A bi-criteria decision support system for the Brazilian hydrothermal operation planning

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ABSTRACT. Electric energy generation in a hydroelectric prevalent system is a time dependent process, since the present hydroelectric energy generation impacts the storage level of the reservoirs in the future. This fact implies dealing with economic and hydrologic uncertainties. This paper discusses the robustness of the techniques presently adopted for decision under uncertainty in the hydrothermal operation planning of the Brazilian system, and proposes the development of a bi-criteria decision support system that would systemize the necessary human participation in the decision.

KEYWORDS. Multicriteria analysis; Decision support system; Hydrothermal operation planning.

1. HYDROTHERMAL OPERATION PLANNING IN BRAZIL FROM 1973 TO 2009

Electrical energy is a product specially immersed in uncertainties. There are unreliable data, measuring errors, possibility of equipment and human failures, macroeconomic and hydrological unpredictability, exposition to atmospheric storms, instability in fuel availability and pricing, geopolitics questions and hidden competitive strategies.

In thermal prevalent generation systems, however, operation planning is not affected by these uncertainties. In this case, the decisions can be obtained by sorting the thermal plants in increasing order of their operating costs, subject to electric reliability constraints. In a hydroelectric prevalent system, however, energy generation is a time dependent process, since the present hydroelectric energy generation impacts the storage level of the reservoirs in the future. This fact implies that, for deciding between thermal or hydro generation, there are uncertainties to deal with: macroeconomic and hydrological unpredictability and instability in fuel availability and pricing.

Hydrothermal operation planning of the Brazilian system started in 1973, year in which an international treaty was signed between Brazil and Paraguay to build Itaipu, the world's largest power plant until August 2009. It was established since 1973 that only the hydrological uncertainties would be considered, and that the Brazilian hydro plants would be represented, in pluri-annual analysis, by one equivalent energy reservoir by region (Fortunato et al., 1990).

Since 1974, the operation planning decisions were taken to protect the system against the repetition of the worst historic hydrological conditions, represented by the critical period of the recorded historical inflows for the Brazilian Southeast region. The critical period is defined as the period in which the energy storage goes from completely full to completely empty, considering a fixed generation in every month since 1931. For the Southeast, the critical period starts in 1952 and finishes in 1956.

This method was replaced, in 1979, by a probabilistic approach, based on Stochastic Dynamic Programming (Terry et al., 1986), with the minimum cost criteria for a five-year horizon. This method required that a cost should be attributed to energy shortages.

Due to the curse of dimensionality, since 1998, when the North-South interconnection was launched, the operation planning methodology used in Brazil is based on Stochastic Dual Dynamic Programming (Pereira, 1989), implemented in a computer model called NEWAVE. Under this method, the strategy along a five-year horizon is calculated for a selected set of states, which are defined by the trajectories resulted from the simulation of a sample of possible inflow sequences.

This approach reigned until the 2001/2002 rationing period in Brazil. After that, a risk aversion curve for the reservoirs storage was defined. It was implemented in the NEWAVE model, leading to the use of all thermal generation whenever the storage is below the risk aversion curve (Kligerman et al., 2005). This risk aversion approach, though, is still probabilistic, and in some cases the decisions given by the model have been overruled by deterministic considerations.

In 2008, the wet period in the Southeast region, instead of starting in December, had not begun until mid-January. This caused a special fear that put in motion the development of Short Term Operative Procedures (ONS, 2008), in which a security storage level is defined for the current month, based on a high confidence that minimum storage levels defined for the next two years are accomplished.

In short, in 2009, the hydrothermal operation planning in Brazil is at the same time based on stochastic optimization and deterministic assurance. It results in huge processing resources and time to provide mostly overruled decisions that, given all uncertainties that are not considered, should never have been called optimal solutions (Clímaco, 2001). These facts create a condition that claims for the development of a decision support system (DSS) as a natural evolution for the recent Brazilian operation planning migration from a minimum cost criteria to an energy security criteria.

2. THE HYDROLOGICAL UNCERTAINTY REPRESENTATION

As hydrological uncertainties shall be considered by the proposed DSS, stochastic and deterministic approaches are analyzed in this paper. The deterministic approach has the advantage of allowing the detailed representation of the hydroelectric generation, at the expense of considering only one possible future inflow sequence.

The stochastic optimization can be read as obtaining the minimum expected cost for a sample of inflow sequences, while the deterministic optimization can be read as obtaining the minimum cost for the expected inflow sequence (Figure 1).

