



LINEAR PROGRAMMING AND GENETIC ALGORITHM FOR GENERATION MAINTENANCE SCHEDULING AND HYDROTHERMAL DISPATCH CONSIDERING UNCERTAINTIES IN MULTICRITERIA DECISION MAKING

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RESUMO

Este artigo apresenta uma técnica híbrida para resolver o problema de agendamento de máquinas geradoras de energia coordenadas com despacho hidrotérmico baseados no algoritmo genético Chu-Beasley e programação linear. O modelo matemático proposto foi executado e a melhor solução apresentou um custo 10.72% menor que o plano base. Um conjunto de 80 soluções foi utilizado para a tomada de decisão. Os métodos multicritério AHP e TOPSIS foram utilizados considerando os critérios Custo, Racionamento e Distância para cinco diferentes cenários, do pessimista ao otimista. Uma ordenação final foi obtida e as alternativas foram analisadas. O modelo matemático e as estratégias para tomada de decisão podem auxiliar acadêmicos e praticantes neste campo de pesquisa.

PALAVRAS CHAVE. Otimização em sistemas elétricos, Planejamento de manutenção de unidades geradoras de energia, Tomada de Decisão Multicritério com Incertezas.

MH – Metaheurísticas, EN – PO na Área de Energia, ADM – Apoio à Decisão Multicritério

ABSTRACT



This paper presents a hybrid technique for solving the generation maintenance scheduling problem coordinated with hydrothermal dispatch based on the Chu-Beasley genetic algorithm and linear programming. The mathematical model proposed was ran and the better solution had a cost 10.72% lower than the base plan. A set of 80 solutions was used for decision making. The multicriteria methods AHP and TOPSIS were used considering the criteria Cost, Rationing and Distance for five different scenarios, from pessimistic to optimistic. A final order was obtained and the alternatives were analyzed. The mathematical model and the strategies for decision making may help academics and practitioners in this field of research.

KEYWORDS. Optimization in electrical systems. Generation Maintenance Scheduling. Multicriteria Decision Making with Uncertainties.

MH - Metaheuristics, EN - OR in Energy, ADM - Multicriteria Decision Support



Nomenclature

The notation used throughout this paper is reproduced below for quick reference.

Parameters

t : Number of periods
 nch : Number of hydro plants
 nt : Number of thermal plants
 fp : Final period of planning term
 cr : Penalty cost for non supplied electricity
 cs_j : Cost of water spillage at period j
 $v_{i,0}$: Volume of hydroplant i at period 0
 vf_i : Final reservoir storage of hydro plant i
 \overline{gt}_i : Maximum limit of power at thermal plant i
 $a_{i,j}$: Water inflow of hydro plant i at period j
 d_j : Load demand at period j
 \overline{gh}_i : Maximum limit power of hydro plant i
 \overline{gu}_i : Maximum power generation of unit i
 $\overline{u}_i, \underline{u}_i$: Maximum and minimum limit of water discharge at hydro plant i
 $\overline{v}_i, \underline{v}_i$: Maximum and minimum limit of volume at hydro plant i
 fto_i : Water discharge constant of hydro plant i
 $v_{i,0}$: Initial volume of hydroplant i
 $\overline{c}_i, \underline{c}_i$: Maximum and minimum operating cost at generation i
 $\overline{s}, \underline{s}$: Maximum and minimum water spillage among initial population
 n_{pop} : Population size
 n_{mut} : Mutation rate
 n_{tor} : Number of tournaments
 n_{cand} : Number of candidates to tournament
 gen : Number of generations
 α, β : Rationing and spillage weighting factor

Variables

gr_j : non served power at period j
 $s_{i,j}$: Water spillage of hydro plant i at period j
 $gh_{i,j}$: Hydro generation of plant i at period j
 $gt_{i,j}$: Thermal generation of plant i at period j
 $gu_{i,j}$: Power generation of unit i at period j
 $v_{i,j}, u_{i,j}$: Volume and water discharge of the hydro plant i at period j
 $r_{i,j}, s_{i,j}$: Rationing and water spillage of spring i at generation j
 $c_{i,j}$: Operating cost of spring i at generation j
 $ffit$: Fitness function of the genetic algorithm
 $\gamma_{i,j}$: Infeasibility equalization factor
 I : Normalized infeasibility

