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RESEARCH ARTICLE

Neural Hierarchical Interpolation Time Series (NHITS) for Reservoir Level Multi-Horizon Forecasting in Hydroelectric Power Plants

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ABSTRACT Energy planning in systems heavily influenced by hydroelectric power is based on assessing the availability of water in the future. In Brazil, based on the soil moisture active passive, the National Electricity System Operator defines electricity dispatch concerning a stochastic optimization problem. Currently, machine learning models are an alternative for improving forecasts, and could be a promising solution for predicting reservoir levels at hydroelectric dams. In this paper, neural hierarchical interpolation for time series (NHITS) is applied to improve forecasts and thus help decision-making in the management of electric power systems. The NHITS model achieved a root mean square error of 4.64×10^{-4} for a 1-hour forecast horizon, and 1.03×10^{-3} for a 10-hour forecast horizon, being superior to multilayer perceptron (MLP) neural network, long short-term memory (LSTM), convolutional neural network with long short-term memory (CNN-LSTM), recurrent neural network (RNN), Dilated RNN, temporal convolutional neural (TCN), neural basis expansion analysis for interpretable time series forecasting (N-BEATS), and deep non-parametric time series forecaster (DeepNPTS) deep learning approaches.

INDEX TERMS Energy planning, hydroelectric power plants, neural hierarchical interpolation, time series forecasting.

I. INTRODUCTION

In some countries the planning of the dispatch of the electricity generation system is based on the evaluation of a stochastic optimization problem [1] that considers the level

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of the reservoirs and rainfall forecasts that consequently increase the level of the hydroelectric dams [2]. Currently, the Brazilian energy planning is carried out based on the soil moisture accounting procedure (SMAP) model [3].

The SMAP is a physical model that is based on categorizing the flow of surface and subsurface runoff [4]. The national system operator receives the dam level data and information from SMAP to define each plant's dispatch, thus guaranteeing future energy security and the lowest cost based on the use of hydro resources [5]. With the advances in research on machine learning (ML) models, it is promising to evaluate their potential application regarding reservoir level forecasting [6].

Every day more applications of innovative methods are being presented [7], [8], [9], [10], [11], [12], [13]. Proposals of hybrid ML methods are emerging to be applied to time series forecasting. Ensemble learning approaches combine several weak learners to generate a more powerful forecasting model [14], and the application of deep learning (DL) strategies show promise [15]. Therefore, there is a trade-off between the need to process non-linear features and the computational effort required to carry out this task to improve the model's performance [16].

An approach gaining prominence is applying filters to reduce non-linearities in time series [17]. High frequencies often do not represent the trend variation of the signal, which is why there are methods that apply filters to reduce noise, resulting in a more linear time series, in which the prediction model can achieve better performance [18].

Among the most common denoising techniques for time series, stand out the wavelet transform [19], variational mode decomposition methods, Christiano-Fitzgerald random walk filter [20], seasonal-trend decomposition using locally estimated scatterplot smoothing [21], and seasonal decomposition using moving averages [22]. The use of filters is indicated when the time series has high frequencies that do not correspond to the trend of variation. When the signal does not have these features, it is not worth it to apply denoising techniques because the signal can lose its fundamental characteristics, this is the case with the signal evaluated in this paper.

Several ML approaches have been applied for time series forecasting, resulting in a challenging task in the model definition. The multilayer perceptron (MLP) neural network, long short-term memory (LSTM) [23], recurrent neural network (RNN) [24], Dilated RNN [25], temporal convolutional neural (TCN) [26], neural basis expansion analysis for interpretable time series forecasting (N-BEATS) [27], and deep non-parametric time series forecaster (DeepNPTS) [28] are examples of promising strategies in this regard.

Since energy planning is directly related to the level of power plant dams [29], this paper proposes to use a neural hierarchical interpolation for time series (NHITS) to forecast the reservoir levels of hydroelectric power plants supporting the decision-making concerning electricity management in a matrix that has a strong presence of hydroelectric plants. The multi-horizon term is evaluated to present a complete analysis of the possibilities of forecasting.

The level variation of the dams is especially important to forecast in the southern region, considering the history of floods faced in this region due to abrupt variations in the level of the river caused by a large amount of rainfall in a short period [30]. Based on this challenge, the NHITS model is applied to predict water variation at the Barra Grande hydroelectric power plant in Santa Catarina, Brazil.

This paper has the following contributions:

- Improving dam level forecasting can improve the management of the electricity system by providing more accurate information for decision-making regarding the dispatch of hydroelectric plants.
- The NHITS model is stable when various experiments are carried out, maintaining low variability. The results showed that the NHITS is promising for multi-horizon forecasting being generalized to other tasks.
- The NHITS outperforms the MLP, LSTM, RNN, Dilated RNN, TCN, N-BEATS, and DeepNPTS approaches, for very short-term (VST) and short-term (ST) forecasting.

The remainder of this article is organized as follows: In Section II related works focused on time series forecasting in hydroelectric power plants are presented. In Section III the problem description that gives the motivation of the application covered here and the considered dataset are described. In Section IV the NHITS architecture is explained, and the setup for comparison is detailed. In Section V the results are presented and finally in Sections VI a conclusion and future work direction is drawn.

II. RELATED WORKS

Significant development has been made in applying ML and DL methods in reservoir inflow and streamflow forecasting. These methods often improve predictive accuracy over traditional statistical approaches.

Herbert et al. [31] introduced a multi-step forecasting approach utilizing an Encoder-Decoder algorithm, comparing the performance of LSTM and convolutional neural network (CNN) models. Their study focused on improving long-term forecasting accuracy for reservoir inflows, demonstrating that the LSTM encoder-decoder model achieved superior results to traditional statistical and process-based models.

Latif et al. [32] examined the performance of DL models in the context of daily reservoir inflow forecasting. Their study, conducted on the Durian Tunggal Reservoir, showed that LSTM models performed better than classical ML techniques such as support vector machines (SVM) and artificial neural networks (ANNs), as evidenced by higher coefficient of determination values and lower error metrics like mean absolute error (MAE) and root mean square error (RMSE).

