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MODELO CONCEITUAL DE PREVISÃO DE VAZÃO PARA ESTAÇÕES DE MEDIÇÃO EM SÃO PAULO

CONCEPTUAL MODEL OF INFLOW FORECASTING FOR MEASUREMENT STATIONS AT SAO PAULO

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***Resumo** – O planejamento da operação das usinas hidrelétricas depende da previsão de vazões aos reservatórios. Neste artigo, analisamos o modelo conceitual "Soil Moisture Model Accounting Procedure" (SMAP). O objetivo é avaliar seu desempenho, a fim de melhorar a precisão das vazões previstas para suportar os tomadores de decisão no processo de geração de energia. Aplicamos o SMAP para um conjunto de estações de medição selecionadas e avaliamos sua saída usando hidrogramas e quatro indicadores de desempenho. As etapas para avaliar o SMAP consistem na coleta de dados, calibração, ajuste, validação, aplicação e análise do modelo. Concluímos que o SMAP apresenta um bom desempenho. Portanto, sob as condições observadas, o SMAP pode contribuir para aumentar a eficiência das usinas hidrelétricas e reduzir os custos de complementação térmica.*

Palavras-chave: Modelo hidrológico. Sistema hidrelétrico. Indicadores de desempenho. Reservatórios.

***Abstract** - The operation planning of hydropower plants depends on the water inflow forecasting into the reservoirs. In this paper we analyze the conceptual model "Soil Moisture Model Accounting Procedure" (SMAP). The objective is to evaluate its performance in order to improve the accuracy of the predicted water inflows to support the decision-makers in the power generation process. We applied SMAP to a set of selected measurement stations and assessed its output by using hydrographs and four performance indicators. The steps to evaluate SMAP consist of data collection, calibration, adjustment, validation, application, and analysis of the model. We have concluded that SMAP presents a good performance. Therefore, under the observed conditions, SMAP can contribute to increase the hydropower plants efficiency and to reduce the thermal complementation costs.*

Keywords: Hydrological model. Hydropower system. Performance indicators. Reservoirs.

I. INTRODUCTION

The hydropower system planning should assure an economic and safe operation policy, managing the water stored in the reservoirs. The main operation decision is to determine the amount of water discharged by the turbines or spillways. Since these values depend on the future resource availability, the accuracy of this information is very important. However, water inflow forecasting is a complex task that has led to the development of several conceptual, empirical, and hybrid prediction models.

The conceptual models consider the physical processes of the water system in their functions, taking into account the rainfall-runoff relationship. In these models, the predicted rainfall is used as input for the calculation of the future runoff. Some physical phenomena, such as infiltration, evapotranspiration, and groundwater flow are included in those calculations, subject to different precision levels. The conceptual models can be divided into two subclasses: concentrated and distributed. The former considers the basin as a single system, whereas the latter divides the basin in sub-basins. MGB IPH is an example of the distributed subclass (ANEEL, 2020). Soil Moisture Model Accounting Procedure (SMAP) is the concentrated conceptual model that our research focuses on (ONS, 2019a; LAUDANNA *et al.* 2005; CASTANHARO *et al.* 2007).

The empirical ones, in turn, use mathematical techniques to set up a relationship between the input and output data without necessarily considering the water physical processes. Usually, the input data are the observed water inflows, and both the observed and predicted rainfalls. The output data are the predicted water inflows. Stochastic and statistic models are empirical. Inside the empirical set, we highlight PREVIVAZ which is a linear stochastic model employed to predict inflows for most Brazilian hydropower plants. Furthermore, models based on techniques of neural networks are also empirical. They are used in the water inflow forecasting, as shown in Ballini, Soares Filho, Andrade (2003), Batista (2009), Sousa, Sousa (2010), and Gomes, Montenegro, Valença (2010).

The hybrid models are those that combine the characteristics of conceptual and empirical ones, i.e., they employ knowledge about water physical processes and mathematical tools. This approach is intended to take advantage of the best features of each model type joined in a single system. An example of this sort of model is Fuzzy Recurrent Model (ROCHA; MOREIRA, 2007).