1. Introduction

The Generation Maintenance Scheduling Problem (GMSP) deals with a combination of different maintenance plans for the generation units. It determines when the units should be taken offline for preventive maintenance. The Hydrothermal Dispatch (HTD) seeks to determine the use of water and fuel resources for hydro and thermal electricity generation. The interconnection between these two problems (GMSP and HTD) searches for determining the operating levels of the system, optimizing the water sources available while complying with electricity demand and



minimizing cost. At the same time pursues assuring the system reliability and security of the power system. Uncertainty regarding future events troubles the maintenance scheduling analysis. Decision making, in this case, takes only into account the variables modeled in the problem, but it does not measure the probability of different scenarios.

The unit maintenance scheduling has been tackled by several authors in the literature. Many different types of formulations were proposed, Due to the features of the problem they commonly applied Genetic Algorithms (GA) to solved it [Wang and Edmund Handschin, 1999; Bisht, 2012; Samuel and Rajan, 2012; Martínez et al., 2014].

At the end of the optimization process an approximated Pareto set of solutions is given to the decision maker (DM). If the DM considers just the lowest cost criterion, the solution with the lowest value will be the choice. However, in real-life problems, this hardly happens. Commonly, the DM faces a more complex situation: a set of feasible solutions with different values to the criteria implemented. Moreover, the uncertainties regarding the future events make the problem more difficult to solve. One of the approaches available to deal with uncertainty and minimizing the impact of the future events is the modeling of uncertainty through multicriteria analysis [Durbach and Stewart, 2012b].

According to Hashemkhani Zolfani et al. [2016], multicriteria decision making considering scenarios is in the focus of the data analysts and experts. This approach allows to evaluate how uncertainties about future topics can affect the decision making process. The scenario analysis is one of five different types of modeling uncertainties provided by Durbach and Stewart [2012b]. In this case, a set of solutions of an optimization problem is exposed to different variations of parameters, one or various multicriteria decision making methods are applied and subsequently, a ranking of alternatives is obtained.

In this work, we proposed a hybrid solution for the generation maintenance scheduling problem based on a metaheuristic that combines a specialized GA based on the Chu-Beasley work [Chu and Beasley, 1997] and linear programming. A set of solutions was obtained from the optimization model. This set of solutions was subject to variations of scenarios in water inflows and demand. Three criteria were taking into account in the multicriteria decision process. They are cost, rationing and distance to the base plan. With the rankings obtained by the MCDM methods, we sought to aggregate the alternatives to obtain a final ordering that reflected the preferences of the DM regarding the multicriteria methods and the scenarios analyzed.

The paper is organized as follows: Section 2 contextualizes the generation maintenance scheduling problem combined with hydrothermal dispatch and presents and discusses the genetic algorithm used and the mathematical formulated proposed. Section 3 provides a briefly presentation about the MCDM methods, especially AHP and TOPSIS, and their application based scenarios. Section 4 describes the research methodology and the procedure of this study. Section 5 presents and discusses the results. Finally, Section 6 presents conclusion, limitations and recommendations for future studies.

2. Generation Maintenance Scheduling Coordinated with Hydrothermal Dispatch

The generation maintenance scheduling problem is a complex combinatorial problem studied since early 70s throughout exact methods and heuristics. Traditionally, in hydrothermal systems preventive maintenance must be performed on a number of power units within a fixed planning term, while minimizing cost and providing the power capacity to comply with expected demand. This problem has different approaches depending on whether the power system is open or centralized. In both cases, genetic algorithms (GA) have been applied to find solutions [Wang and Edmund Handschin, 1999].

Hydrothermal dispatch, also known as scheduling, coordination or planning, is the problem of determining the use of water and fuel resources in hydro and thermal plants respectively in order to minimize the operating thermal cost while fulfilling demand and operating constraints.



This problem is massively constrained with a large number of variables [Wang and Edmund Hand-schin, 1999; Jimenez and Paucar, 2007; Martínez et al., 2014]. It is stochastic typed derived from the uncertainty in demand, fuel cost and water inflows. Just the IEEE Explore data base reports more than 400 papers addressing HTD since 1954, most of them contributions of Brazilian authors. Several and diverse techniques have been proposed in the literature to find solutions to this problem. Again, genetic algorithms are used in many papers of the list.