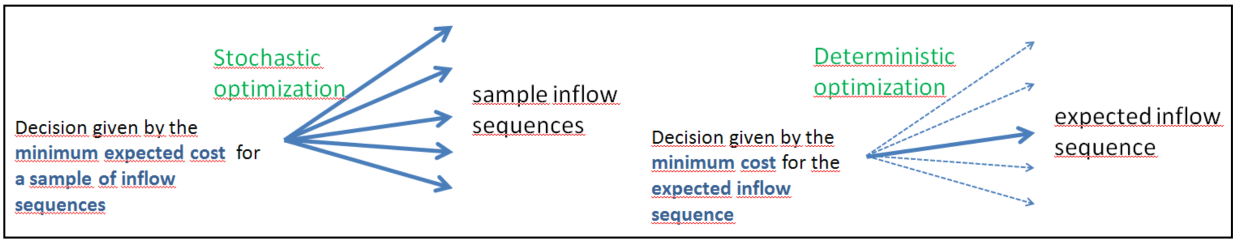

Figure 1: Stochastic and deterministic optimization approaches

It is known that if a decision is taken many times for random scenarios using stochastic optimization, the average result is the optimal cost. In the operation planning, though, a decision is taken only once, and only the real life scenario happens. Based on this, after solving the stochastic optimization for a certain month, it would be possible to adjust a specific energy inflow sequence by region that would result, through deterministic optimization, in the same optimal cost of the stochastic optimization. This can be assured, because both the inflows and the cost are continuous variables. So, in fact we are comparing two deterministic optimizations, one with the expected inflow sequence, and another with a certain specific inflow sequence (Figure 2).

Considering the hydrological uncertainty and some other uncertainties that are not represented, the two approaches can be taken as equivalent. As deterministic optimization is a faster procedure, it was chosen to be used in the proposed DSS.

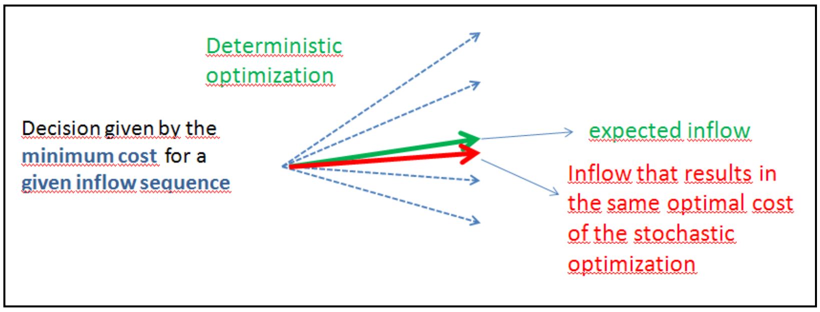

Figure 2. Stochastic reduced to deterministic optimization

3. THE PROPOSED DECISION SUPPORT SYSTEM

3.1. The role of the human decision-maker

Decision is a consequence of what is wanted, of what is known, and of what is possible. In the absence of uncertainty, each possible decision leads to a unique consequence. Once the desired consequence is chosen, the decision is taken. Thus, Decision Theory is not applicable to such situations. While uncertainty matters, however, a new question arises: who is the best decision maker: a human being or the machine?

It can be stated that the machines are rational, while human choices are influenced by limited rationality. On the other hand, machines are not able to model all the available information, while a human decision maker can not only deal with all the available information, but also make associations. Computers, in their turn, are ideal for unbounded data storage and calculation, something impossible for humans. These facts imply that human beings and computers are complementary, and we state that decision making it is a role for humans, helped by computers.

3.2. Workflow and criteria of the proposed DSS

The proposed decision support system can be represented as in Figure 3. Models, tools and all available data are accessible by the decision maker through a powerful interface.

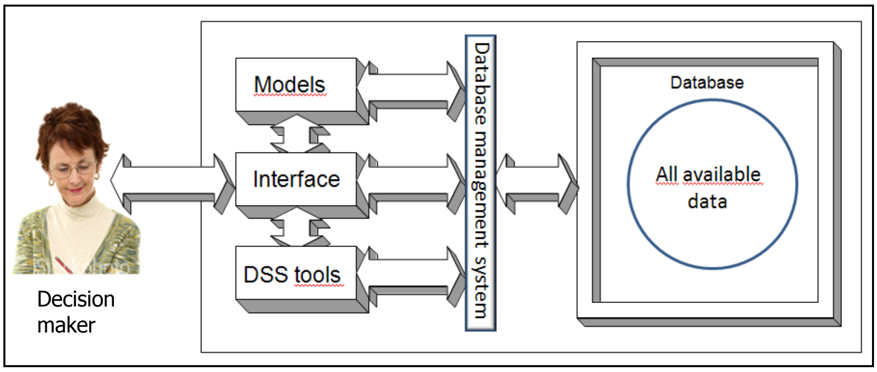

Figure 3. The proposed DSS structure

The workflow of the proposed DSS has the following steps:

- Generation of a set of feasible solutions.
- Selection of a reduced set of solutions, based on additional information.
- Multicriteria analysis decision aid to choose the solution that will give the decisions to be taken.