As we have pointed, to predict water inflows is a complex task and, despite the large number of available models, the general accuracy is not satisfactory yet (ANDRADE *et al.* 2012). For instance, there are reports of average errors to 26% in the inflow forecasting (COLONESE; XAVIER; ARAUJO, 2015). The magnitude of the errors is so high that they may severely disturb operation plans, leading to inefficient management of water resources.

In this research, we have studied the potential of SMAP model to predict daily water inflows. SMAP has been chosen due its conceptuais features and the growing interest in it. It has already been applied to Grande, Paranapanema, and Paranaíba river basins (LAUDANNA *et al.* 2005). The highlight of this paper is that we analyze the behavior of SMAP using an important Brazilian basin as background. We pointed out that the efficiency of any model is limited by a series of factors, such as internal assumptions of the model, quality of the available data, and size of the time horizon. We applied SMAP using the database of the Tietê River basin to assess its absolute efficiency, showing an alternative option for decision-makers of the hydropower operation. We have used hydrographs and four performance indicators to evaluate the model.

II. SOIL MOISTURE MODEL ACCOUTING PROCEDURE (SMAP)

SMAP is a deterministic conceptual model of the type rainfall-runoff transformation. It uses the water cycle concept (ONS, 2019).

SMAP uses parameters and input variables. The parameters are related to the physical conditions. They are relatively stable, but they need to be estimated or calculated, calibrated and validated before their use. The input variables, in turn, refer to the environmental conditions. They are linked to faster changing values that can be measured or estimated, but do not undergo to the calibration and validation processes (ROCHA *et al.* 2016).

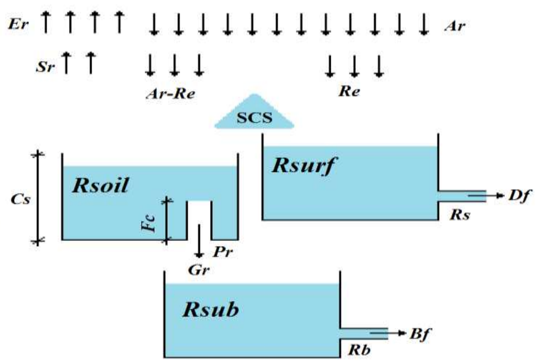
Table I presents all parameters and input/output variables of SMAP model. For each one, the symbol, description, and unit are shown. SMAP uses a set of six parameters. Three of them are estimated parameters based on physical processes related to vegetation type, soil type, and flow rate in the studied area: initial abstraction (mm), field capacity (%), and recession constant of basic flow (day). The remaining three are calculated parameters based on historical series of rainfall and water inflow: capacity of soil saturation (mm), recession constant of surface flow (day), and groundwater recharge (%). The model also needs seven input variables: average rainfall in the basin (mm), evaporation rate (mm), drainage area (km^2), initial humidity, initial basic flow (m^3/s), initial superficial flow (m^3/s), and observed water inflow in the day (m^3/s). The output is the predicted water inflow in the day (m^3/s). Once all parameters and input variables are loaded, the model is carried out to calculate the output variable.

There are some versions of SMAP model. Here, we focus on the daily version that consists of the three mathematical representations of the water reservoirs that are considered inside the calculations, as shown in Figure 1. The first of the reservoirs is the soil reservoir (*Rsoil*) that corresponds to the aerated zone; the second is the surface reservoir (*Rsurf*) associated with the basin runoff; and the last is the underground or subterranean reservoir (*Rsub*) that simulates the saturated zone. SMAP also uses five transfer functions to calculate the amount of water in the reservoirs for each day. They are surface runoff (*Sr*), real evapotranspiration (*Re*), groundwater recharge (*Gr*), direct flow (*Df*), and basic flow (*Bf*). In Figure 1, SCS means Soil Conservation Service. Further details about the internal features of SMAP can be found at ONS (2019).