2.1. Genetic Algorithm of Chu-Beasley

In this work, we are solving hydrothermal dispatch and generation maintenance scheduling in a coordinated way by using a GA based on the work presented by Chu and Beasley [Chu and Beasley, 1997]. These two authors developed a genetic algorithm, meant for the generalized assignment problem (GAS), but successfully applied in transmission expansion planning [Silva et al., 2006]. We adapted their technique to the GMSP. The steps involved in our adapted version of the Chu-Beasley GA are as follows:

1. Generate an initial population of N solutions. Part of the solutions are randomly generated, another part are heuristics built on the knowledge of hydrothermal systems.
2. Check diversity. In this algorithm all individuals must be different in each generation, so it is the offspring that enters the population.
3. Decode the solution to obtain the fitness value, which is based on the cost and the degree of infeasibility. That includes the spillage and the unserved power cost.

$$f_{fit} = c_{op} + \gamma * I \quad (1)$$

$$\gamma = \frac{\bar{c}_{op} - \underline{c}_{op}}{\bar{I} - \underline{I}} \quad (2)$$

The numerator in (2) represents the difference between the maximum and the minimum operating cost. Meanwhile, the denominator is computed as the difference between the extreme values (maximum and minimum) of the normalized infeasibility. All values are related to the initial population. The normalized infeasibility is calculated by $I = \alpha(r/\bar{r}) + \beta(s/\bar{s})$

4. Select the parents for reproduction in a tournament selection method.
5. Generate a child solution by applying one-point crossover operator. The crossover point is selected randomly.
6. According to the mutation rate, accomplish mutation.
7. An individual of the population will be replaced by the offspring in the following cases: a) The offspring is infeasible. If its degree of infeasibility is lower than the most infeasible of the current population and it complies diversity. b) The offspring is feasible. If its cost is lower than the cost of all individuals in the current population and it complies diversity. Otherwise, the algorithm steps forward to the next generation without accomplishing replacement.

2.2. Mathematical Modeling

The solution is divided in two stages: Firstly the genetic algorithm that solves the maintenance scheduling. Secondly the linear programming optimization part that solves the HTD problem. The genetic algorithm generates the maintenance scheduling proposals. Each proposal is evaluated in terms of the cost, rationing and spillage by the linear technique.



In order to keep the HTD model linear, the following strategy was adopted: Instead of considering the binary variables that represent the units maintenance outages, this work subtracts the power capacity of the unit to be maintained from the total capacity of its respective power plant.

Consequently, the mathematical model is an LP (Linear Programming) typed. It searches for the optimal maintenance scheduling that minimizes the cost function that comprises three terms: operating cost of thermal generation, rationing cost and spillage cost. Consequently, the model does not include the cost associated to the maintenance task and optimizes the energy resources available. The reason is that we are solving the problem from the point of view of the Integrated System Operator in assuming a centralized electric scheme.

This model is an extension of previous works on HTD [Bisht, 2012; Jimenez and Paucar, 2007; Martínez et al., 2014] and GMSP. This model considers linear operating costs for thermal generation. It is subjected to constraints related to: the manpower availability to carry out the maintenance task specifies that no two units can be simultaneously maintained by the same crew at the same power plant; that no more than tree units can be simultaneously maintained by different crews (crew constraints); completion of maintenance operation guarantees that the maintenance for each unit must occupy the required time duration without interruption (maintenance completion constraint) [Samuel and Rajan, 2012] all maintenance schedules generated by the GA comply with the previous constraints. The HTD model evaluates the maintenance schedules and has the following constraints: energy balance, water balance, maximum thermal and hydro generation, productivity of the hydro plants maximum and minimum limits of water discharge for the hydro plant maximum and minimum volume limits for the water reservoirs and minimum energy storage; finally the variables are defined.

