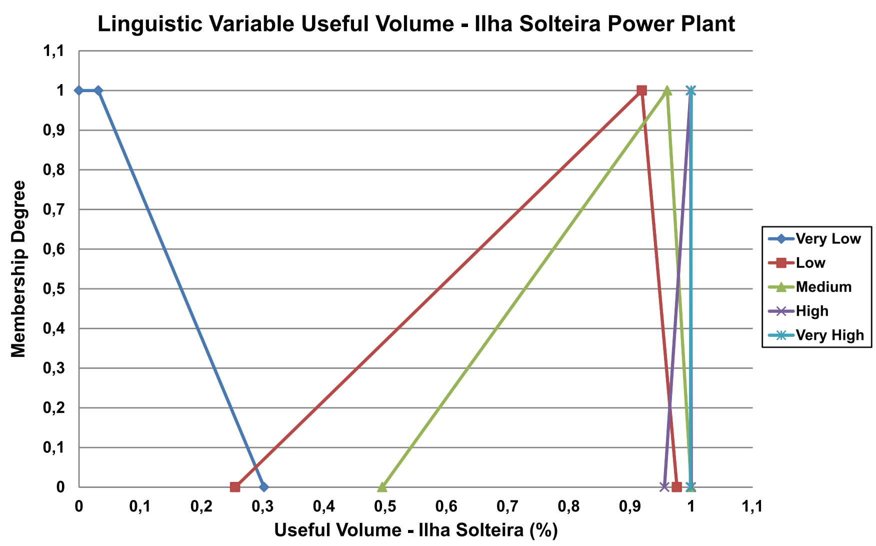

Fig. 8. Linguistic Variable Representing the Useful Volume of Ilha Solteira Power Plant.

operating rules based on mathematical polynomial and exponential functions (RORMF) (Carneiro & Kadowaki, 1996; Soares & Carneiro, 1993), the rule of parallel operation (RORP) (Marques et al., 2005) and the operation rule based on Takagi-Sugeno fuzzy systems (RORTS) (Rabelo et al., 2009b); the operation simulations are performed considering the same remaining operating conditions. Therefore, differences in behavior in the operation of the hydroelectric system will result only from the operational rules used. In this study, the computer model of operation simulation of hydroelectric systems was used, to evaluate the performance of RORs (Rabelo et al., 2009a).

Computer models of optimization and simulation, as well as the various rules of operation of reservoirs were implemented using the programming language C++ (Stroustrup, 2000). The developed software was run on an Intel Core 2 Duo 1.83 GHz, 3.00 GB of RAM on a Microsoft Windows Vista operating system with 32 bits.

4.1 Operating conditions

Five case studies were carried out, considering the water inflow of plants for the periods from 1936 to 1941, from 1951 to 1956, from 1971 to 1976, from 2000 to 2005 and with data from LTA (Long Term Average), in order to make a comparison between the RORs implemented in the simulation model under various hydrological conditions. To determine the target of hydraulic generation (demand or electric power market), the optimization of the energy operation of the hydroelectric system was performed with the actual water inflows occurred during the periods in order to obtain the solution with the perfect knowledge of water inflows for the entire planning horizon. The natural water inflows used in the operational simulations correspond to the flow rates recorded for the same periods of history. The month of May was adopted (dry season for the river basin of the system) as the starting month for all case studies. In all case studies, the initial volume stored in the reservoirs was considered as being equal to the maximum operating volume.

4.2 Results

The results illustrated by Figures 9 and 10 show fluctuations in the volume of the reservoirs depending on the location of the plant in the cascade through the application of RORGFS. With the predominant influence of the head effect (Read, 1982), the plant of Furnas, located upstream of Grande River, presented the highest levels of fluctuations in the reservoir, causing the reservoir to be operated at lower levels when compared to other plants in the cascade, such as Água Vermelha and Ilha Solteira. Ilha Solteira plant is operated with its reservoir full during most of the planning horizon. As the energy stored in a system is valued by the productivity of the plants further downstream, the power plant Ilha Solteira behaves like a run-of-river plant and appreciates all the water of the hydroelectric system, to be operated with maximum productivity. Água Vermelha plant, with an intermediate location in the cascade, has milder fluctuations in the reservoir storage than the Furnas plant, however exhibits more severe oscillations when compared to Ilha Solteira plant. Thus the application of RORGFS emphasized the filling of the reservoirs downstream to upstream, and the emptying of reservoirs upstream to downstream.

