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Representation of Wind Energy Scenarios in the Stochastic Dual Dynamic Programming for Hydrothermal Systems Operation

Marcos T.B. de Oliveira * **Alexandre S. Fernandes** **
Elisa Oliveira *** **André L. M. Marcato** ****
Lucas R. Conceição †

* *Faculdade de Engenharia Elétrica, Universidade Federal de Juiz de Fora, MG, (e-mail: oliveira.marcos@engenharia.ufjf.br).*
** *Faculdade de Engenharia Elétrica, Universidade Federal de Juiz de Fora, MG, (e-mail: alexandre.fernandes@engenharia.ufjf.br).*
*** *Faculdade de Engenharia Elétrica, Universidade Federal de Juiz de Fora, MG, (e-mail: elisa.oliveira@engenharia.ufjf.br).*
**** *Faculdade de Engenharia Elétrica, Universidade Federal de Juiz de Fora, MG, (e-mail: andre.marcato@ufjf.edu.br).*
† *Faculdade de Engenharia Elétrica, Universidade Federal de Juiz de Fora, MG, (e-mail: lucasrcon@gmail.com).*

Abstract: This article presents a methodology for including wind power generation in the medium-term planning ofhydrothermal systems, where Stochastic Dual Dynamic Programming (SDDP) is widely applied in the literature to solve this class of problem. To assess the impact of the intermittent generation, wind power scenarios were generated through Weibull Distribution, which were applied to reduce the load, generating several demand scenarios. Thus, the aim of this paper is to improve the computational effort of the conventional SDDP with demand scenarios, where the main contribution of the work consists of applying the Immediate Cost Function (ICF) to accelerate the SDDP convergence process. The proposed methodology was analyzed using part of the Brazilian system, considering a wind farm.

Keywords: Hydrothermal Systems; Power System Operation; Renewable Energy; Stochastic Dual Dynamic Programming; Wind Generation.

1. INTRODUCTION

Renewable energy sources such as wind and solar have grown remarkably fast in the last ten years due to their diverse benefits, such as, e.g., being low cost and being clean energy sources, in addition to diverse the energy matrix Patel (2005). In Brazil, wind represents 8.5% of generation capacity, with the possibility of reaching 12.7% in 2024 (Lucena and Lucena, 2019).

The main advantage of wind energy is that it is a renewable source of energy, i.e., its resources are inexhaustible. Besides, wind energy has several environmental advantages, since it reduces the emission of greenhouse gases, also, can offer a reduction in operating costs to attend the demand in energy planning analyzes. The main challenges related to wind generation are related to the intermittent and stochastic characteristics of the wind, requiring the application of methodologies that can guarantee a reliable analysis of the insertion of this renewable generation (Mohtasham, 2015).

There are several papers in the literature that address the wind energy and wind energy and its challenges. In Han et al. (2019) an optimization model that takes into account not only water inflow uncertainty, but, also, wind speed and solar irradiation uncertainty is implemented. Also, Mummey (2017) evaluates a stochastic representation for wind power generation through historical wind speed data of 16 coordinates from the Northeast and South of Brazil and Witzler (2015) develop a methodology for reconstruction historical series of wind generation enabling studies of complementarity between energy sources in the Brazilian energy system.

There are also articles in the literature carrying out studies relating wind energy to the energy planning of hydrothermal systems. In Morillo et al. (2020), it is proposed a methodology for the management of hydro dominated power systems coupled with wind energy storage applying a Risk-averse Stochastic Dual Dynamic Programming (SDDP). Besides that, in Papavasiliou et al. (2017) the SDDP is applied to solve the problem of a multistage stochastic formulation of a transmission-constrained economic dispatch subject to multi-area renewable production uncertainty.

Therefore, based on the previous arguments, this work presents a way to insert efficiently, the wind generation in the medium term energy planning. To consider the intermittency of wind generation, several scenarios of wind power were generated through the Weibull Distribution

(Stevens and Smulders, 1979), which is known in the literature for applications related to wind speed. The wind power scenarios will be applied as load reduction, thus, several demand scenarios will be generated for the system planning horizon.