$$\min \sum_{i=1}^{nt} \sum_{j=1}^t cost_{ij} \cdot g_{i,j} + \alpha \sum_{j=1}^t cr_j \cdot gr_j + \beta \sum_{i=1}^{nh} \sum_{j=1}^t cs \cdot s_{i,j}$$

subject to

$$\sum_{i=1}^{nh} gh_{i,j} + \sum_{i=1}^{nct} gt_{i,j} + gr_j = d_j; \quad j = 1..t$$

$$v_{i,j} = v_{i,j-1} + a_{i,j} - u_{i,j} - vv_{i,j}; \quad i = 1..nh, j = 1..t$$

$$\underline{gh}_i \leq gh_{i,j} \leq \overline{gh}_i; \quad i = 1..nh, j = 1..t$$

$$\underline{gt}_i \leq gt_{i,j} \leq \overline{gt}_i; \quad i = 1..nt, j = 1..t$$

$$gh_{i,j} = fto_i \cdot u_{i,j}; \quad i = 1..nh, j = 1..t$$

$$\underline{u}_i \leq u_{i,j} \leq \overline{u}_i; \quad i = 1..nh, j = 1..t$$

$$\underline{v}_i \leq v_{i,j} \leq \overline{v}_i; \quad i = 1..nh, j = 1..t$$

$$v_{i,fp} = vf_i; \quad i = 1..nch$$

$$gh_{i,j}, gt_{i,j}, u_{i,j}, v_{i,j}, s_{i,j} \in R^+$$

3. Multicriteria Decision Making Methods

Multicriteria decision making methods aims to choose the best alternative according to established criteria [Saaty, 2008; Opricovic and Tzeng, 2004]. These methods have been used in a variety of research fields, including power management, renewable energy and power systems [Yamamoto et al., 2001; Lin et al., 2006; Mardani et al., 2015].

Several MCDM methods are available in the literature [Mardani et al., 2015]. Their application in many fields of research help in selecting the best alternatives based on decision-makers



preferences. Mardani et al. [2015] reviewed systematically MCDM techniques and approaches from 2000 to 2014. The methods were grouped into 15 fields. Energy was ranked as one of the top three areas that have applied MCDM techniques and approaches.

Moreover, Mardani et al. [2015] explored the wide variety of applications of those methods in the various fields of research. Note also that aggregation DM methods have a large number of applications. This line of research about the future is in the focus on the data experts and decision-makers [Hashemkhani Zolfani et al., 2016]. Furthermore, Durbach and Stewart [2012b] emphasized that one of the most important issues in integrating the use of scenarios combined with multicriteria analysis is how to compare and aggregate results from different scenarios.

3.1. AHP Method

The Analytic Hierarchy Process (AHP) was created in 80's by Thomas L. Saaty [1980]. This method is one of the most popular in the literature. According to Saaty, through the comparisons between the alternatives and criteria decomposed into hierarchies, the priorities calculated in the method are able to capture measures based on experience, intuition and physical data to solve the problem.

Ho [2008] provided a literature review of the applications of the integrated AHP. Note that there are many applications of this method as well as combinations with other methods. In addition, many authors use the weight of the criteria based on AHP in their ability to represent measures regarding criteria judgments. Namely, this strategy is adopted in this current article. The weights obtained by the AHP were combined to represent the value of the criteria in another multicriteria method. For simplicity, the stepwise procedure for AHP is not detailed in this paper, however it can be read in Saaty [2008] and Ho [2008].

3.2. TOPSIS Method

The Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method, proposed by Tzeng and Huang [1981], which is based at choosing the best alternative, that is with the shortest Euclidean distance from the positive ideal solution (PIS) and the farthest from the negative ideal solution (NIS). For instance, PIS maximizes the benefit and minimizes the cost, whereas the NIS maximizes the cost and minimizes the benefit. It means that each criterion require to be maximized or minimized. Its applicability has received much attention, especially in supply chain management and logistics and design, engineering and manufacturing systems fields [Behzadian et al., 2012]. Moreover, Behzadian et al. [2012] provided a state-of the-art literature survey on TOPSIS applications and methodologies. According to these authors, the following steps are used to evaluate the method, see Fig. 1.