Table I – Parameters and input/output variables of SMAP model.

Symbol	Description	Unit
Ai	initial abstraction (estimated)	mm
Fc	field capacity (estimated)	%
Rb	recession constant of basic flow (estimated)	day
Cs	capacity of soil saturation (calculated)	mm
Rs	recession constant of surface flow (calculated)	day
Pr	groundwater recharge (calculated)	%
Ar	average rainfall in the basin (input)	mm
Er	evaporation rate (input)	mm
Da	drainage area (input)	km^2
Ih	initial humidity (input)	-
Ib	initial basic flow (input)	m^3/s
Is	initial superficial flow (input)	m^3/s
W_i^{obs}	observed water inflow in the day *i* (input)	m^3/s
W_i^{pred}	predicted water inflow in the day *i* (output)	m^3/s

Figure 1 - Water mathematical reservoirs of SMAP model.



Source: ONS, 2019a (adapted).

III. METHODOLOGY

3.1 – Steps and Procedures

Our goal was to study the potential of SMAP and we carried out this task applying the model to selected points in a chosen basin. The process has three major steps, each one divided in a certain number of procedures. In the overall, first, we got a database with historical data series of rainfall and runoff of the basin. The input parameters were estimated or calculated, calibrated, adjusted, and validated. The input variables were estimated or recovered from the database. The SMAP was feed with these values and ran. Then, we used a set of quantitative statistics and a visual analysis of hydrographs to assess the accuracy of SMAP.

For each step, a description of the procedures is presented in Table II. In procedures 2.1 and 2.3, the Solver tool of *Microsoft Excel* was used, employing the Generalized Reduced Gradient (GRG2) for optimizing of nonlinear problems (EXCEL, 2020). According to Moriasi *et al.* (2007) a good calibration procedure uses multiple quantitative statistics and, then, we used the quantitative statistics described in the next sub-section.

In procedure 2.2, the estimated and calculated parameters of the model can be manually re-calibrated in order to get better precision. During this process, each quantitative statistic should be tracked for balancing the

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model ability and potential errors in the observed data (BOYLE; GUPTA; SOROOSHIAN, 2000).

Table II – Description of the procedures used to apply SMAP model.

Procedure	Description
1.1	*Selection of Study Scope*: choose the basin and the measurement stations of interest (hydropower plants may be included as stations).
1.2	*Definition of the Past Events Set*: choose the periods for the model calibration, adjustment, and validation (the chosen period should include dry and wet periods).
1.3	*Rainfall and Water Inflow Data Collection*: gather and organize data series about observed (past) rainfall and water inflow in the selected stations.
1.4	*Correction of Water Inflow Data Series*: look for constant values along consecutive days, absent values, or wrong values and correct the found inconsistencies by using a linear interpolation or a more suitable mathematical technique.
2.1	*Parameters Automatic Calibration*: calibrate the calculated parameters of SMAP using proper tools in automatic mode.
2.2	*Parameters Manual Calibration*: manually re-calibrate the estimated and calculated parameters of SMAP in order to get better precision.
2.3	*Stations Weight Definition*: adjust the weight of the measurement stations to indicate the importance of each one in the basin context.
2.4	*Validation of the Model*: validate the model output applying SMAP to a period not used for the calibration.
3.1	*SMAP Operation*: use the model with previously found parameters and input variables to predict the water inflows into the basin.
3.2	*Post-Operation Analysis*: assess the output of SMAP using a set of quantitative statistics and an expert-based visual exam of the hydrographs.

3.2 – Quantitative Statistics

A set of quantitative statistics was used to assess the output of SMAP. We adopted three performance indicators recommended by Moriasi *et al.* (2007): Nash-Sutcliffe efficiency (NSE), Percent bias (PBIAS), and Ratio of the root mean square error to the standard deviation (RSR).

Trying to reach a better understanding of the SMAP performance, we have added an extra indicator to the analyses: Percentage relative deviation (PRD).