Recent research has also explored hybrid modeling approaches. Khorram et al. [33] developed a model that combines LSTM and CNN for reservoir inflow forecasting. The hybrid CNN-LSTM was shown to have higher predictive accuracy than several other models, including SVM, adaptive neuro-fuzzy inference system (ANFIS), and autoregressive integrated moving average (ARIMA), suggesting its effectiveness in capturing the nonlinearities present in inflow data.

Sushanth et al. [34] investigated the integration of high spatial resolution weather forecasts with ML models, employing explainable ML techniques to enhance real-time inflow forecasting. Their work on the Tenughat catchment indicated that an LSTM model, when combined with bias-corrected Global Forecasting System data, could provide accurate predictions up to three days in advance, illustrating the potential of combining weather forecasts with ML models for real-time forecasting applications.

In the area of long-term streamflow forecasting, Vatanchi et al. [35] analyzed the effectiveness of several DL models, including ANFIS, ANN, bidirectional LSTM (BiLSTM), and a hybrid CNN-GRU-LSTM model, in predicting daily streamflow for the Colorado River, where GRU is the gated recurrent unit (GRU). Their findings suggested that the ANFIS model had superior performance in terms of metrics such as normalized RMSE, MAE, and Nash-Sutcliffe efficiency coefficient, indicating that traditional models may still have advantages in certain long-term forecasting scenarios.

Additional studies have further explored the application of DL models in streamflow prediction. Ayana et al. [36] conducted monthly streamflow predictions using various ML and DL techniques, including linear regression, support vector regression, random forest, and bidirectional GRU (BiGRU) models. Their results showed that the BiGRU model outperformed both ML algorithms and other DL models.

Xu et al. [37] examined the effects of spatial and temporal scale on predictive performance when using a hybrid CNN-GRU model for monthly streamflow prediction across watersheds with varying hydroclimatic characteristics. Their results indicated that the model performed better in larger drainage areas and highlighted the importance of extended training periods for improving predictive accuracy.

Khullar et al. [38] addressed the challenge of water quality forecasting using a BiLSTM model, finding that it outperformed traditional ML models in predicting water quality factors in the Yamuna River, India. This study emphasizes the potential application of DL techniques in ecological and water resource management.

In daily streamflow forecasting, Rahimzad et al. [39] compared the accuracy of various ML models, including LSTM, MLP, SVM, and linear regression, within the Kentucky River basin. Their findings supported using the LSTM model as a reliable tool for capturing time series behaviors in hydrological modeling. Hybrid models are increasingly being used to improve prediction performance [40].

Sahoo et al. [41] focused on low-flow time series forecasting using LSTM-RNN, demonstrating that this model outperformed traditional RNN and naïve methods, making LSTM-RNN a reliable artificial intelligence (AI) technique for streamflow forecasting, particularly in low-flow scenarios. Rajesh et al. [42] presented a framework combining multiple ML algorithms for short-range reservoir inflow forecasting, including LSTM, random forest, and gradient boosting approach. Their ensemble approach resulted in improved predictive performance and reduced uncertainty, particularly for tropical reservoirs.

Li et al. [43] explored the application of deep feature learning architectures, such as deep restricted Boltzmann machines and stacked autoencoders, for daily reservoir inflow forecasting. Their results showed that these deep neural networks provided better predictive performance compared to traditional models like feedforward neural networks and ARIMA, highlighting the potential of DL in handling large datasets and complex feature extraction.

Dharpure et al. [44] investigated the use of various ML models, including BiLSTM, for daily streamflow forecasting in the western Himalayas. Their study showed that the BiLSTM model achieved higher accuracy in capturing hydrological variability in glacierized catchments, suggesting its applicability in regions with complex hydrological regimes.

Shekar et al. [45] conducted a comparative analysis of LSTM and several AI models for rainfall-runoff modeling in the Murredu River basin. Their findings indicated that the LSTM model performed exceptionally well during both calibration and validation periods, demonstrating its effectiveness in accurately modeling the rainfall-runoff relationship in watershed management.

LSTM models are frequently noted for their strong performance across diverse hydrological settings, often outperforming traditional approaches. Hybrid models, particularly those integrating weather forecasts, have shown potential in improving predictive accuracy, though traditional methods like ANFIS remain relevant in some long-term scenarios. The research highlights the importance of model selection based on specific forecasting needs and suggests that combining different methodologies can effectively address the complexities of hydrological forecasting [5].

Everything considered, there is a wide application of ML and DL techniques in reservoir inflow and streamflow forecasting, with an increasing trend toward more complex and hybrid models incorporating various data sources. In this context, several authors have carried out studies on inflow, while specific analyses of the reservoir level as carried out in [46] are rarer. Based on this need, this paper presents an analysis of dam-level multi-horizon forecasting.

III. PROBLEM DESCRIPTION

The dispatch of the electrical power systems in Brazil is considering a stochastic optimization that considers the level of water in the hydroelectric power plants and the weather forecasting to estimate the future level of the dams in these power plants [47]. Given the advances in ML for time series forecasting, the NHITS model presented in this paper could be used to give additional information regarding available water in a hydroelectric-based power system. Additionally, especially in southern Brazil floods are a concern since the cities are usually close to the rivers, and abrupt variation in river levels is a problem that needs attention [48]. Given an ML-based model, the forecasting in dams in hydroelectric power plants could help to highlight emergencies, which would improve flood management.

The operators monitor the increase in dam levels hourly via the power plant's control system. This information is passed on to the national system operator, which defines the operating strategies for the electrical power system, thereby being responsible for assessing the best use of the water resource, ensuring the security of the energy supply, and the lowest future price of electricity.

A further consideration regarding the assessment of dam levels is the flooding that occurs in their surroundings due to abrupt variations in rainfall. These concerns are taken into account when the plant's operating strategies are defined. For this reason, predicting the dam's level can help plan its use. Based on these needs, this paper evaluates the prediction of the water volume in the dam to support decision-making regarding the use of the water resource [6].