The hydrothermal operation planning is affected mostly by four conflicting criteria: cost, electric reliability, energetic security, and environmental security.

Nevertheless, considering the Brazilian recent increase of energy security concerns into a strategy historically based on the minimum expected cost criteria, the proposed DSS is bi-criteria, dealing with cost and energetic security.

4. GENERATION AND SELECTION OF A SET OF FEASIBLE SOLUTIONS

To provide the set of feasible solutions to be considered in the proposed DSS, we propose to solve 76 deterministic optimization problems, each one using a different inflow sequence. These inflow sequences (ONS, 2008b) are based on the historical record, available from 1931 to 2007. The optimization horizon is from the current month up to November of the year after.

November is the last month before the wet season in the Southeast region. In consequence, a security target level is regulated by law, and applied to the Southeast and the Northeast energy storage levels at the end of November of each year. The deterministic optimization takes into account this target levels, and the optimization for each one of the 76 inflow sequences provides 76 solutions. Each solution corresponds to a thermal generation decision for the current month, and some solutions may result in the same decision. Therefore, the first selection is to keep only one solution for each different amount of thermal generation.

4.1. Selecting decisions based on additional information

Besides the official data that is used to generate the feasible solutions, the National Independent System Operator, ONS, performs its own climatologic and macroeconomic studies that provide additional information capable of improving the decision making. It is possible, from these studies, to obtain the forecast of load consumption deviation from the official data and the forecast of deviation from the autoregressive expected energy inflow. This information is considered up to the month of November of the current year, and consolidated according to expression (1):

$$\Delta = \sum_{s=1}^{NS} T_s - \sum_{s=1}^{NS} D_s \,, \tag{1}$$

where Δ = consolidated deviation based on additional information;

s = subsystem (region) index;

NS = number of subsystems;

D_s = forecast of load consumption deviation up to November; and

T_s = forecast of deviation from the autoregressive expected energy inflow up to November.

Each of the inflow sequences can also be compared with the autoregressive expected energy inflow, and will have a consolidated deviation according to expression (2):

$$\Delta(\text{inflow sequence}_i) = \sum_{s=1}^{NS} A_{i,s} - \sum_{s=1}^{NS} E_s, \tag{2}$$

where $\Delta(\text{inflow sequence}_i)$ = consolidated deviation from the autoregressive expected value;

i = inflow sequence index;

$A_{i,s}$ = energy of the inflow sequence i up to November in the subsystem s; and

E_s = expected autoregressive energy inflow up to November in the subsystem s.

The decisions are selected based on the similarity of the consolidated inflow sequence deviation of expression (2) and the consolidated deviation based on additional information of expression (1). The percentage of selected decisions from the available set depends on the reliability of the additional information, varying from 20% for high reliability to 50% for low reliability.

5. MULTICRITERIA ANALYSIS DECISION AID TO DETERMINE THE DECISION

ELECTRE III and PROMETHEE II are two commonly used outranking methods for decision aid in multicriteria decision making (Collette and Siarry, 2003).

PROMETHEE II was chosen to be used in the prototype of the proposed DSS for two main reasons, both considering its use in such sensitive issue as the electric system operation planning. First, because it has a transparent influence of each criterion and weight on the solution, which permits an investigation into the steps taken to reach the decision. Second, because it results in a complete rank order, letting the decision to be reproducible (Beynon, 2008).

This method is based on a preference intensity measure associated with the distance $d_j(a,b)$ between two different solutions a and b for each criterion j. Each criterion may have a different preference function, in which the preference intensity varies from 0 (indifference) to 1 (strict preference). In the proposed DSS, the preference functions showed in Figures 4a and 4b were given for the two criteria, cost and energetic security (measured as a risk). In these graphics, L_s, L_{inf} and L_{sup} shall be defined by the decision maker.