Thus, for the solution of the mid-term hydrothermal dispatch problem, the Dual Stochastic Dynamic Programming with Demand Scenarios (SDDP-DS), which is already known in the literature, will be applied. However, the conventional methodology presents a considerable computational effort to determine medium term planning in the presence of several demand scenarios, therefore, this article presents a modification in the SDDP-DS through the Immediate Cost Function (ICF), where it will be possible to accelerate the convergence process without loss in the results quality.

After this background, the main contributions of this paper are:

- Insertion of wind generation in medium-term energy planning;
- Improve SDDP-DS computational time through ICF, making it possible to calculate the dispatch of the plants in the system.

2. CLASSICAL FORMULATION

The mathematical formulation proposed for planning the operation of hydrothermal systems in the medium term with individualized plants, considering the various demand scenarios, is presented in the Linear Problem (LP) (1 - 6), obtained from simplifications and adaptations of the models expressed in Metello (2016) and da Silva Fernandes et al. (2019). The LP is solved internally using the SDDP-DS algorithm. Each stage of the problem represents a month of operation, given by the sub-indices t. The sub-indices i refer to hydroelectric plants and j represent thermoelectric plants. The p sub-indices are related to the different wind generation scenarios, and consequently, demand scenarios. The variables are in bold spelling to differentiate from the known constants and parameters.

$$\text{Min } \alpha_t = \mathbb{E}_p \left[\sum_j c_j \cdot \boldsymbol{g_{t,j,p}} + cd \cdot \boldsymbol{d_{t,p}} \right] + \boldsymbol{\alpha_{t+1}} \tag{1}$$

Subject to:

$$\boldsymbol{v_{t+1,i}} = v_{t,i} + C \cdot (a_{t,i} + \sum_{m \in \Theta_m} (\boldsymbol{q_{t,m}} + \boldsymbol{s_{t,m}}) - \boldsymbol{q_{t,i}} - \boldsymbol{s_{t,i}}) \quad \forall i \in I \tag{2}$$

$$\boldsymbol{e_{t,p}} + \sum_j \boldsymbol{g_{t,j,p}} + \boldsymbol{d_{t,p}} = \delta_t - wg_p \quad \forall p \in P \tag{3}$$

$$\sum_p \mu_p \cdot \boldsymbol{e_{t,p}} = \sum_i \rho_i \cdot \boldsymbol{q_{t,i}} \tag{4}$$

$$\boldsymbol{\alpha_{t+1}} \geqslant \sum_i (\pi^k_{t+1,i} \cdot \boldsymbol{v_{t+1,i}}) + \epsilon^k_{t+1} \quad \forall k \in K \tag{5}$$

$$x^{min} \leqslant \boldsymbol{x} \leqslant x^{max} \tag{6}$$

Where:

$\boldsymbol{g_{t,j,p}}$	Generated energy by the thermoelectric j at the stage t related to the p wind generation scenario;
I	Set of the hydroplants of the system;
P	Set of the generated wind scenarios;
$\boldsymbol{d_{t,p}}$	Energy deficit in the stage t related to the p wind generation scenario;
I	Set of the Future Cost Function (FCF) cuts;
$\boldsymbol{\alpha_{t+1}}$	Future cost associated with the stage t;
$\boldsymbol{v_{t+1,i}}$	Stored volume by the hydro plant i at the end of the stage t;
$\boldsymbol{q_{t,i}}$	Turbined flow by hydro plant i at t stage;
$\boldsymbol{s_{t,i}}$	Spilled flow by hydro plant i in t stage;
$\boldsymbol{e_{t,p}}$	Generated energy by all hydroelectric plants in the stage t, related to the p wind generation scenario;
$\boldsymbol{x}$	Represents all variables of the problem;
α_t	Total Cost in the t stage;
c_j	Generation cost of the j thermoelectric plant;
cd	Cost associated with the energy deficit;
$v_{t,i}$	Stored volume by the i plant at the beginning of the t stage;
C	Constant used for converting units from m^3/s to hm^3 (2.592);
$a_{t,i}$	Inflow of the i plant in the t stage;
Θ_m	Set of hydro plants immediately upstream of i plant;
δ_t	Demand at t stage;
wg_p	Wind generation in the p scenario;
μ_p	Probability of occurrence of the p scenario;
ρ_i	Production coefficient of hydro plant i;
$\pi^k_{t+1,i}$	Coefficient of FCF cut k for hydro plant i's storage, $v_{t+1,i}$
ϵ^k_{t+1}	Constant term of FCF;
x^{min}	Minimum value of $\boldsymbol{x}$;
x^{max}	Maximum value of $\boldsymbol{x}$;
$\mathbb{E}_p$	Weighted average operator.