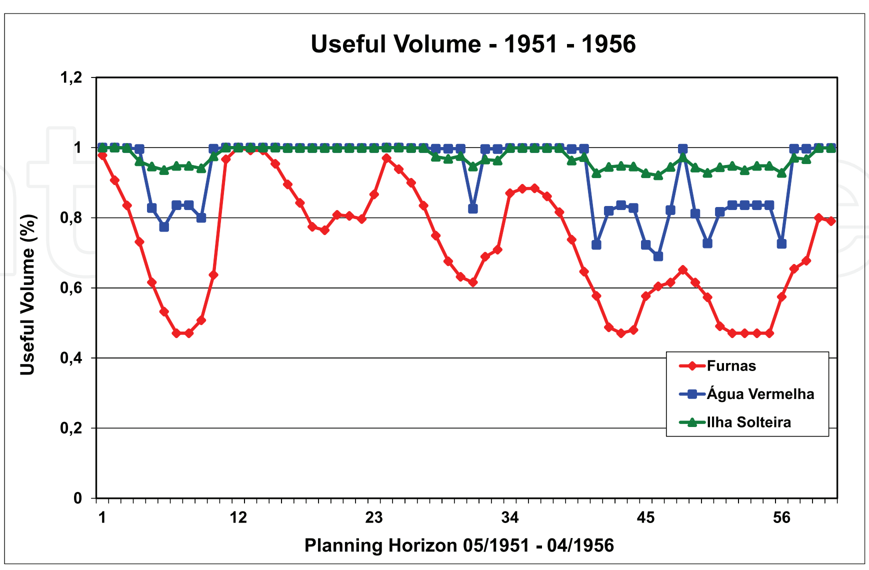

Fig. 9. Trajectories of Volume of some Reservoirs (1951 - 1956).

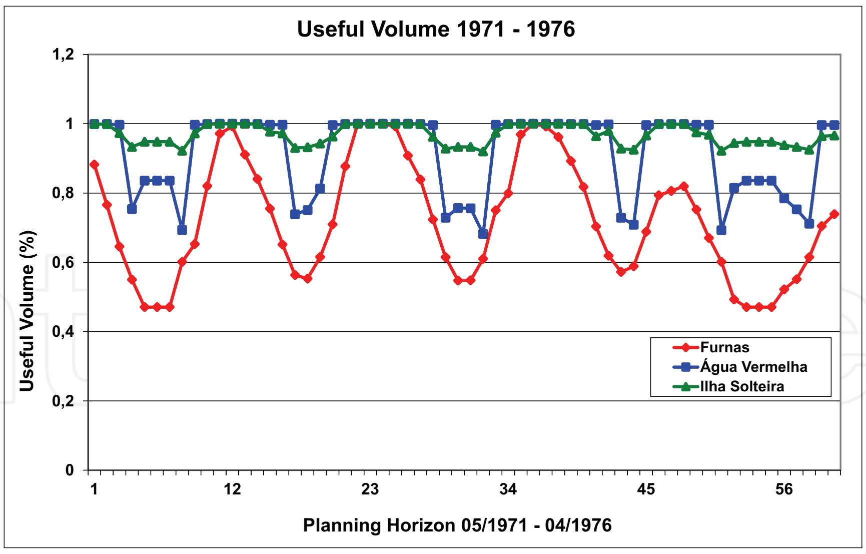

Fig. 10. Trajectories of Volume of some Reservoirs (1971 - 1976).