A. DATASET

This paper considers the Barra Grande Hydroelectric Power Plant, located on the Pelotas River, about 43 kilometers from its confluence with the Canoas River, between Anita Garibaldi/SC and Pinhal da Serra/RS municipalities. The dam is 185 meters high and 665 meters long. This structure forms the reservoir that covers an area of 90 square kilometers [49].

The considered time series is measured at one-hour intervals during a 31-day month (July 2020), corresponding to 744 records. This level variation as a percentage of the usable volume for generating electricity is presented in Figure 1.

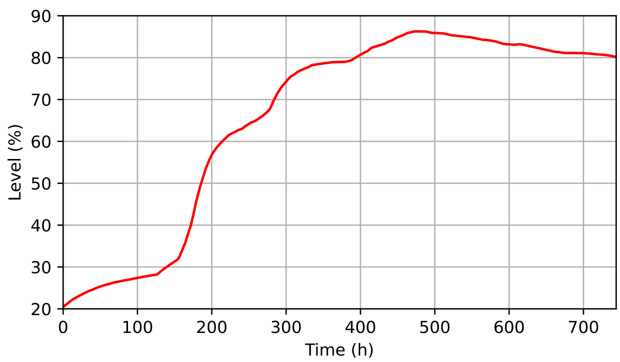

FIGURE 1. Useful level of the power plant over time.

The data under consideration is from measurements of this plant's automatic hydraulic control system during a flood event, in which, in less than a month, the dam's water level rose from 20.46% to 86.27%. This highlights how the river level can be variable, showing that there is a need for an accurate prediction model to have an adequate strategy for better use of the water and reducing the impact of floods. For a fair prediction evaluation, the observed dam level measure is normalized using the following equations:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{1}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \mu)^2} \tag{2}$$

$$\mathbf{y} = \frac{\mathbf{y} - \mu}{\sigma} \tag{3}$$

where μ is the mean of the considered values, σ is the standard deviation, n is the number of i samples, and $\mathbf{y}$ is the normalized values used for network training and testing.

IV. METHODOLOGY

The interpolation of time series data has a long history, with methods ranging from simple linear and polynomial techniques to more sophisticated spline and kernel-based methods [50]. Recently, ML approaches, particularly DL models like RNNs and transformers, have demonstrated superior performance in capturing the intricate patterns in time series data [51]. ML and DL models could be an alternative for improving water level forecasting in hydroelectric plants.

A. WATER LEVEL IN HYDROELECTRIC PLANTS

The operation of a hydroelectric plant typically follows the daily electro-energetic program, which the operation programming division of the National Electric System Operator issues [52]. This program includes updates or changes to operational restrictions for national energy generation and transmission facilities, daily load forecasts, automatic generation control programming, and reservoir operation conditions forecasts [53], which is the main focus of this paper.

The water level control of the hydroelectric plant relies on the difference in water flow at the dam. This is determined by the accumulated flow ($F_{\mathrm{A}cc}$), which is the difference between the inflow ($F_{\mathrm{A}ff}$) and the outflow ($F_{\mathrm{D}ef}$), expressed as:

$$F_{\mathrm{A}cc}(t) = F_{\mathrm{A}ff}(t) - F_{\mathrm{D}ef}(t). \tag{4}$$

When the inflow ($F_{\mathrm{A}ff}$) exceeds the outflow ($F_{\mathrm{D}ef}$), the water level of the dam rises. The outflow ($F_{\mathrm{D}ef}$) results in downstream flow ($F_{\mathrm{D}ow}$), which is the sum of the turbine flow ($F_{\mathrm{T}ur}$) and the spilled flow ($F_{\mathrm{S}pi}$), given by:

$$F_{\mathrm{D}ow}(t) = F_{\mathrm{T}ur}(t) + F_{\mathrm{S}pi}(t). \tag{5}$$

The waterfall ($F_{\mathrm{W}at}$) determines when the plant can turbine water and then generate energy [54]. This takes into account that the upstream flow ($F_{\mathrm{U}ps}$) is related to the inflow ($F_{\mathrm{A}ff}$). Therefore, the waterfall is calculated according to:

$$F_{\mathrm{W}at}(t) = F_{\mathrm{U}ps}(t) - F_{\mathrm{D}ow}(t). \tag{6}$$

There is currently a discussion about how hydroelectric dams can help control floods, observing the power plants' operation conditions [46], which have a major impact in Brazil. Models that help predict the rise in dam levels can also provide important information to help the teams that work on the mitigation of the effects of floods on the people who live near the rivers.

Selecting the appropriate method to perform water level prediction can be challenging, given that several models have shown satisfactory results in time series forecasting [55]. Typically, ML and DL models often focus on a single level of data granularity, which can limit their ability to generalize across different temporal scales [56]. The NHITS method builds upon these needs by incorporating a hierarchical modeling framework, which enables simultaneous learning of global and local temporal patterns.

B. NEURAL HIERARCHICAL INTERPOLATION

Long-horizon forecasting poses significant challenges due to prediction volatility and computational complexity. To address these issues, the neural hierarchical interpolation for time series (NHITS) was proposed by Challu et al. [57]. The architecture of the NHITS model is presented in Figure 2.

The predictions of the different levels are combined to generate a final model prediction, and the model error is calculated as the difference between the combined stacked prediction value and the observed value.

NHITS builds on the N-BEATS model and enhances its performance by specializing in partial outputs for different time series frequencies through hierarchical interpolation and multi-rate input processing [27].

In the NHITS, multi-rate processing narrows the MLP input width for most blocks. This reduction decreases the memory footprint, lowers computational requirements, and minimizes the number of learnable parameters, thus mitigating overfitting while preserving the original receptive field. Given the block ℓ of the input $\mathbf{y}_{t-L:t,\ell}$, the operation can be formalized as follows:

$$\mathbf{y}^{(p)}_{t-L:t,\ell} = \mathbf{MaxPool}(\mathbf{y}_{t-L:t,\ell}, k_\ell) \tag{7}$$

where $\mathbf{y}_{t-L:t}$ is the overall network input, k_ℓ is the pooling kernel size, and L are the lags. For the first block input $\ell = 1$; $\mathbf{y}_{t-L:t,1} \equiv \mathbf{y}_{t-L:t}$ [57].