NSE, Eq. (1), is a normalized statistic that determines the relative magnitude of the residual variance compared to the observed data variance. It ranges from -∞ to 1. The closer to 1, the more accurate is the model.

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(W_i^{obs} - W_i^{pred}\right)^2}{\sum_{i=1}^{n}\left(W_i^{obs} - W^{obs}\right)^2} \quad (1)$$

where: W_i^{obs} = observed water inflow in the time period i [m³/s]; W^{obs} = observed average water inflow [m³/s]; W_i^{pred} = predicted water inflow for the time period i [m³/s]; i = time period [day]; n = number of periods [days].

PBIAS, Eq. (2), measures the average tendency of the predicted values to be larger or smaller than the observed ones. The optimal value of PBIAS is 0. Positive values indicate overestimation bias, whereas negative values indicate model underestimation bias (MORIASI *et al.* 2007).

$$PBIAS = \frac{\sum_{i=1}^{n}\left(W_i^{obs} - W_i^{pred}\right) * 100}{\sum_{i=1}^{n}\left(W_i^{obs}\right)} \quad (2)$$

RSR, Eq. (3), is calculated as the ratio of the root mean square error (RMSE) and standard deviation of measured data (MORIASI *et al.* 2007). RSR varies from the optimal value of 0 to a large positive value. The lower RSR, the better is the model performance.

$$RSR = \frac{RMSE}{SDEV} = \frac{\sqrt{\sum_{i=1}^{n}\left(W_i^{obs} - W_i^{pred}\right)^2}}{\sqrt{\sum_{i=1}^{n}\left(W_i^{obs} - W^{obs}\right)^2}} \quad (3)$$

Performance ratings of NSE, PBIAS, and RSR for model evaluation are presented in Moriasi *et al.* (2007). Table III shows the ratings for the three quantitative statistics; where: V.g. = very good; Go. = good; Sat. = satisfactory; Uns. = unsatisfactory).

Table III – Performance ratings (MORIASI *et al.* 2007).

Rate	NSE	PBIAS (%)	RSR
V.g.	0.75<NSE≤1.00	PBIAS<±10	0.00≤RSR≤0.50
Go.	0.65<NSE≤0.75	±10≤PBIAS<±15	0.50<RSR≤0.60
Sat.	0.50<NSE≤0.65	±15≤PBIAS<±25	0.60<RSR≤0.70
Uns.	NSE ≤ 0.50	PBIAS ≥ ±25	RSR > 0.70

PRD, Eq. (4), shows the average difference between the value of the predicted water inflows and the value of the observed water inflows. The value is expressed as a percentage. The closer to 0, the better the results.

$$PRD = \frac{1}{n}\left[\frac{\sum_{i=1}^{n}\left|W_i^{obs} - W_i^{pred}\right|}{W_i^{obs}}\right] * 100 \quad (4)$$

The quantitative statistics provided a numerical analysis of the results, but they were considered insufficient for the overall process. Thus, we included in our toolkit a graphical technique named hydrograph to improve the analyses, once it provides a visual comparison of the predicted and observed data and a first overview of the model performance. A hydrograph is a time series plot of predicted and measured flow. It can show differences in timing and magnitude of peak flows and the shape of recession curves. Hydrographs can also show the model tendency to underestimate or overestimate flow values on the whole horizon.

IV. CASE STUDIES AND RESULTS

In this section, we describe the three steps of the methodology that were carried out. Each procedure of Table II is described in the following.

5.1 – Procedure 1.1: Selection of Study Scope

We selected three measurement stations of rainfall and river flow located at the Tietê River basin, in São Paulo State, Brazil. They are called Invernada Recreio (INR), Gavião Peixoto (GAP), and Fazenda São Benedito (FSB). INR station covers an area of 1,800 km² and is located in Bocaina city. GAP station is established in Gavião Peixoto city and extends an area of 2,430 km². FSB station covers an area of 2,710 km² and is located in Ibitinga city. The three

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selected stations are managed by AES Tietê company. They are chosen due to their importance to São Paulo state.