The operation rules based on the implementation of fuzzy genetic systems have established a specialized profile for all reservoirs set so as to maximize the stored energy in the hydroelectric system. This different behavior is obtained by different settings in the linguistic output variable in each of the seven fuzzy inference systems. The results presented by Figures 11, 12 and 13 illustrate the most efficient use of the generation hydroelectric resources by the operation rule based on genetic fuzzy systems. A more severe depletion of all the reservoirs can be verified when using RORP, RORMF and RORTS, which implies a more efficient use of water from reservoirs by RORFGS. It can also be pointed out that, throughout the planning horizon, the RORGFS always showed higher values of energy stored in the system, confirming that the operation rule for the reservoirs need to use less water to meet the same electricity market. Additionally, at the end of the planning horizon, one can see that RORP, RORMF and RORTS do not reach the storage levels achieved by RORGFS, making the reliability and the cost of operation extremely committed to the continued operation of the system. Therefore, RORGFS allows that the operation simulation of the hydroelectric system is consistent with the continuity of operation of the system, since it does not cease to be operated at the end of the planning horizon.

Thus, one can verify that RORGFS can ensure a more reliable and economic supply of electricity. It is economical because it requires less generation hydraulic resources (water) than the RORP, RORMF and RORTS. And it is reliable because it allows the operation of the hydroelectric system with higher levels of storage in the reservoirs, reducing the possibility of hydraulic deficits of the hydrothermal generation system. Therefore, the potential of RORGFS on optimizing the use of water resources, aimed at generating electricity can be verified. Moreover, RORGFS is quite consistent with the objectives of the planning of the energetic operation of hydrothermal systems as the optimization of water resources seeks to minimize additional generation. Thus, the higher the performance of the operation rules of the reservoirs for the use of hydroelectric generation resources, the lower necessary complementation to supply the electric power market.

Table 3 shows the average of energy stored in the system, during the planning horizon, to allow a numerical verification of the efficiency of each rule in the simulation of the operation of the plants in the hydroelectric system.

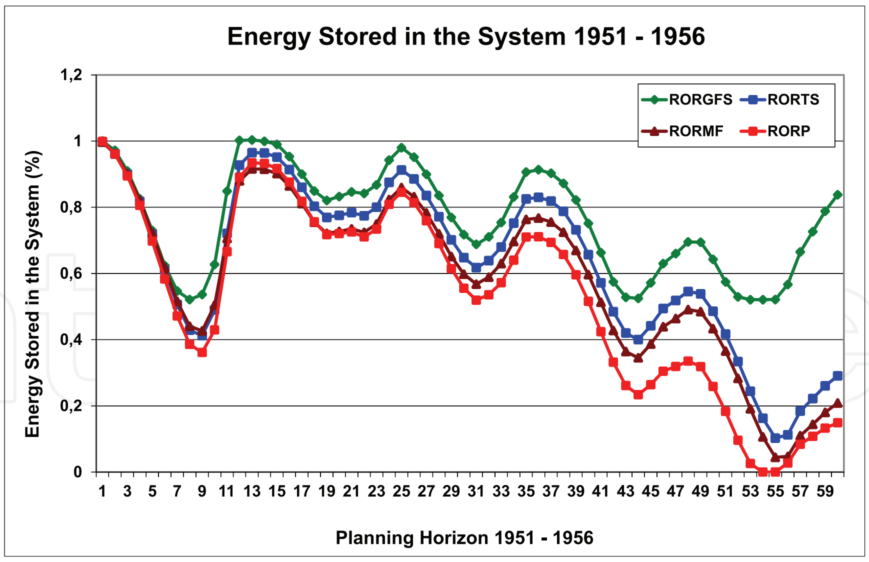

Fig. 11. Trajectories of Energy Stored in the System (1951 - 1956).