The block ℓ examines its input and applies nonlinear regression to compute the forward interpolation coefficients θ^f_ℓ and the backward interpolation coefficients θ^b_ℓ. This process involves learning the hidden vector $\mathbf{h}_\ell \in \mathbb{R}^{N_h}$, linearly projected according to:

$$\begin{aligned} \mathbf{h}_\ell &= \mathbf{MLP}_\ell(\mathbf{y}^{(p)}_{t-L:t,\ell}) \\ \theta^f_\ell &= \mathbf{LINEAR}^f(\mathbf{h}_\ell) \\ \theta^b_\ell &= \mathbf{LINEAR}^b(\mathbf{h}_\ell). \end{aligned} \tag{8}$$

The coefficients are then used to generate the backcast output $\tilde{\mathbf{y}}_{t-L:t,\ell}$ and the forecast output $\hat{\mathbf{y}}_{t+1:t+H,\ell}$ of the block.

According to Perera et al. [58], the effectiveness of forecasting approaches is influenced by both the resolution and the horizon of the task, being a challenge to evaluate multi-horizon forecasting. In several multi-horizon forecasting approaches, the model's number of predictions equals the horizon's dimensionality H.

In transformers, the decoder attention layer cross-correlates the horizon output embeddings with encoded input embeddings [59]. This results in a rapid increase in computational effort and an unneeded expansion of the model's complexity with higher horizons. The temporal interpolation was proposed in [57] to solve this issue. To restore the original sampling rate and forecast all points in the considered horizon, the interpolation function (g) is applied, where:

$$\begin{aligned} \hat{y}_{\tau,\ell} &= g(\tau, \theta^f_\ell), \quad \forall \tau \in \{t+1, \ldots, t+H\}, \\ \tilde{y}_{\tau,\ell} &= g(\tau, \theta^b_\ell), \quad \forall \tau \in \{t-L, \ldots, t\}. \end{aligned} \tag{9}$$

The linear interpolator $g \in C^1$ with the time partition,

$$\mathrm{T} = \{t+1, t+1+1/r_\ell, \ldots, t+H-1/r_\ell, t+H\} \tag{10}$$

is

$$g(\tau, \theta) = \theta[t_1] + \left(\frac{\theta[t_2]-\theta[t_1]}{t_2-t_1}\right)(\tau - t_1) \tag{11}$$

where

$$t_1 = \arg\min_{t \in T: t \le \tau}(\tau - t), \quad t_2 = t_1 + 1/r_\ell. \tag{12}$$

The hierarchical interpolation operates by allocating expressiveness ratios across blocks in sync with multi-rate sampling. Blocks nearer to the input feature smaller r_ℓ and larger k_ℓ, meaning they produce low-granularity signals through more aggressive interpolation. These input blocks also need to consider more sub-sampled signals. The final hierarchical forecast $\hat{\mathbf{y}}_{t+1:t+H}$ is constructed by aggregating the outputs of all blocks, effectively combining interpolations from various levels of the time-scale hierarchy [57].

$$\hat{\mathbf{y}}_{t+1:t+H} = \sum_{l=1}^{L} \hat{\mathbf{y}}_{t+1:t+H,\ell} \tag{13}$$

$$\mathbf{y}_{t-L:t,\ell+1} = \mathbf{y}_{t-L:t,\ell} - \tilde{\mathbf{y}}_{t-L:t,\ell} \tag{14}$$

The backcast residue generated in the prior hierarchy is removed from the input of the following hierarchy level. This increases the focus of the next level's block on out-of-band signals that the members of the previous hierarchy have already processed.

In other words, hierarchical interpolation enhances time series forecasting by decomposing the input data into components of varying frequencies and scales, allowing for more accurate and efficient predictions. In NHITS, the model processes the input time series through multiple layers, each designed to capture different aspects of the data. Initially, the model applies multi-rate signal sampling, where the input is downsampled at various rates to focus on different frequency components. Subsequently, each