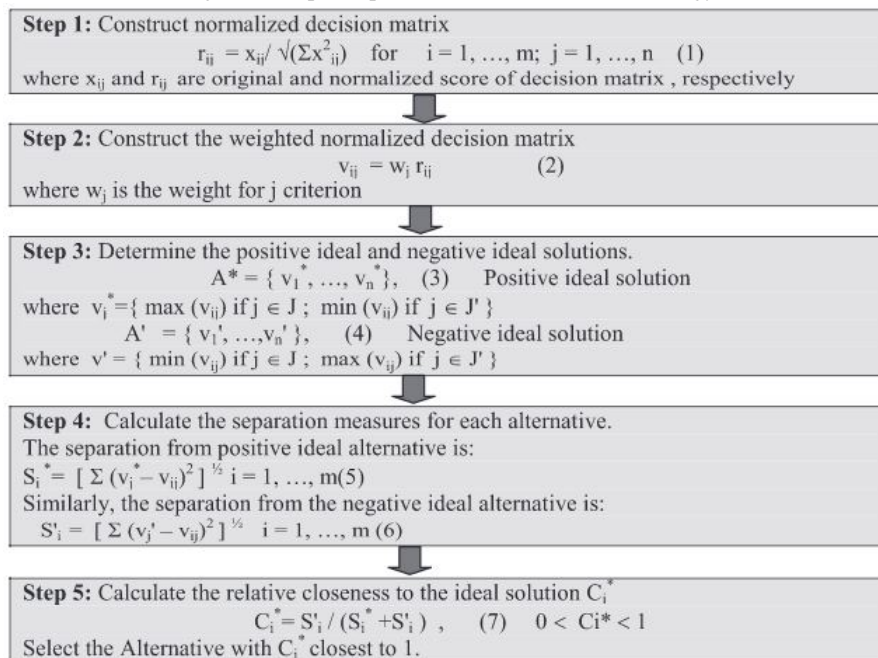
3.3. Multicriteria Decision Analysis based on Scenarios

According to Polasky et al. [2011], the major advantages of decision theory are that it provides a clear statement of the problem and objective for DM. However, the authors pointed out the importance of “to consider not only the future impacts of current decisions, but also the potential for learning from decisions that can help inform future decisions”.

Decision-making under uncertainty scenarios deals with “sets of plausible stories, supported with data and simulations, about how the future might unfold from current conditions under alternative human choices” [Polasky et al., 2011]. Durbach and Stewart [2012b] considered at least five types of modeling uncertainties. And Durbach and Stewart [2012a] provided a general formulation for uncertainty modeling. The evaluation expected of an alternative A_i takes into consideration the weight associated with a specific scenario, the number of scenario used and the evaluation of alternative A_i on criterion C_j . Aggregation over scenarios were recommended by the authors.



Figure 1: Stepwise procedure for TOPSIS methodology



Source: Behzadian et al. [2012]

4. Research Methodology

4.1. Optimization Problem

As stated above, this paper aims at performing a solution for HTD and GMSP in a coordinated way by using an adapted version of the Chu-Beasley GA. Our meta-heuristic technique combines a specialized genetic algorithm and linear programming. This technique was adapted, as described in 2.1. Firstly, the GA solves the GMSP and then the linear programming makes a local search of the HTD part of the solution, subtracting the power capacity of the unit to be maintained from the total capacity of its respective power plant. The proposed model was inspired by previous works on HTD and GMSP [Jimenez and Paucar, 2007; Bisht, 2012; Martínez et al., 2014]. It is important to remark that non exact techniques do not guaranty the optimal solution, but a good quality solution that eventually might be the global optimum. At the end of the evolution process of the GA, the individuals represent good quality solutions, in this case that means, individuals of low cost and eventually without rationing. Considering cost as the only criterion, the decision maker will prefer the solution with lowest value. In this research, in order to analyze how the MCDM methods can be applied, we opted for solutions with greater variability, that is, we stopped the GA before its convergence to have a set of solutions diversified in the evaluated criteria. Keeping the same mathematical model (see 2.2), parameters of demand and water inflow were varied. Data presented by Martínez et al. [2014] were used. The authors took real data published by the UPME (Mining and Energy Planning Unit of Colombia, in English) and consider a planning term of 52 weeks.

4.2. Decision Making Considering Scenario Analysis

A set of 80 solutions was obtained through the proposed model, i.e. 80 maintenance plans. These 80 alternatives were evaluated on following criteria: Cost (C_1): related to cost for each alternative; Rationing (C_2): related to rationing for each individual of GA; Distance (C_3): related to distance between the individual and Base Plan.