The equation (1) represents the objective function of the problem to be minimized, given by the sum of the immediate cost, due to the thermoelectric generation and possible deficits, with the future cost, which is associated with the level of water storage in the reservoirs of the plants. In (2) is presented the water balance equation in each hydroelectric plant. Besides the system's demand equation for each scenario is represented in (3), where the sum of hydroelectric energy with thermoelectric energy and the deficit is equal to the net demand ($\delta_{t,p}$), which is given by the demand in the t stage subtracted by the wind generation in the p scenario, as (7).

$$\delta_{t,p} = \delta_t - wg_p \tag{7}$$

It can be stated through (7), that the P wind generation scenarios are considered in the planning as a reduction in the system demand, thus, P demand scenarios will be generated to be used in the simulations.

The equation (4) shows that the weighted average of the hydroelectric energy generated in each demand scenario is equal to the sum of the energy generated by each hydroelectric plant, with each portion being given by the product between the production coefficient and the flow turbined by each plant. The inequality (5) brings the cuts in the future cost function (FCF), also called the Benders cut. Finally, the operating limits of the variables are defined in (6).

Through the LP (1 - 6), it is possible to observe a large number of variables in the demand attendance equations, due to the fact that several wind generation scenarios are considered. Thus, solving the hydrothermal dispatch problem in the conventional way can become computationally inefficient, especially when using a large number of scenarios.

3. PROPOSED METHODOLOGY

As previously discussed, the classic formulation of SDDP-DS, considering several scenarios of wind generation, will require a large computational time to solve the hydrothermal dispatch problem, due to the large number of equations. Thus, to reduce the computational effort, this article presents a modification in the formulation presented in (1 - 6) through the Immediate Cost Function (ICF), which will be presented in details in the following subsections.

3.1 Analytical Representation of ICF

The ICF refers to the cost of thermal plants operation associated with a hydroelectric power dispatch decision, which is represented for each month of planning. In summary, ICF is a piecewise linear function that associates each hydroelectric generation decision (e_t) with a thermal operating cost (β_t). Therefore, the modification in ICF proposed in this paper was adapted from the work presented in Metello (2016). The main goal of application of the ICF is to reduce the problem dimensions, making it possible to solve the hydrothermal dispatch problem considering a large number of wind scenarios.

The ICF can be obtained by the resolution of LP (8 - 13) for different values of hydroelectric energy (e_t). In other words, for each (e_t) the solution of LP (8 - 13) provides the thermal operating cost (β_t), therefore, it results in a piecewise linear function between the hydroelectric generation decision (e_t) and the thermal operating cost (β_t). However, the optimization problem (8 - 13) would demand more computational effort than the conventional Benders cut.

$$\text{Min } \beta(e) = \mathbb{E}_p \left[\sum_j c_j \cdot \boldsymbol{g_{j,p}} + cd \cdot \boldsymbol{d_p} \right] \quad (8)$$

Subject to:

$$\boldsymbol{e_p} + \sum_j \boldsymbol{g_{j,p}} + \boldsymbol{d_p} = \delta_{t,p} \qquad \forall p \in P \quad (9)$$

$$\sum_p \mu_p \cdot \boldsymbol{e_p} = e \quad (10)$$

$$0 \leqslant \boldsymbol{e_p} \leqslant e^{max} \qquad \forall p \in P \quad (11)$$

$$0 \leqslant \boldsymbol{g_{j,p}} \leqslant g_j^{max} \qquad \forall j \in J, p \in P \quad (12)$$

$$\boldsymbol{d_p} \geqslant 0 \qquad \forall p \in P \quad (13)$$

To overcome these difficulties, this article applies a step-by-step process to reduce the number of times that the LP (8 - 13) should be performed, presented in da Silva Fernandes et al. (2019). Another possibility to calculate the ICF is presented in the Fig. 1, where the LP (8 - 13) requires to be solved for specific values of (e_t), as follows:

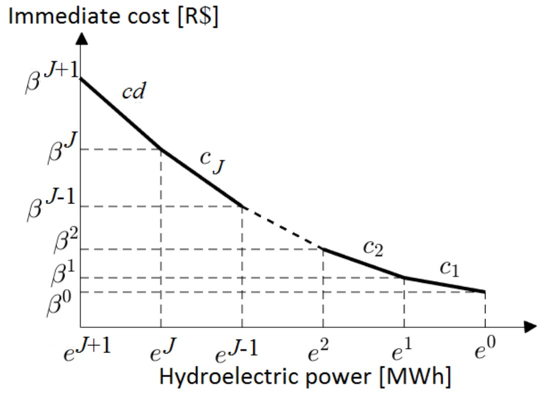

Figure 1. Relation between immediate cost (β_t) and hydropower generation (e_t)(Metello, 2016)

From Fig. 1, note that thermoelectric plants are ordered in relation to generation cost: $c_1 < c_2 < \ldots < c_{J-1} < c_J < c_d$.

- The value of e^0 is the hydropower required to attend the demand considering that the all thermal power generation is off. In this case, it should be observed the possibility of energy deficit;
- The value of e^1 is the hydropower required to attend the demand considering the use of the total thermal generation capacity of thermoelectric 1. In this case, the remaining thermal generations are off. As well as e^2 is the hydropower required to attend the demand considering the use of the total thermal generation capacity of thermoelectrics 1 and 2. Again, the remaining thermal generations are off. Similar procedures are adopted for the remaining (e_t).

3.2 Obtaining the ICF

The step-by-step algorithm of the ICF is presented in detail below. The subscript t, representing the stage, is suppressed in the variables in order to not overload the notation. In addition, it is important to emphasize that the proposed algorithm should be applied in each stage t, considering all respective p scenarios.

STEP-1: Ordering the thermoelectric plants in ascending generation cost: $c_1 < c_2 < \ldots < c_{J-1} < c_J < c_d$.

STEP-2: Calculate the vectors of hydroelectric generation:

- The points of maximum generation of hydroelectric energy are given in the condition of minimum use of thermoelectric energy:

$$e_p^0 = min\{\delta_p, e^{max}\} \qquad \forall p \in P \quad (14)$$

- Minimal hydroelectric generation:

$$e_p^{J+1} = 0 \qquad \forall p \in P \quad (15)$$

where J is the number of thermoelectric power plants in the system.

- The other values of hydroelectric energy are determined by the sequential insertion of each thermoelectric to the system:

$$\zeta = max\{\delta_{t,p} - \sum_j g_j^{max}, 0\}$$
$$e_p^j = min\{\zeta, e^{max}\} \qquad \forall p \in P, j \in J \quad (16)$$

STEP-3: In the previous step, $(J+2)$ vectors were generated with P values of hydroelectric energy. The previous determination of these vectors allows a reduction of the LP (8 - 13), with the transformation of the hydroelectric generation variable e into known constants and that should be solved for each $m = 0, 1, ..., J+1$.

$$\text{Min } \beta^m = \mathbb{E}_p \left[\sum_j c_j \cdot \boldsymbol{g_{j,p}} + cd \cdot \boldsymbol{d_p} \right] \qquad (17)$$

Subject to:

$$\sum_j \boldsymbol{g_{j,p}} + \boldsymbol{d_p} = \delta_{t,p} - e_p^m \qquad \forall p \in P \qquad (18)$$
$$0 \leqslant \boldsymbol{g_{j,p}} \leqslant g_j^{max} \qquad \forall j \in J, p \in P \qquad (19)$$
$$\boldsymbol{d_p} \geqslant 0 \qquad \forall p \in P \qquad (20)$$

The resolution of the LP for the $(J+1)$ hydropower generation vectors generates the immediate costs β^m. Thus, the set of points (e^m, β^m) is used in the next step to determine the cuts of the ICF being $e^m = \sum_p \mu_p \cdot e_p^m$.