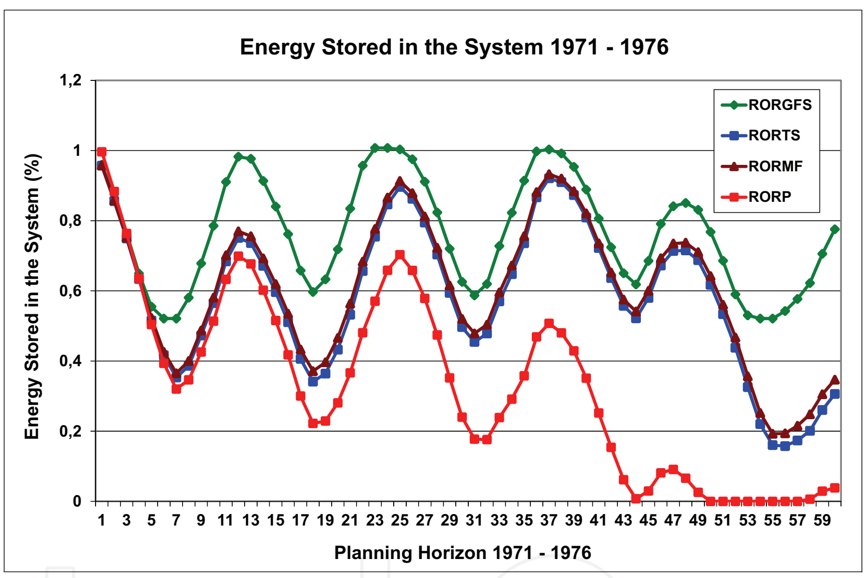

Fig. 12. Trajectories of Energy Stored in the System (1971 - 1976).

Planning Horizon	RORP	RORMF	RORTS	RORGFS
1936-1941	27865.82	29773.74	32299.55	35858.53
1951-1956	24232.82	26817.27	28851.86	34674.15
1971-1976	14329.13	27517.44	26544.69	34791.76
2000-2005	18151.44	21761.86	25847.11	36068.96
MLT	17171.52	25950.09	27437.61	36881.12

Table 3. Average of Energy Stored in the System [MW].

The reservoir operation rules based on the implementation of Genetic Fuzzy Systems have established a specialized profile for all reservoirs so as to maximize the stored energy in the hydroelectric system. This different behavior is obtained by different settings in the linguistic

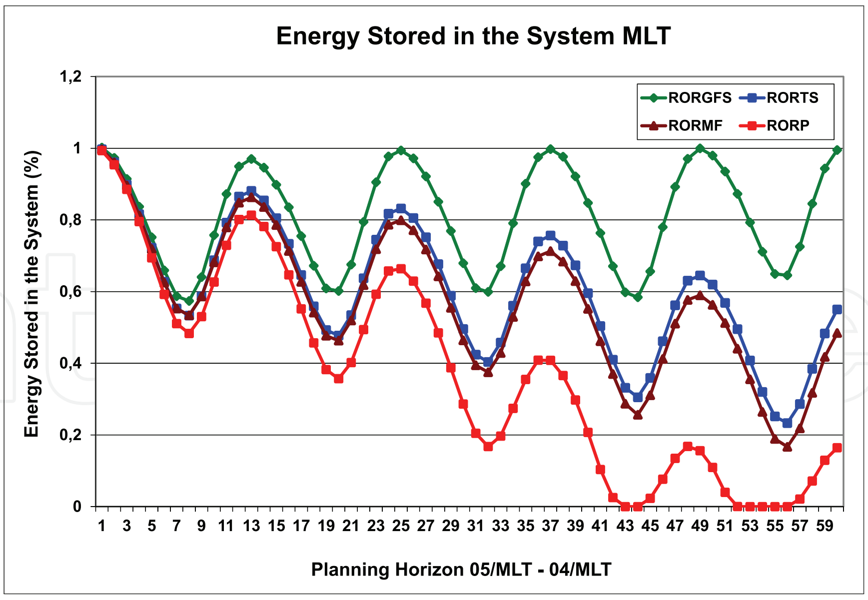

Fig. 13. Trajectories of Energy Stored in the System (MLT).

output variable in each of the seven fuzzy inference systems. With the predominant influence of the head effect, the plants where the volume of the reservoir have no great influence on the productivity of the system have drawdown priority. On the other hand, the plants whose operating volume of the reservoir has great influence on the productivity of the system have filling priority. As the energy stored in the system is valued by the productivity of the plants further downstream, the operating rules emphasize the filling of the reservoir downstream to upstream, and the drawdown of the reservoir from upstream to downstream. Thus, the reservoirs upstream, with the additional function of regulating the seasonal nature of water inflows, are those who present higher fluctuations in their level of storage. As for the reservoirs downstream, with the function of maintaining maximum productivity, they do not usually show high fluctuations being operated as run of river plants.