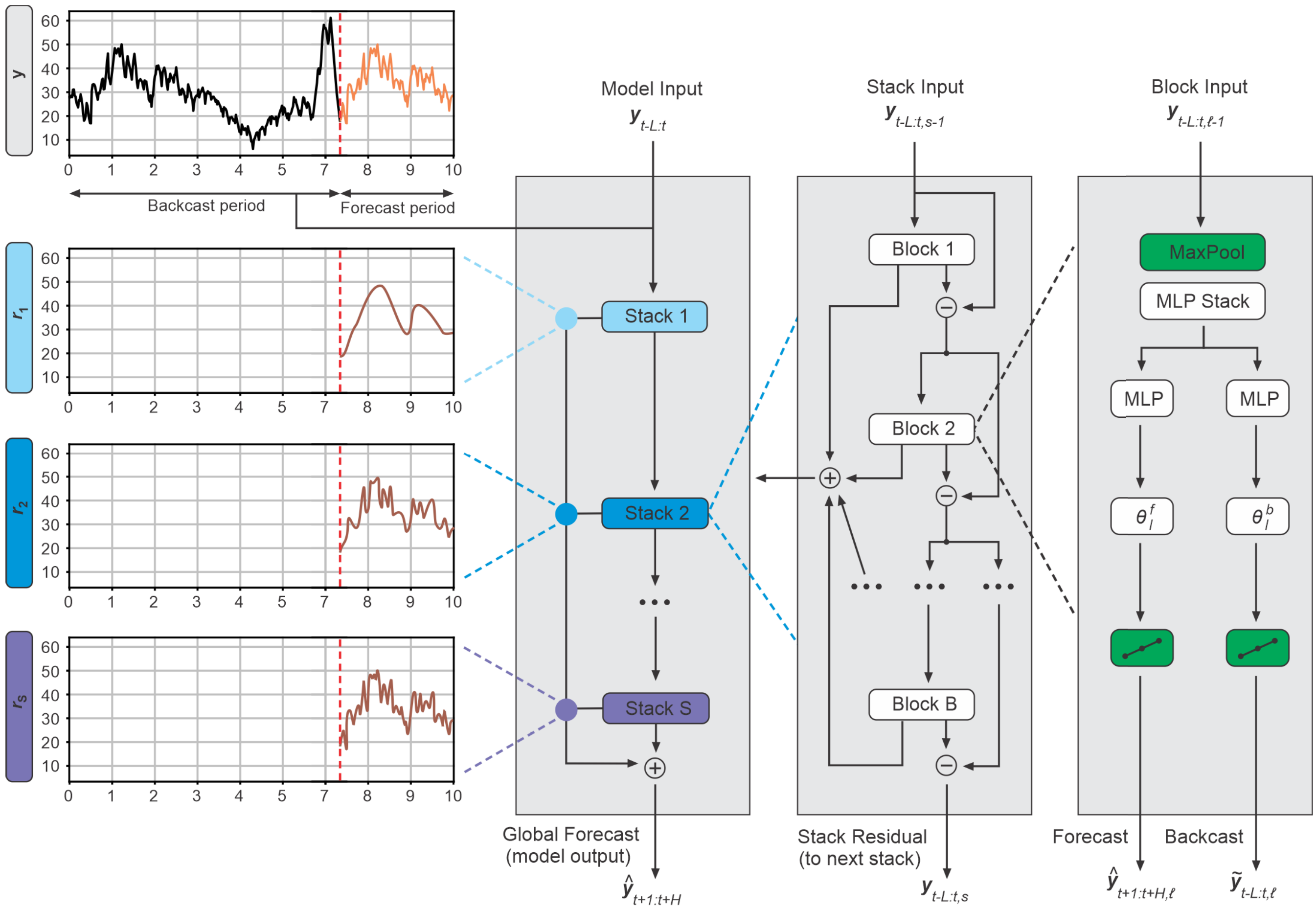

FIGURE 2. Architecture of NHITS.

layer performs nonlinear regression to predict forward and backward interpolation coefficients. These coefficients are then used in the hierarchical interpolation step to reconstruct the time series at different scales, effectively capturing both short-term fluctuations and long-term trends. The final forecast is assembled by combining the outputs from all layers, resulting in a comprehensive prediction that accounts for various temporal patterns [57].

According to Mancuso et al. [60], when handling hierarchical time series, it is essential to generate accurate forecasts and choose an appropriate method for generating reconciled forecasts. This involves adjusting forecasts to ensure they are consistent across the hierarchy.

C. EVALUATION METRICS

The evaluation measures considered in this paper were RMSE, root mean squared percentage error (RMSPE), MAE, and median absolute error (MedAE). These measures are from the `statsmodels` library, specifically available in `statsmodels.tools.eval_measures` library.[1]

[1] https://www.statsmodels.org/dev/_modules/statsmodels/tools/eval_measures.html

RMSE is a measure of the differences between values predicted by a model and the values observed [61]. The RMSE is defined as follows [62]:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{15}$$

where n is the number of observations, y_i is the observed value for the i-th observation, and $\hat{y}_i$ is the predicted value for the i-th observation.

RMSPE is a measure of the relative differences between predicted and observed values, expressed as a percentage. It is particularly useful when you want to understand the prediction error relative to the magnitude of the observed values [63]. The RMSPE is calculated by,

$$\mathrm{RMSPE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2}. \tag{16}$$

MAE measures the average magnitude of errors between predicted values and actual values, given by:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{17}$$

MAE provides an intuitive measure to determine which model has lower average errors, thereby identifying the better-performing model [64]. MedAE is used to evaluate the performance of forecasting models by measuring the median of the absolute differences between the observed and predicted values, given by:

$$\text{MedAE} = \text{median}|y_i - \hat{y}_i| \tag{18}$$

considering the absolute error $|y_i - \hat{y}_i|$ equal x, the median of x is calculated according:

$$\text{median}(x) = \begin{cases} x[\frac{n+1}{2}] & \text{if } n \text{ is odd} \\ \frac{x[\frac{n}{2}] + x[\frac{n}{2}+1]}{2} & \text{if } n \text{ is even.} \end{cases} \tag{19}$$

MedAE is applied when the data set is expected to contain outliers [65]. Since the median is not affected by extreme values, it provides a more reliable estimate of the typical error.

D. EXPERIMENT SETUP

Python is the language chosen to write the NHITS algorithm. To compute the experiments, the back-end of Google compute engine (`Colab`) was used, using a graphics processing unit NVIDIA Tesla T4 with 15 GB of random-access memory.

To evaluate the stability of the model, after fine-tuning, the mean, median, mode, range, variance, standard deviation (std. dev.), 25th percentile (%ile), 50th %ile, 75th %ile, interquartile range (IQR), skewness, and kurtosis are analyzed considering 50 runs with random seed.

For a comparative analysis, the MLP, LSTM [23], CNN-LSTM [66], RNN [24], Dilated RNN [25], TCN [26], N-BEATS [67], and DeepNPTS [28], are compared to the NHITS. These models use the default settings from the `nixtla` repository [68].

V. RESULTS AND DISCUSSIONS

To achieve a promising result in time series forecasting, it is necessary to evaluate the model's parameters in such a way as to make the best use of its potential. The best results of the comparative analysis presented in this section are highlighted in bold. Considering that the number of steps the model considers to perform the forecast makes a difference to the performance results, Table 1 shows an evaluation considering the variation of an acceptable maximum number of steps.

The best result was achieved using 2,500 steps as the maximum for prediction. A limit value greater than 5,000 steps results in an increase in the complexity of the calculation without improving performance, which is why this value was set as the limit in this evaluation. It should be noted that the number of steps is directly related to the characteristics of the signal since there is a difference in the application when considering long or short-term signals.

To better assess the influence of using the signal for prediction, Table 2 shows the prediction error results considering the change in input size. This evaluation took into account the maximum number of 2,500 steps.

TABLE 1. Evaluation of the maximum number of steps.