STEP-4: The coefficients of each line (cut) are obtained from the equations (21) and (22).

$$\lambda^l = \frac{\beta^{l+1} - \beta^l}{e^{l+1} - e^l} \qquad l = 0, 1, ..., J \qquad (21)$$
$$\Omega^l = \beta^l - \lambda^l \times e^l \qquad l = 0, 1, ..., J \qquad (22)$$

Therefore, the ICF can be obtained from the set of inequalities expressed in (23):

$$\boldsymbol{\beta} \geqslant \lambda^l \times \boldsymbol{e} + \Omega^l \qquad l = 0, 1, ..., J \qquad (23)$$

It must be emphasized that, during execution of STEP 3 - intended to obtain the set $(e^m, \beta^m), m = 0, 1, ..., J+1$ - equal points may be generated. Therefore, in order to obtain the coefficients of the lines, repeated points must be excluded, the, it is not generated incompatibility in the resolution of the equation (21). Thus, it is important to mention that the number of ICF cuts generated by the algorithm is at most equal to the number of thermoelectric power plants in the system plus one, i.e. that $l_{max} = J+1$. The time required to survey the FCI's at each stage is negligible compared to the time spent in the simulations.

3.3 SDDP-DS-ICF

The previous section is used to determine the ICF cuts to be inserted in the LP (1 - 6). Thus, the proposed SDDP-DS-FCI can be written as follows:

$$\text{Min } \alpha_t = \boldsymbol{\beta_t} + \boldsymbol{\alpha_{t+1}} \qquad (24)$$

Subject to:

$$\boldsymbol{v_{t+1,i}} = v_{t,i} + C \cdot (a_{t,i} + \sum_{m \in \Theta_m} (\boldsymbol{q_{t,m}} + \boldsymbol{s_{t,m}}) - \boldsymbol{q_{t,i}} - \boldsymbol{s_{t,i}}) \qquad \forall i \in I \qquad (25)$$
$$\boldsymbol{e_t} = \sum_i \rho_i \cdot \boldsymbol{q_{t,i}} \qquad (26)$$
$$\boldsymbol{\beta_t} \geqslant \lambda^l \cdot \boldsymbol{e_t} + \Omega^l \qquad \forall l \in L \qquad (27)$$
$$\boldsymbol{\alpha_{t+1}} \geqslant \sum_i (\pi_{t+1,i}^k \cdot \boldsymbol{v_{t+1,i}}) + \epsilon_{t+1}^k \qquad \forall k \in k \qquad (28)$$
$$x^{min} \leqslant \boldsymbol{x} \leqslant x^{max} \qquad \forall i \in I \qquad (29)$$

It is important to emphasize that the maximum hydroelectric generation used in the new LP (24 - 29) is given by the maximum energy value obtained in the ICF algorithm, that is, it refers to the value $e^0 = \sum_\tau e_\tau^0$ of Fig. 1.

Although the LP (1 - 6) e LP (24 - 29) problems are very similar, we can observe that the demand attendance equations have been replaced by ICF cuts. Considering that were used P scenarios for each month of study, then the problem consisted of P demand attendance equations for each month. Therefore, with the application of ICF, there is a considerable reduction in the dimensions of the problem, especially when the number of wind scenarios are large. Thus, reducing the number of constraints and the variables, the computational time to solve the problem is improved.

4. WIND SCENARIOS REPRESENTATION

The power generated by a given wind turbine (wg_p) can be calculated using the power curve provided by the manufacturer, performing a linear interpolation with the wind speed. Therefore, its generated power was calculated for each hour in the history, however, as the objective of this work is to analyse medium-term planning, the hourly powers of each month are added, thus obtaining a monthly history of power generated by the wind farm. The values of the power curve of the 1MW wind turbine used are shown in Fig 2.

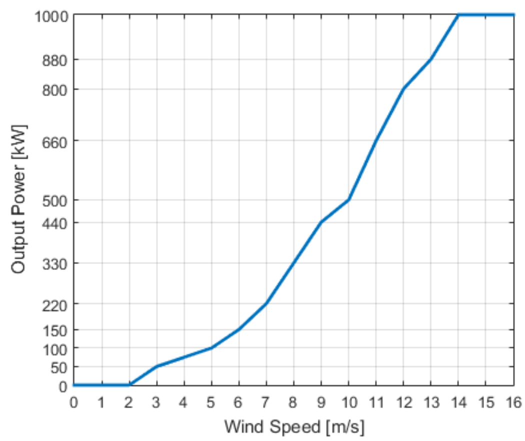

Figure 2. Wind Turbine Power Curve.