According to Polasky et al. [2011], decision-making under uncertainty scenarios deals with “sets of plausible stories, supported with data and simulations”. More than that, Durbach and



Stewart [2012b] argued that previous works showed that people focus on optimistic scenarios and ignore pessimistic scenarios when predicting their own performance. Given the above, we created 5 different scenarios modifying the parameters of water inflows and demand. They are: Standard (S_1): same parameters of the optimization model; Low Pessimistic (S_2): low hydrology and low demand; Very Pessimistic (S_3): low hydrology and high demand; Low Optimistic (S_4): high hydrology and high demand; Very Optimistic (S_5): high hydrology and low demand. The distance to the base plan was the same for all scenarios.

In order to get the weight of the criteria, the AHP method was invoked giving higher degree of preference for the alternatives with lower cost and less demand. The weights obtained from the AHP were: C_1 : 0.4660, C_2 : 0.4328 e C_3 : 0.1012. Then, the TOPSIS method was executed for each scenario. Five different rankings were obtained. They represent the preferences of the decision maker regarding the weights used and reflect the ordering of each alternative for each scenario, based on variations of water inflow and energy demand.

Subsequently, as suggested by Durbach and Stewart [2012b] we compare and aggregate the results from different scenarios in order to get a single final ordering. In this step, we adopt different weights for each scenario seeking to safe against some future event.

The current solution for the optimization process was built on C++ language. CPLEX solver was invoked for the linear part of the solution. The multicriteria analysis was implemented in Matlab R2015a.

5. Results and Discussion

5.1. Optimization Process

Computational results show that the Base Plan presents no water spillage along the planning term, but rationing (non served power demand) of 549.812 *MW* at the first period. The cost for this plan is \$1,346,739.060.

Table 1 contains the parameters of the genetic algorithm for the best solution found by our GA algorithm: The crossover mechanism selected for the solution is 1-point typed.

Table 1: Parameters of the genetic algorithm.

n_{pop}	n_{mut}	n_{tor}	n_{cand}	α	β	γ	gen
80	0.0022	2	2	1	5	9,914.705	1,000

The best solution obtained by our GA-based meta-heuristic has a cost of 1,202,232 *MU*. The vector containing the initial week of the maintenance schedule is [18 28 24 22 30 26 36 24 32 26 0 9 17 0 37 45 41 47 16 20 30 13]. This is a better solution compared to the Base Plan since the cost is 10.72% lower (a reduction of 144,355.002 *MU*). Besides, the Best Solution presents no rationing at all. The population turns entirely feasible within 53 iterations (generations) and meets the incumbent within 555 generations. A remarkable result is the fact that after the generation 852, the 80 individuals of the population are equal in cost. Due to the diversity characteristic of this particular GA, this means that in fact we have 80 alternative best solutions, judging only from the cost point of view.

The best performance of our algorithm is reached when two parents participate in the tournament. A higher number of parents increases the cost of the solution. When setting the population size at 60 individuals, the algorithm gets trapped in the same value (a local optimum) from the first generation. The best maintenance scheduling (lowest incumbent) shows up when population size equals 80 individuals.

Machine Specifications: The tests were performed in a machine Intel (R) Core (TM) i7 -4770 3.40 GHz processor, 16 GB RAM, Windows 7 64-bit operating system. No parallel processing was carried out. Average run time of the algorithm is 16810174ms (4.67 hours) for 1,000



iterations. This means that each iteration takes about 16.81 seconds. The computational complexity of the algorithm is $O(n_1^2 * n_2)$. For this specific machine, the time constant for the algorithm mc is calculated as the quotient between an iteration time and the complexity: $mc = 16.81/(n_1 * n_2^2)$ where $n_1 = 22$ (number of generation units) and $n_2 = 52$ (number of time periods)

5.2. Decision Making

It is known the best solution provided by GA-based meta-heuristic has low cost (compared with the base plan) e presents no rationing at all. Based on that, for we got a set of diversified solutions, some generations of the genetic algorithm were executed, but the algorithm was stopped before convergence. The TOPSIS method was performed using the weights obtained by the AHP method. This process resulted in 5 different rankings. For the sake of simplicity, only the index of the first 20 alternatives of each scenario were summarized in Table 2. The interpretation indicates in which position each of the listed alternatives was ranked by TOPSIS method in each scenario. The A_1 alternative was ranked at 40th in the S_1 scenario, 70th in the S_2 scenario and so on.