Max Steps	RMSE	RMSPE	MAE	MedAE
25	5.32×10^{-2}	7.61×10^{-1}	4.58×10^{-2}	5.01×10^{-2}
50	5.51×10^{-2}	7.88×10^{-1}	4.70×10^{-2}	4.65×10^{-2}
100	4.80×10^{-2}	6.86×10^{-1}	4.12×10^{-2}	4.16×10^{-2}
250	4.01×10^{-2}	5.72×10^{-1}	3.51×10^{-2}	3.79×10^{-2}
500	3.70×10^{-2}	5.27×10^{-1}	3.23×10^{-2}	3.35×10^{-2}
1,000	3.35×10^{-2}	4.78×10^{-1}	2.91×10^{-2}	3.00×10^{-2}
2,500	$\mathbf{3.22}\times10^{-2}$	$\mathbf{4.59}\times10^{-1}$	$\mathbf{2.78}\times10^{-2}$	$\mathbf{2.73}\times10^{-2}$
5,000	3.83×10^{-2}	5.46×10^{-1}	3.35×10^{-2}	3.78×10^{-2}

TABLE 2. Analysis of the use of different input sizes.

Input Size	RMSE	RMSPE	MAE	MedAE
50	5.56×10^{-2}	7.93×10^{-1}	4.89×10^{-2}	6.30×10^{-2}
75	4.52×10^{-2}	6.47×10^{-1}	3.66×10^{-2}	3.66×10^{-2}
100	3.31×10^{-2}	4.73×10^{-1}	2.71×10^{-2}	2.66×10^{-2}
125	3.05×10^{-2}	4.37×10^{-1}	2.56×10^{-2}	2.56×10^{-2}
150	3.02×10^{-2}	4.30×10^{-1}	2.65×10^{-2}	2.87×10^{-2}
175	2.88×10^{-2}	4.07×10^{-1}	2.43×10^{-2}	2.94×10^{-2}
200	$\mathbf{1.52}\times10^{-2}$	$\mathbf{2.17}\times10^{-1}$	$\mathbf{1.25}\times10^{-2}$	1.17×10^{-2}
225	3.66×10^{-2}	5.30×10^{-1}	2.40×10^{-2}	$\mathbf{1.02}\times10^{-2}$
250	3.87×10^{-2}	5.63×10^{-1}	2.46×10^{-2}	1.14×10^{-2}

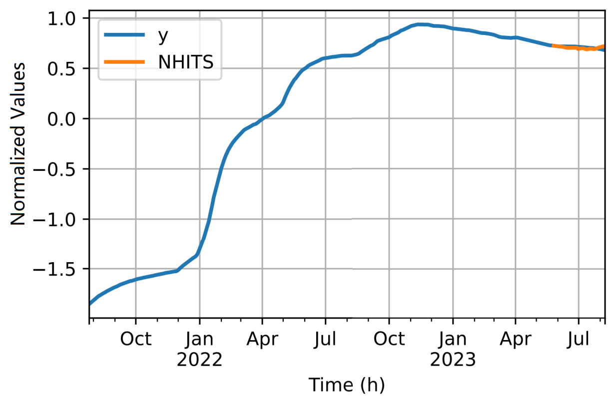

FIGURE 3. Comparison of the observed (y) to the prediction values using a horizon equal to the size of the test dataset.

The best result when evaluating the use of input data was with an input size of 200. Based on these preliminary results, Figure 3 shows the NHITS prediction values compared to the original signal, considering 90% of the data used for training and 10% for testing the model.

Multi-horizon forecasting is a significant challenge, as the longer the horizon, the more difficult the prediction becomes. This can be seen in Figure 3, as the last forecast values were higher than the observed values, showing that the longer the prediction horizon, the more difficult it is for the model to predict the value with the lowest error. Specifically for this challenge, an analysis is carried out concerning the variation of the horizon and the use of the data set, the results of which are presented in the next subsection.

TABLE 3. Analysis of the use of different input sizes.

Train / Test (ratio)	Horizon (hours)	RMSE	RMSPE	MAE	MedAE
60 / 40	1	2.12×10^{-3}	1.61×10^{-2}	2.12×10^{-3}	2.12×10^{-3}
	5	6.33×10^{-3}	4.76×10^{-2}	5.68×10^{-3}	6.23×10^{-3}
	10	9.87×10^{-3}	7.35×10^{-2}	8.19×10^{-3}	5.50×10^{-3}
	15	1.31×10^{-2}	9.72×10^{-2}	1.18×10^{-2}	1.44×10^{-2}
	20	2.12×10^{-2}	1.55×10^{-1}	1.86×10^{-2}	2.17×10^{-2}
	25	3.26×10^{-2}	2.37×10^{-1}	2.77×10^{-2}	2.68×10^{-2}
70 / 30	1	$\mathbf{4.64}\times10^{-4}$	$\mathbf{4.17}\times10^{-3}$	$\mathbf{4.64}\times10^{-4}$	$\mathbf{4.64}\times10^{-4}$
	5	3.53×10^{-3}	3.18×10^{-2}	2.99×10^{-3}	2.81×10^{-3}
	10	1.03×10^{-3}	9.33×10^{-3}	7.64×10^{-4}	5.12×10^{-4}
	15	1.50×10^{-2}	1.36×10^{-1}	1.15×10^{-2}	8.90×10^{-3}
	20	2.05×10^{-2}	1.86×10^{-1}	1.57×10^{-2}	1.02×10^{-2}
	25	3.51×10^{-2}	3.20×10^{-1}	2.79×10^{-2}	2.15×10^{-2}
80 / 20	1	1.87×10^{-3}	2.11×10^{-2}	1.87×10^{-3}	1.87×10^{-3}
	5	3.52×10^{-3}	3.97×10^{-2}	3.22×10^{-3}	2.41×10^{-3}
	10	9.12×10^{-3}	1.03×10^{-1}	7.10×10^{-3}	5.07×10^{-3}
	15	1.65×10^{-2}	1.88×10^{-1}	1.29×10^{-2}	1.03×10^{-2}
	20	2.15×10^{-2}	2.44×10^{-1}	1.77×10^{-2}	1.80×10^{-2}
	25	1.85×10^{-2}	2.09×10^{-1}	1.51×10^{-2}	1.76×10^{-2}
90 / 10	1	1.11×10^{-3}	1.53×10^{-2}	1.11×10^{-3}	1.11×10^{-3}
	5	1.17×10^{-3}	1.63×10^{-2}	1.00×10^{-3}	8.97×10^{-4}
	10	1.64×10^{-3}	2.28×10^{-2}	1.42×10^{-3}	1.47×10^{-3}
	15	2.14×10^{-3}	2.97×10^{-2}	1.82×10^{-3}	2.05×10^{-3}
	20	6.56×10^{-3}	9.14×10^{-2}	4.99×10^{-3}	2.92×10^{-3}
	25	8.12×10^{-3}	1.13×10^{-1}	5.97×10^{-3}	3.85×10^{-3}