In this work, the wind speed is modeled using the Weibull distribution Stevens and Smulders (1979), which is a function of two parameters, being known in the literature for representing efficiently the probability density distribution of the wind speed. Thus, the Weibull function provides an adequate modeling of the wind, allowing to obtain the power generated by a wind farm inserted in the network, obtaining simulations with reliable results. The Weibull distribution in this work was used to generate scenarios of power from the wind turbine. The generic formulation of Weibull distribution is shown in (30).

$$f_w(wg) = \frac{k}{c}\left(\frac{wg}{c}\right)^{k-1} \cdot exp\left[-\left(\frac{wg}{c}\right)^{k}\right] \tag{30}$$

Where:

wg Random Wind Power (MW);
k Shape Factor;
c Scale Factor.

Weibull parameters are calculated from historical wind power series, as shown below.

$$k = \left(\frac{\sigma}{\bar{wg}}\right)^{-1{,}086} \tag{31}$$

$$c = \frac{\bar{wg}}{\Gamma\left(1+\frac{1}{k}\right)} \tag{32}$$

Where:

$\bar{wg}$ Historical average;
σ Standard deviation from history;
Γ Gamma Distribution Function.

In order to generate wind scenarios in a more realistic way, the Weibull distribution was applied for each month of the speed history, thus, each month, from January to December, has its respective Form and Scale Factors. Thus, when generating the desired scenarios, it is possible to maintain them with the characteristic seasonality present in the history to be used. A monthly boxplot for the scenarios is shown in Fig. 3 and were generated using hourly data from the Chuí wind farm in Southern Region of Brazil, available at INMET (2020). The selection of data was made according to the availability of history, however the methodology extends to other data.

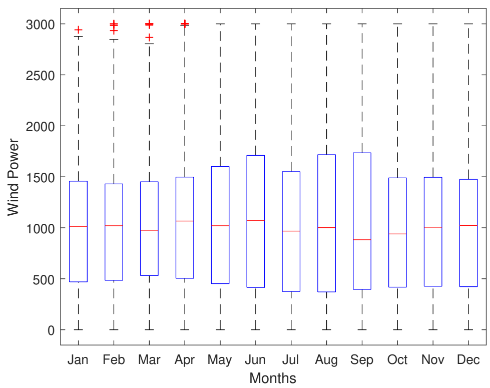

Figure 3. Wind Power Scenarios - Boxplot

5. OPERATION AND POLICY SIMULATION

The operation of hydrothermal systems in the medium/long term is carried out in two stages, as shown in Fig. 4. First, the Operation Policy (OP) stage is performed, where the Future Cost Function (FCF) cuts for each stage of the problem are obtained, which are adjusted in order to obtain the minimum operating cost in the analyzed period. The OP stage can be performed by SDDP-DS or by the proposed SDDP-DS-FCI methodology, as described above. Then, after the FCF adjustments, the Operation Simulation step is performed, where the optimal dispatch of the system is determined for each combination of the n inflow scenarios and the p demand scenario, according to Algorithm in Fig. 5.

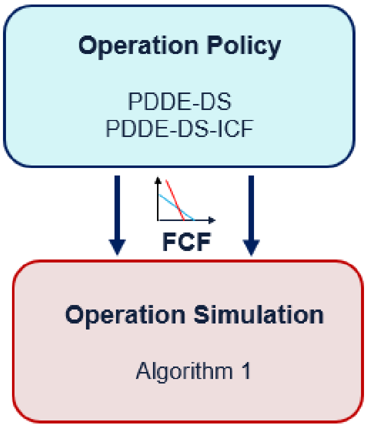

Figure 4. Steps of OP and OS. Source: Author's elaboration

Algorithm 1: Operation Simulation

Data: Set of FCF cuts for each stage; $a^n_{t,i}$ and δ^p_t
Result: Optimal Dispatch of the System's Plants
for p = *1,2,...,P* **do**
  for n = *1,2,...,N* **do**
    for t = *1,2,...,T* **do**

$$\text{Min } \alpha_t = \sum_j (c_j \cdot g_{t,j}) + cd \cdot d_t + \alpha_{t+1}$$