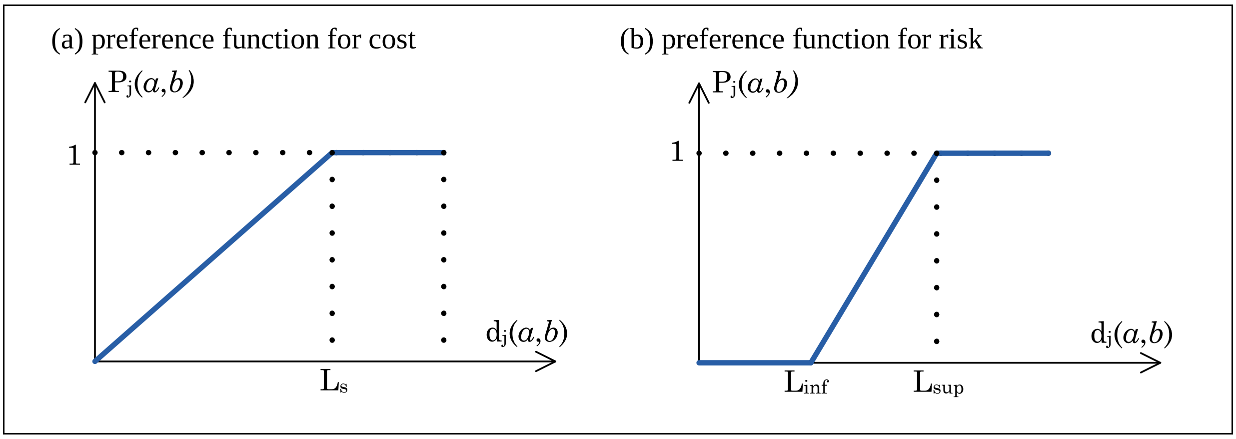

Figure 4: Preference functions chosen for the proposed DSS

This method follows with the calculation of the global preference for each pair of solutions, as in expression (3), using a normalized weight k_j for each criteria, given by the decision maker:

$$\prod(a,b) = \sum_{j} k_j \times P_j\,(a,b) \qquad (3)$$

The input and output flows for each solution are also calculated. The input flow, $\Phi^+(a)$, means the intensity that a is preferred to the other solutions, and the output flow, $\Phi^-(a)$, means the intensity that the other solutions are preferred to a:

$$\Phi^+(a) = \frac{1}{N-1}\sum_{i=1}^{N-1}\prod(a,a_i) \qquad \Phi^-(a) = \frac{1}{N-1}\sum_{i=1}^{N-1}\prod(a_i,a) \qquad (4)$$

where N is the number of competing solutions in this phase. Finally, the general flow (5) is calculated for each solution:

$$\Phi(a) = \Phi^+(a) - \Phi^-(a). \qquad (5)$$

The chosen decision is that with the greatest general flow.

6. CASE STUDY: MAY 2009

A case study was performed, considering the same conditions observed in May 2009. In this month, there were two relevant additional informations not considered in the original operation planning strategy. Concerning the energy inflow forecasts, the occurrence of the El Niño phenomenon in 2009 was already established at that time. Inflow forecasts should also consider the effect of the corresponding Pacific-Ocean surface temperatures. The deviation above the expected autoregressive energy inflow up to November amounted to 3,400 MWmonth. Concerning the load consumption, the effects of the financial crisis was not entirely considered in the official data, and a negative deviation was forecasted, reaching 1,000 MWmonth up to November.

The solutions that were selected considering the additional information are shown in Table 1. Risk, in this table, represents the percentage of historic inflow sequences for which the adequate thermal generation in the first month should be greater than the amount given by the considered solution.

Table 1. Selected solutions based on the additional information

Solution index	Inflow sequence	Thermal generation (MW)	Cost (10^3 R$)	Risk (%)
16	1953	1,980	170,113.50	36.5
19	1958	1,574	118,055.17	51.4
24	1947	570	21,130.79	62.1
25	1955	370	7,636.15	67.6
26	1993	114	1,590.34	74.3
27	1935	0	0.00	75.7

Using PROMETHEE II, with weights 0.6 for cost and 0.4 for risk, L_{inf} = 5%, L_{sup} = 10%, and L_s = R$ 152,650,000.00, the chosen solution is given by the greatest general flow, as shown in Table 2.