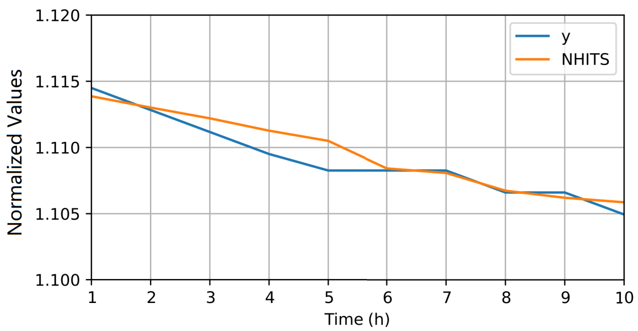

FIGURE 4. Comparison of the observed value to the prediction values using a 10-hour horizon.

TABLE 4. Statistical assessment results.

	RMSE	RMSPE	MAE	MedAE
Mean	0.011094	0.154477	0.008623	0.008032
Median	0.011080	0.154283	0.008717	0.008072
Mode	0.008660	0.120575	0.006867	0.005012
Range	0.004426	0.061626	0.003494	0.005321
Variance	0.000001	0.000149	0.000001	0.000001
Std. Dev.	0.000876	0.012205	0.000717	0.001130
25th %ile	0.010584	0.147380	0.008206	0.007216
50th %ile	0.011080	0.154283	0.008717	0.008072
75th %ile	0.011700	0.162920	0.009105	0.008912
IQR	0.001116	0.015541	0.000899	0.001695
Skewness	-0.352559	-0.352747	-0.257351	-0.289161
Kurtosis	0.392839	0.393276	0.124540	0.112018

A. MULTI-HORIZON ANALYSIS

For action to control the dam, a one-step-ahead prediction would be enough to alert the teams in an emergency [46]. However, a prediction using a longer horizon can improve the ability to manage the problem, so there is a trade-off between a longer prediction horizon and an acceptable error. Table 3 presents this evaluation.

The results show that the longer the horizon, the greater the prediction error. If it were defined that the entire test set would be predicted, as some authors have done, a greater error would be achieved by using less data to train the model and more data for testing. However, the worst results were achieved when the horizon increased, which is unrelated to the dataset split. This indicates that the model struggles to predict long time series.

Considering the RMSE, when horizons greater than 10 hours were evaluated, errors greater than 10^{-2} were achieved. A horizon equal to 10 hours was considered an adequate horizon since 10 hours ahead would be sufficient to take the necessary measures to control the power plant since the monitoring is based on an hourly measurement. The prediction result for this horizon is shown in Figure 4.

Comparing the data split for this evaluation, the best result was achieved using 70% of the data for training and 30% of the data for validation, resulting in an RMSE of 4.64×10^{-4} for a 1-hour forecast horizon, and 1.03×10^{-3} for a 10-hour forecast horizon. Since not all the models converged when using one step ahead, this configuration was not used in further analysis.

The comparative analyses considered 90% of the data for training, 10% for testing the network, and 50 maximum steps for all models.

To make it clearer what influence the variation in horizons has on the model's results, Figure 5 shows a comparison between different forecast horizons, with a specific model trained for each horizon.

The forecasting results show that the model has difficulty making predictions with a horizon greater than 10 steps ahead. This result is to be expected, since the longer the forecast horizon, the more difficult it becomes for the model

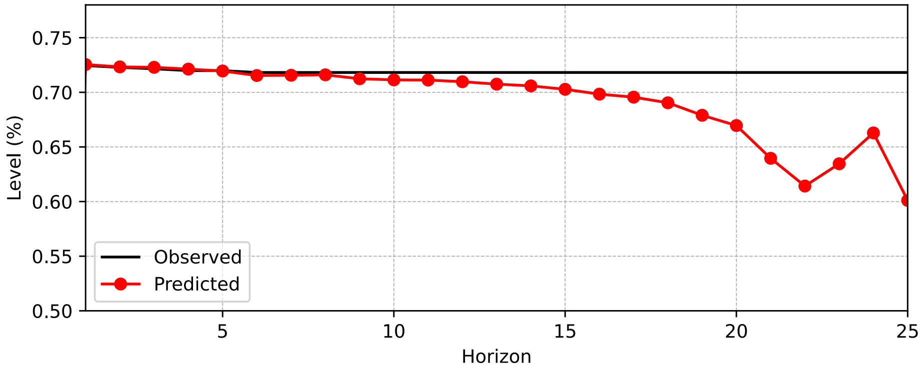

FIGURE 5. Comparison of the observed value to the prediction values using a 10-hour horizon.

TABLE 5. Comparative analysis of DL models.