Subject to:

$$v_{t+1,i} = v_{t,i} + C \cdot (a^n_{t,i} + \sum_{m \in \Theta_m} (q_{t,m} + s_{t,m}) - q_{t,i} - s_{t,i}) \quad \forall i \in I$$

$$\sum_i e_{t,i} + \sum_j g_{t,j} + d_t = \delta^p_t$$

$$e_{t,i} = \rho_i \cdot q_{t,i} \quad \forall i \in I$$

$$\alpha_{t+1} \geqslant \sum_i (\pi^k_{t+1,i} \cdot v_{t+1,i}) + \epsilon^k_{t+1} \quad \forall k \in K$$

$$x^{min} \leqslant x \leqslant x^{max}$$

      → Store the problem variables
      → Update the stored volume of each hydroelectric plant: $v_{t+1,i} = v_{t,i}$ $\forall i \in I$
    end
  end
end

Figure 5. Operation Simulation Algorithm

6. RESULTS

The codes used in this work were implemented and executed in Matlab, version R2019a, on a computer with the following configuration: Intel® Core™ i5-6300HQ Processor with 2.30 GHz and 16 GB of RAM, Windows 10. For the execution of the SDDP, 100 forwards series were sampled, from an inflow tree with 2 openings obtained by random values form the flow history (Pereira, 1989) (Pereira et al., 2015). A 18-month planning horizon was also considered and the wind plant have 10 wind turbines presented in Fig. 2. The system data is presented in Appendix A.

As previously mentioned, the SDDP algorithm is applied in the methodologies. After the SDDP convergence, the algorithm provides the total operation cost in each forward series (affluence scenario) considered. Thus, Table 1 briefly presents the data obtained in the simulations considering 10, 100, 500 and 1000 wind generation scenarios, containing the average operation cost and the computational time for the Operation Policy step, in order to evaluate the computational efficiency of the SDDP-DS-FCI, in comparison with the SDDP-DS.

Table 1. Comparison Between Methodologies.

Wind Scenarios	Methodologies	Average Cost (R$)	Time (s)
10	SDDP-DS	949204	601.85
	SDDP-DS-ICF	948291	514.46
100	SDDP-DS	1035695	1132.30
	SDDP-DS-ICF	1045837	581.81
500	SDDP-DS	940823	2714.81
	SDDP-DS-ICF	940636	660.26
1000	SDDP-DS	875269	7715.56
	SDDP-DS-ICF	875256	721.27

Note that the computational efficiency of SDDP-DS-FCI increases in relation to that of SDDP-DS the greater the number of demand scenarios used in the modeling, due to the decrease in the dimensions of the problem, in terms of the number of variables and restrictions. The Fig. 6 presents a comparison of the speed-up between the methodologies. The proposed approach proves to be better to solve the problem. as the number of wind scenarios increases.

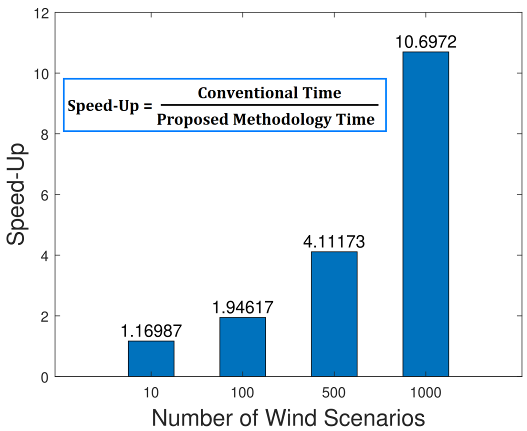

Figure 6. Speed-Up Between Methodologies.

Due to the stochasticity of wind generation, the assembly of the FCF cuts is made more realistically as the number of scenarios increases, as more possibilities for wind generation are considered in the Operation Policy. Thus, as shown in Fig. 6, the proposed methodology proves to be superior for efficiently inserting wind generation scenarios, since with a large number of scenarios the computational gain is much higher than the conventional methodology.

The Fig. 7 presents the cost per affluence scenario determined in the SDDP-DS and SDDP-DS-FCI methodologies, considering 1000 wind generation scenarios.