Table 2: Index of the 20 best alternatives of each scenario

A_n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
S_1	40	17	42	18	5	4	22	24	20	39	3	9	1	48	63	62	8	2	32	51
S_2	70	27	73	29	9	8	35	50	45	72	7	24	4	3	2	1	13	6	5	38
S_3	75	33	73	32	14	8	37	44	28	66	7	15	5	4	2	1	19	6	3	29
S_4	52	10	26	20	9	8	54	27	28	72	7	12	4	3	2	1	33	6	5	41
S_5	73	26	69	25	10	8	34	40	27	66	7	13	4	3	2	1	15	6	5	32

According to Durbach and Stewart [2012a] the evaluation of uncertainty includes aggregation of scenarios. The evaluation expected of an alternative A_i takes into consideration the weight associated with a specific scenario, the number of scenarios used and the evaluation of alternative A_i on criterion C_j . It is also known that the good method of decision making is one that reflects the preferences of the decision maker. When adding different scenarios, these preferences must be taken into account. Thus, adopting a conservative decision, the following weights were used for the scenarios: S_1 : 0.4, S_2 : 0.2, S_3 : 0.1, S_4 : 0.2, S_5 : 0.1. In order to obtain aggregated ranking each alternative was multiplied by the weight of scenario, i.e. $\sum_{i=1}^N \sum_{j=1}^J [w_j * A_i^j]$, where w_j is the weight associated with criterion j and A_i^j is the evaluation of alternative i on criterion j . Finally, the final ordering was obtained. The final result with the first 20 alternatives was summarized in Table 3.

Table 3: Final ordering using scenarios

Ranking	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
A_n	13	18	11	6	5	65	41	12	55	30	19	17	34	64	2	69	14	66	4	68

After comparing the results of the best ranked alternative (A_{13}) with the least cost alternative of each scenario (among those obtained by our GA-based meta-heuristics) it is realized that this alternative presented an average increase of 2.40% on criterion Cost (C_1). However, this same alternative offers benefits when it is compared to the other two criteria, Rationing (C_2) and Distance (C_3). The gains over C_2 are little expressive, but it has an expressive gain compared with C_3 , even if this criterion has the lowest weight obtained by the AHP method. The distance from the alternative obtained by the aggregation of the methods is, on average, 2.38 times smaller than the plan base. These results were summarized in Table 4.

The aggregation analysis demonstrates that although cost remains as a fundamental criterion, other impacts should not be neglected in a GMSP + HTD energy decision-making. The strategy of using different scenarios and considering weights for each scenario, given the probability of occurrence or the preferences of the decision maker may improve the decision making process



Table 4: Differences between the values of the best alternative from the rankings aggregated with the lowest alternative of least cost in each scenario

Criterion	Scenarios				
	S_1	S_3	S_3	S_4	S_5
C_1	+1.91%	+0.41%	+4.58%	+3.79%	+1.32%
C_2	0%	0%	+0.01%	+0.41%	0%
C_3	-411%	-343%	-306%	-366%	+235%

minimizing losses in case of future changes.

6. Conclusion

The Generation Maintenance Scheduling Problem aims to determining when the units in power systems should be taken offline for preventive maintenance. The combination with Hydrothermal Dispatch seeks to determine the use of water resources for hydroelectricity generation, minimizing the costs and upgrading the reliability of whole system.

We have presented a hybrid solution for the GMSP based on a meta-heuristic that combines a specialized genetic algorithm and a linear programming. The model was suitable for solving this problem. Some generations of the GA were executed, but the algorithm was stopped before convergence to have a set of solutions diversified and to do the decision making analysis. The multicriteria method AHP was used to get the weight of the following criteria: Cost (C_1): 0.4660, Rationing (C_2): 0.4328 and Distance to the base plan (C_3): 0.1012. Five uncertainty scenarios were created to help clarifying the effects of future impacts of current decisions, varying parameters of water inflows and demand. These scenarios were aggregated and a single final ordering was obtained. The solution best ranking by the aggregation was compared with the least cost solution of each scenario, despite an average increase of 2.40% in cost, the alternative has low difference in relation to rationing and presents a reduction of 2.38 times in the distance to the base plan.

The data used in this paper come from a practical real-life problem of maintenance planning. The mathematical model proved to be suitable for the problem, but it is known that there are many investigations in this field of research. Regarding decision-making, scenario analysis have received potential attention from researchers and practitioners. A test system built and the strategies for decision making is available for further interested in this field of research.

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