5.2 – Procedure 1.2: Definition of the Past Events Set

Three study periods were defined for the model calibration, adjustment, validation, and application. The period from 12/2003 to 08/2005 was used for the model calibration and adjustment because it contains dry and wet periods. The period from 12/2005 to 08/2007 was employed for the validation phase. The model was applied from 2009 on. The 2009 data were used because they are available at the beginning of this work, have a low error rate and require low pre-processing, they are also representative of the regions hydrology and have been used in other studies.

5.3 – Procedure 1.3: Rainfall and Water Inflow Data Collection

The rainfall and water inflow data series were obtained from SISPREV (HIDALGO *et al.* 2015). SISPREV is a system for managing inflow forecasting studies. It contains data of nine hydropower plants and fifteen measurement stations. SISPREV stores observed/predicted rainfalls and observed water inflows.

5.4 – Procedure 1.4: Correction of Water Inflow Data Series

We found missed information in the three stations: INR, GAP, and FSB. The water inflow values equal to zero were corrected using linear interpolation.

5.5 – Procedure 2.1: Parameters Automatic Calibration

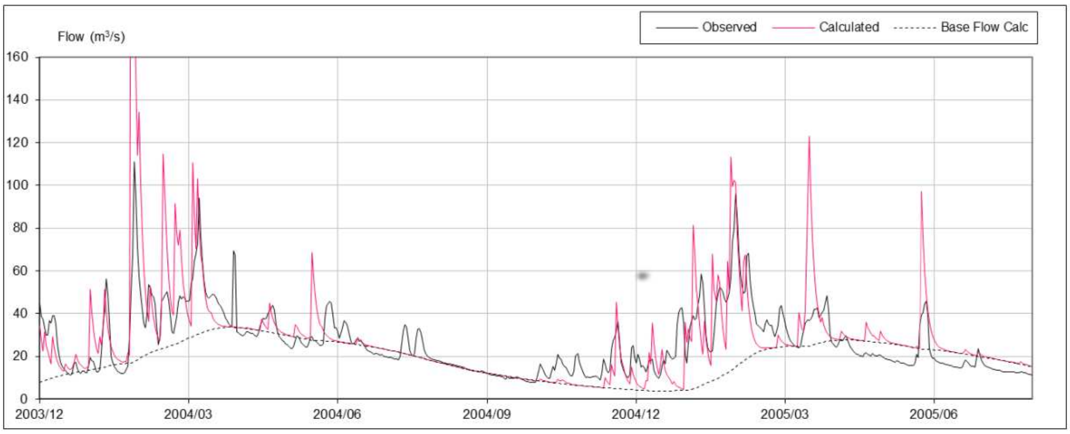
An electronic spreadsheet was prepared to carry out the calculations and it was loaded with the parameters, input variables, and data series. Thus, the Solver tool of *Microsoft Excel* was employed to calibrate the calculated parameters using the performance indicators (quantitative statistics) as objective function.

5.6 – Procedure 2.2: Parameters Manual Calibration

The same electronic spreadsheet was used to proceed a manual re-calibration of the estimated and calculated parameters, trying to reach a better precision in their adjustment. A trial-and-error process was employed to improve the hydrograph bringing closer predicted and observed data.