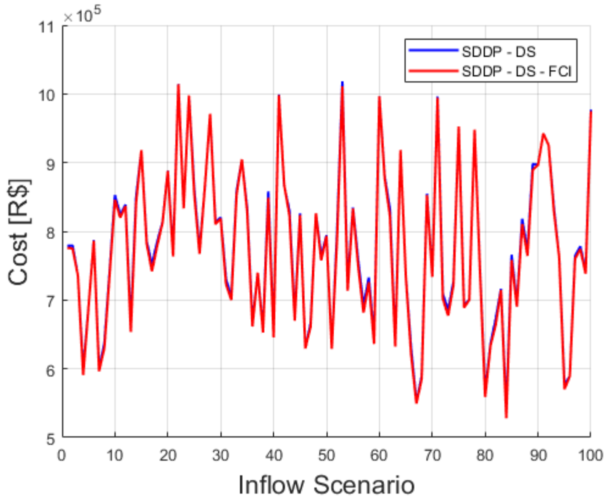

Figure 7. Total Operating Cost by Inflow Scenario.

The average percentage difference in operating costs between both methodologies was 0.26%. Thus, it can be said that the ICF is well modeled and its insertion in the proposed methodologie achieved satisfactory results.

After defining the operation policy, having calculated all the cuts in the future cost function, it is possible to perform the Operation Simulation step, according to Fig. 4. Table 2 presents the results of the simulation using the calculated cuts, considering the average of the all inflow scenarios and the occurrence of a especific generated wind scenario, among all the 1000 generated wind scenarios.

Table 2. Costs (in million R$).

Methodologie	N° of the Simulated Wind Scenario			
	1	250	500	1000
SDDP-DS	0.9857	1.1272	0.8459	0.9617
SDDP-DS-ICF	0.9857	1.1269	0.8459	0.9514

Through the Table 2, the effectiveness of the proposed SSDP-DS-FCI methodology is highlighted. Specific wind scenarios were used in the Operation Simulation and the operating costs presented by SDDP-DS and SDDP-DS-FC were close, however the proposed methodology presents the Operation Policy solution with less computational effort, showing that its application is effective.

7. CONCLUSION

The present work brought a proposal for insertion of wind generation in SDDP, for planning the operation of hydrothermal systems in the medium term. The wind generation scenarios were modeled through the Weibull distribution were used to reduce load, consequently, several demand scenarios were generated, thus requiring the use of SDDP with Demand Scenarios.

However, the computational inefficiency of the SDDP-DS was verified as the number of wind generation scenarios increased. Thus, the Immediate Cost Function (ICF) was used to accelerate the convergence process. The models were then tested in simplified real systems in order to verify their performance.

The main contribution of the article is the incorporation of several scenarios of wind generation in the energy planning model, providing reliability to the system operator. Another contribution is the significant reduction in the computational time of the SDDP-DS-FCI compared to the SDDP-DS, due to the reduction of the dimensions of the problem without impairing the reliability of the results, since the error in the analytical representation of the FCI's were small. Therefore, the SDDP-DS-FCI presents the necessary robustness to be applied in larger and more complex systems.

8. ACKNOWLEDGMENTS

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Appendix A. HYDRO AND THERMAL PLANTS DATA

The configuration and data of the 7 hydroelectric and 7 thermoelectric plants, shown in Tables A.1 and A.2 used in the simulations are based on the December 2019 Monthly Operation Program (PMO) price deck (CCEE, 2019).

Table A.1. Hydroelectric Plants Data

Name	v^{min} (hm^3)	v^{max} (hm^3)	q^{max} $(\frac{m^3}{s})$	s^{max} $(\frac{m^3}{s})$	ρ $(\frac{MWmed}{m^3/s})$
Furnas	5733	22950	1692	5076	0.7811
Caconde	51	555	94	282	0.8316
Marimbondo	890	6150	2944	8832	0.5020
Camargos	120	792	220	660	0.1995
A. Vermelha	5856	11025	2958	8874	0.4763
E. Da Cunha	14	14	148	444	0.7630
Jaguara	450	450	1076	3228	0.4097

Table A.2. Thermoelectric Plants Data

Name	Cost $(R\$/MWmed)$	Capacity $(MWmed)$
Baixada Flu	88.08	530
Cuiaba G CC	511.77	529
F. Gasparin	399.02	572
Norteflu - 1	50.93	400
St. Cruz Nova	127.40	500
Termomacae	504.65	929
Termorio_L1	216.31	770