5. Conclusions

This chapter emphasized the specification of reservoir operation rules by means of Genetic Fuzzy Systems. Mamdani fuzzy inference systems were used to estimate the operating volume of each hydroelectric plant based on the value of the energy stored in the hydroelectric system. For this, a fuzzy system for each hydroelectric plant was specialized, to represent the different behavior of each reservoir in the optimal operation of the system. Genetic Algorithms were applied to tune the membership functions of the linguistic variable of the consequent of the production rules of the $N = 7$ fuzzy systems.

The reservoir operation rule proposed was implemented and compared, through some case studies, with the rule of parallel operation, and with the operation rule based on mathematical functions, and with the operation rule based on Takagi-Sugeno fuzzy system. The results showed the efficiency of the proposed rule when used in the simulation of energy operation of hydroelectric systems. With respect to the energy stored in the system, the tests illustrated that the proposed operation rule requires less water resources under the same operating conditions than the other implemented rules. With the operation rule based on Genetic Fuzzy Systems, power plants downstream, where possible, remain full in order to keep high productivity and enhance the volume of water flowing through them. Thus, the membership functions of the consequent of the fuzzy inference systems prioritize increasingly higher levels of storage in reservoirs upstream to downstream in the cascade of power plants. With the specialization of a fuzzy inference system for each reservoir plant, the operation of each plant reflects the role that it plays in the hydroelectric system, according to its location in the cascade. Therefore, the hydroelectric system is able to maintain higher levels of stored energy. It can be stated that the simulation of the operation using RORGFS maximizes the hydroelectric benefits of the hydrothermal generation system, because it serves the same electricity market, using less hydroelectric resources. It is noteworthy that at the end of the planning horizon, RORP, RORMF and RORTS were not able to keep the storage levels of reservoirs of the system close to the storage levels established by RORGFS, implying that the reliability and the cost of generation of the hydrothermal system will be severely compromised in the future operation of the system.

When a Mamdani fuzzy inference system is chosen to determine the operation rules of the plants of the hydroelectric system, an action/control strategy is obtained which can be monitored and interpreted by the linguistic point of view. Because the fuzzy inference systems are potentially able to express and manipulate qualitative information, another advantage in the application of Mamdani fuzzy systems is due to the fact that domain experts are able to map their experience and decision-making process, both qualitatively. Thus, the strategy of action/control of the Mamdani fuzzy inference system can be regarded as justified and as consistent as the strategy of domain experts.

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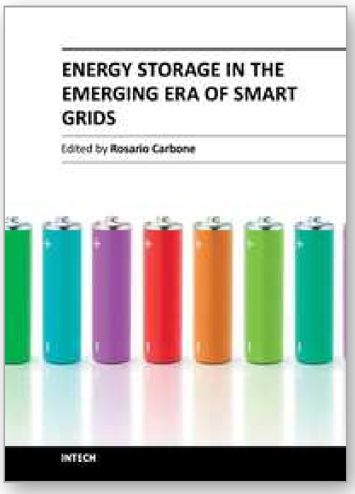

Energy Storage in the Emerging Era of Smart Grids
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Reliable, high-efficient and cost-effective energy storage systems can undoubtedly play a crucial role for a large-scale integration on power systems of the emerging â€œdistributed generationâ€ (DG) and for enabling the starting and the consolidation of the new era of so called smart-grids. A non exhaustive list of benefits of the energy storage properly located on modern power systems with DG could be as follows: it can increase voltage control, frequency control and stability of power systems, it can reduce outages, it can allow the reduction of spinning reserves to meet peak power demands, it can reduce congestion on the transmission and distributions grids, it can release the stored energy when energy is most needed and expensive, it can improve power quality or service reliability for customers with high value processes or critical operations and so on. The main goal of the book is to give a date overview on: (I) basic and well proven energy storage systems, (II) recent advances on technologies for improving the effectiveness of energy storage devices, (III) practical applications of energy storage, in the emerging era of smart grids.

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