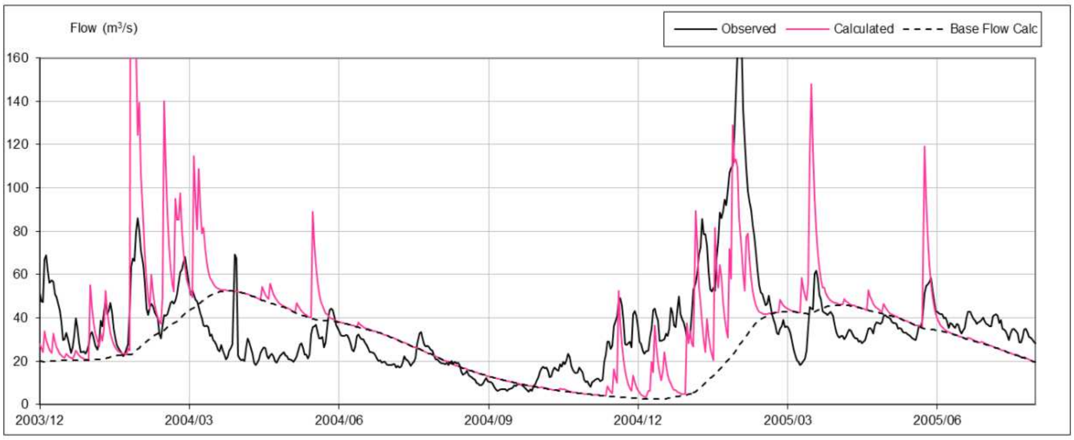
Figures. 2, 3, and 4 show the hydrograph of INR, GAP, and FSB after the model calibration, respectively. From the hydrographs, it is possible to realize that, in general, predicted and observed water inflows are good regarding to time and magnitude of the peaks and shape of the recession curves.

Figure 2 - Hydrograph of INR after the model calibration.



Source: own authorship.

Figure 3 - Hydrograph of GAP after the model calibration.



Source: own authorship.

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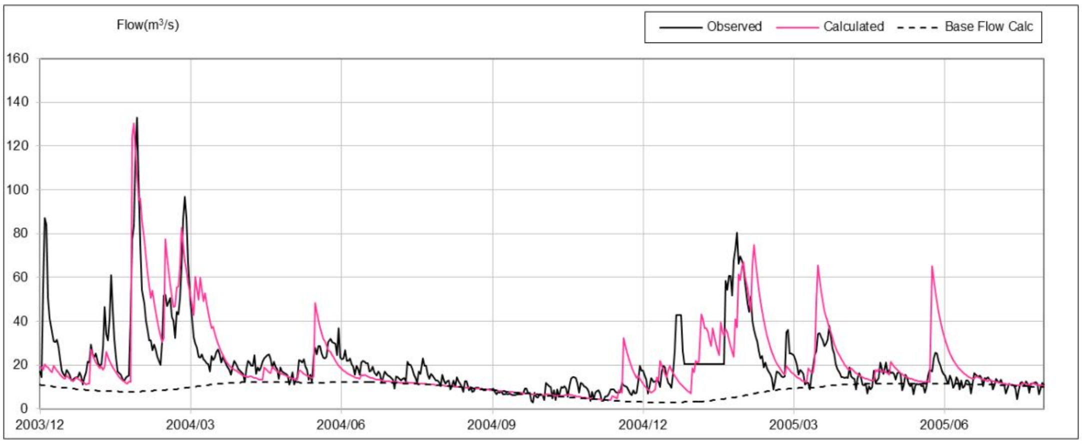
Figure 4 - Hydrograph of FSB after the model calibration.



Source: own authorship.

5.7 – Procedure 2.3: Stations Weight Definition

The electronic spreadsheet was also applied to adjust the weight of the measurement stations to indicate the importance of each one in the basin context. Again, we used Solver tool of *Microsoft Excel* and the performance indicators as objective function.

5.8 – Procedure 2.4: Validation of the Model

SMAP was applied to data series of the elected validation period, which is from 12/2005 to 08/2007. Its output was satisfactory, validating the previous adjustments.

5.9 – Procedure 3.1: SMAP Operation

For each measurement station, SMAP model was applied to four periods of seven days. They are 21-27 of Feb/2009, 08-14 of Mar/2009, 01-07 of Jun/2009, and 01-07 of Nov/2009. These days were chosen because they represent different seasons with dry and wet periods. In Brazil, the summer is between 21/Dec and 20/Mar (the rainiest period), the fall goes from 20/Mar to 20/Jun, the winter starts on 20/Jun and finishes on 22/Sep (the driest period); and the spring goes from 22/Sep to 21/Dec.