Model	Horizon	RMSE	RMSPE	MAE	MedAE	Time (s)
MLP	VST	3.74×10^{-2}	5.19×10^{-1}	3.38×10^{-2}	3.76×10^{-2}	**1.34**
	ST	3.12×10^{-2}	4.34×10^{-1}	2.88×10^{-2}	2.84×10^{-2}	3.42
LSTM	VST	2.56	3.55×10^{1}	2.56	2.57	4.16
	ST	1.63	2.27×10^{1}	1.63	1.62	4.18
CNN-LSTM	VST	1.88×10^{-1}	2.39×10^{-2}	1.54×10^{-1}	1.35×10^{-1}	48.86
	ST	2.24×10^{-1}	2.85×10^{-2}	2.13×10^{-1}	1.93×10^{-1}	54.49
TCN	VST	9.05×10^{-2}	1.25	8.98×10^{-2}	9.51×10^{-2}	1.96
	ST	5.86×10^{-2}	8.16×10^{-1}	5.78×10^{-2}	5.97×10^{-2}	6.23
RNN	VST	2.58×10^{-1}	3.58	2.58×10^{-1}	2.55×10^{-1}	3.67
	ST	2.76×10^{-1}	3.84	2.76×10^{-1}	2.80×10^{-1}	3.40
Dilated RNN	VST	2.30	3.18×10^{1}	2.30	2.30	1.76
	ST	1.64	2.27×10^{1}	1.63	1.63	8.01
N-BEATS	VST	4.36×10^{-3}	6.06×10^{-2}	3.80×10^{-3}	5.19×10^{-3}	1.76
	ST	1.04×10^{-2}	1.45×10^{-1}	9.70×10^{-3}	1.02×10^{-2}	25.37
DeepNPTS	VST	5.48×10^{-3}	7.60×10^{-2}	5.13×10^{-3}	5.52×10^{-3}	1.47
	ST	1.33×10^{-2}	1.85×10^{-1}	1.31×10^{-2}	1.35×10^{-2}	**2.44**
NHITS	VST	4.26×10^{-3}	5.90×10^{-2}	3.94×10^{-3}	4.29×10^{-3}	1.82
	ST	9.01×10^{-3}	1.25×10^{-1}	8.06×10^{-3}	8.70×10^{-3}	16.90
NHITS*	VST	$\mathbf{1.39}\times10^{-3}$	$\mathbf{1.93}\times10^{-2}$	$\mathbf{1.20}\times10^{-3}$	$\mathbf{1.19}\times10^{-3}$	106.41
	ST	$\mathbf{4.72}\times10^{-3}$	$\mathbf{6.57}\times10^{-2}$	$\mathbf{3.65}\times10^{-3}$	$\mathbf{2.48}\times10^{-3}$	129.71

* Model with fine-tuning.

to forecast correctly. Considering that the electricity system is planned on an hourly basis, the model meets the need, using a forecast horizon of one step ahead.

The statistical assessment is presented in Section V-B and the benchmarking is presented in Section V-C. In the comparative analysis between the models, two horizons are considered: VST with a 5-hour-ahead forecast and ST with a 20-hour-ahead forecast.

B. STATISTICAL ASSESSMENT

The statistical analysis presented in Table 4 takes into account the model settings discussed in previous sections. Based on the adjusted model, 50 experiments are carried out with different initializations of the network (seed).

The model's standard deviation of 8.76×10^{-4} for the RMSE shows that the model has low variability, making it promising for the application evaluated here. The variation values (range) of the results concerning the mean are high but acceptable considering the signal's non-linearities.

The results of this analysis show that the model is stable because even when several simulations are carried out with different initializations, the model returns values within the acceptable range. This is confirmed for all the error metrics evaluated in this paper.

C. BENCHMARKING

The comparative analysis presented here aims to compare state-of-the-art models for time series forecasting to the model adopted in this paper. Table 5 shows the results of this evaluation.

The defaults defined in [68] were the remaining settings used. The time presented in this analysis is the sum of the training time and the testing time of the network.

The results showed that even the fitted NHITS outperformed other well-established time series forecasting models evaluated here, across both evaluation horizons. The N-BEATS model, which is from the same family as the NHITS, achieves the second-best result. Although the tuned

NHITS model takes longer to be processed, it still has an acceptable training time, since the decision-making is based on an hourly variation.

In this study, the best setup configuration for the model was using an input size equal to 200, a learning rate of 1×10^{-3}, and batch size equal to 8, using a student's t-distribution loss. The use of the largest input size or different learning rate imparts the model performance during training. The use of other batch sizes did not have a major influence on the performance of the model, therefore a lower batch size was used to avoid overloading the graphics processing unit.

The attempt to use other loss functions resulted in the model not converging. The main hyperparameter that improved the model's performance was the input size adjustment, which is directly related to the characteristics of the data to be used and is therefore a hyperparameter that should always be evaluated.

The hardware configurations that resulted in the processing times presented in Table 5 are described in Section IV-D. Considering that the shortest horizon analyzed in this paper is one hour, a processing time of less than this period is sufficient to meet the requirements of the problem, therefore all the models had acceptable processing times.

In [3] the SMAP is compared to a proposed hypertuned wavelet CNN-LSTM. Given an RMSE of 8.72×10^2 of their proposed method in comparison to the SMAP that had an RMSE of 2.24×10^3, they proved that hybrid DL methods are promising for time series forecasting in hydroelectric power plants. Our method proved to have better results than CNN-LSTM and considering that the evaluated signal has less presence of high frequencies, the method presented in this paper is the better alternative since no denoising is needed.

VI. FINAL REMARKS

Thanks to advances in ML, time series forecasting is becoming increasingly useful to support decision-making in hydroelectric power plants. In particular, the proposed model has shown promise for predicting the reservoir level of hydroelectric power plants and can even be applied to other tasks.

The NHITS outperformed all other compared models for VST and ST forecasting. Tuning the NHITS results in even better results with an RMSE of 1.39×10^{-3} for a 5-hour-ahead forecast and 4.72×10^{-3} for a 20-hour-ahead forecast. The second-best model was the N-BEATS which is from the same family as NHITS, highlighting the power of this class of algorithm for time series forecasting.

Several models had lower performance for in very short-term forecasting when compared to their results for short-term forecasting, although this is not a rule for all approaches, it can be seen that forecasting more long-range horizons can be a challenge for multi-step ahead forecasting models.

Future work can be done analyzing signals with greater non-linearity, such as the inflow from hydroelectric plants. In this case, filters to attenuate the variation are promising so that the focus of the application can be on predicting the trend.

Another approach that can be used in future works is the multi-criteria optimization of the model's hyperparameters. Tree-structured Parzen estimator-based frameworks are currently being used to ensure that the best architecture setup is considered.

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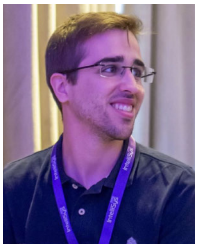

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