Table 2. Solution chosen by PROMETHEE II for the settings defined by the decision maker

	Global preferences $\prod(\mathbf{a},\mathbf{b})$								
Solution	**24**	**16**	**19**	**25**	**26**	**27**	$\Phi^+(a)$	$\Phi^-(a)$	$\Phi(a)$
16	0.00000	0.40000	0.40000	0.40000	0.40000	0.40000	0.4000	0.51804	-0.1180
19	0.20462	0.00000	0.40000	0.40000	0.40000	0.40000	0.3609	0.42735	-0.0664
24	**0.58559**	**0.38097**	**0.00000**	**0.04000**	**0.40000**	**0.40000**	**0.3613**	**0.20258**	**0.1587**
25	0.60000	0.43401	0.05304	0.00000	0.13600	0.24800	0.2942	0.17876	0.1155
26	0.60000	0.45777	0.07680	0.02376	0.00000	0.00000	0.2317	0.26845	-0.0368
27	0.60000	0.46402	0.08306	0.03001	0.00625	0.00000	0.2367	0.28960	-0.0529

The chosen solution, indexed as 24, represents 570 MW of thermal generation in the current month, using thermal plants whose costs amount up to 90.69 R$/MWh.

7. SENSITIVITY ANALYSIS

The proposed DSS is driven by the parameters attributed by the decision maker. To clarify how far the chosen parameters influence the output, we performed a sensitivity analysis, considering the same case study. We first consider that, in a risk aversion approach, the decision maker would assign a weight 0.6 for risk, instead of 0.4. The results obtained by PROMETHEE II are shown in Table 3.

Table 3. Solution chosen by PROMETHEE II considering a risk aversion approach

	Global preferences $\prod(\mathbf{a},\mathbf{b})$								
Solution	**24**	**16**	**19**	**25**	**26**	**27**	$\Phi^+(a)$	$\Phi^-(a)$	$\Phi(a)$
16	**0.00000**	**0.60000**	**0.60000**	**0.60000**	**0.60000**	**0.60000**	**0.60000**	**0.34536**	**0.25464**
19	0.13641	0.00000	0.60000	0.60000	0.60000	0.60000	0.50728	0.35157	0.15571
24	0.39039	0.25398	0.00000	0.06000	0.60000	0.60000	0.38087	0.26839	0.11249
25	0.40000	0.28934	0.03536	0.00000	0.20400	0.37200	0.26014	0.25917	0.00097
26	0.40000	0.30518	0.05120	0.01584	0.00000	0.00000	0.15445	0.40163	-0.24719
27	0.40000	0.30935	0.05537	0.02001	0.00417	0.00000	0.15778	0.43440	-0.27662

In this case, the chosen solution, indexed as 16, corresponds to the use of thermal plants whose costs amount up to 168.12 R$/MWh.

We now assume that the decision maker, considering the risk associated with each solution, increases the limit for increasing preference intensity (L_{sup} in Figure 4b) to 40%, instead of 10%. The new results obtained by PROMETHEE II appear in Table 4.

Table 4. Solution chosen by PROMETHEE II considering increasing risk preference intensity

	Global preferences $\prod(\mathbf{a},\mathbf{b})$								
Solution	**24**	**16**	**19**	**25**	**26**	**27**	$\Phi^+(a)$	$\Phi^-(a)$	$\Phi(a)$
16	0.00000	0.08800	0.18311	0.23200	0.29156	0.30400	0.21973	0.51804	-0.29831
19	0.20462	0.004000	0.05067	0.09956	0.15911	0.17156	0.13710	0.36495	-0.22785
24	0.58559	0.38097	0.00000	0.00444	0.06400	0.07644	0.22229	0.08934	0.13295
25	**0.60000**	**0.43401**	**0.05304**	**0.00000**	**0.01511**	**0.02756**	**0.22594**	**0.07796**	**0.14799**
26	0.60000	0.45777	0.07680	0.02376	0.00000	0.00000	0.23167	0.10721	0.12446
27	0.60000	0.46402	0.08306	0.03001	0.00625	0.00000	0.23667	0.11591	0.12076

The new chosen solution, indexed as 25, corresponds to the use of thermal plants whose costs amount up to 51.93 R$/MWh. It is a slightly risky decision, resulting from the increase in the preference intensity for comparing each pair of solutions with respect to their risks.

This analysis shows the relevance of the decision maker parameter assignments. It also illustrates the adequacy of the proposed DSS, conceived to systematize the trends of the operation planning managers, based on all the available information and on their accumulated experience, preserving at the same time the reproducibility of the decisions.

8. CONCLUSION

The proposed DSS is in line with the Brazilian hydrothermal operation planning recent migration from a minimum cost criteria to an energy security criteria. It provides the necessary systematization to consider additional information and reach a balanced bi-criteria decision making, improving the quality of the operational decisions. All the steps of the proposed DSS should be exactly documented, so as to make it a transparent and reproducible process.

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