5.10 – Procedure 3.2: Post-Operation Analysis

Tables IV, V, and VI show the values and ratings of the performance indicators for INR, GAP, and FSB; respectively, in the four periods of seven days. Regarding to NSE, RSR, and PBIAS indicators; for INR (Table VI) 75 % of the indicators are classified as very good and 25 % as good. For GAP (Table VII) 92 % of the indicators are classified as very good and 8 % as good. For FSB (Table VIII) 75 % of the indicators are classified as very good, 17 % as good, and 8% as satisfactory.

In relation to NSE indicator, the analysis is done comparing SMAP and PREVIVAZ outputs. In the report of annual inflow forecasting – 2019 year (ONS, 2019b), PREVIVAZ shows NSE of 0.64 for the Tietê River basin. Using SMAP model and considering the four periods of the presented case studies, the mean NSE is of 0.82 for INR station, 0.90 for GAP station, and 0.71 for FSB station.

Table IV. Model performance for INR station.

Indicator	**Days 21-27 Feb/2009**		**Days 08-14 Mar/2009**		**Days 01-07 Jun/2009**		**Days 01-07 Nov/2009**	
	Value	**Rate**	**Value**	**Rate**	**Value**	**Rate**	**Value**	**Rate**
NSE	0.75	very good	0.76	very good	0.80	very good	0.99	very good
RSR	0.50	good	0.49	very good	0.45	very good	0.08	very good
PBIAS	-14 %	good	12 %	good	8 %	very good	0 %	very good
PRD	18 %		25 %		17 %		3 %	

Table V. Model performance for GAP station.

Indicator	**Days 21-27 Feb/2009**		**Days 08-14 Mar/2009**		**Days 01-07 Jun/2009**		**Days 01-07 Nov/2009**	
	Value	**Rate**	**Value**	**Rate**	**Value**	**Rate**	**Value**	**Rate**
NSE	0.88	very good	0.82	very good	0.96	very good	0.95	very good
RSR	0.35	very good	0.42	very good	0.19	very good	0.21	very good
PBIAS	-10 %	very good	11 %	good	7 %	very good	-6 %	very good
PRD	14 %		14 %		7 %		7 %	

Table VI. Model performance for FSB station.

Indicator	**Days 21-27 Feb/2009**		**Days 08-14 Mar/2009**		**Days 01-07 Jun/2009**		**Days 01-07 Nov/2009**	
	Value	**Rate**	**Value**	**Rate**	**Value**	**Rate**	**Value**	**Rate**
NSE	0.78	very good	0.74	good	0.97	very good	0.34	very good
RSR	0.47	very good	0.51	good	0.17	very good	0.81	very good
PBIAS	-16 %	satisfactory	9 %	very good	5 %	very good	16 %	very good
PRD	19 %		15 %		5 %		52 %	

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V. CONCLUSIONS

The case studies showed a good performance of SMAP model for the three measurement stations of the Tietê River basin: INR, GAP, and FSB. The result in the application of the model showed a NSE between 0.34 and 0.99. This result are very good compared to the result from the annual evaluation report of the national operator of the electrical system for 2019, which showed a NSE between 0.02 and 0.64 using PREVIVAZ model for the Tiete River basin

The worst result in the application of the model showed for FSB station in the third week of the case study. This poor result may have occurred due to the quality of the observed water inflow data, which have equal values for five of the seven considered days.

Two considerations regarding to the studies should be done. First, the rainfall data are observed, that means, the model dealt with potential errors in the data, but not with uncertainties in the data. Second, the performance ratings applied are adequate for a monthly time step. As the evaluation time step increases, a stricter performance rating is warranted. Therefore, although the data do not include uncertainties the performance ratings employed for model evaluation are stricter than necessary.

As future work the authors have two suggestions. The first one is to apply the methodology proposed in this paper to data from other basins of the national interconnected system. This way, it is possible to benefit the energy sector with alternative tools of water inflow forecasting. The second suggestion is to analyze the impact of the input data quality in the result of the water inflow forecasting. For this, the authors recommend to increase the number of measurement points and the quality of measured data.

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