Optimizing Planning Strategies: A Machine Learning Forecasting Model for Energy Aggregators and Hydropower Producers

Sarah Di Grande[1][a], Mariaelena Berlotti[1][b], Salvatore Cavalieri[1][c] and Roberto Gueli[2][d]
[1]*Department of Electrical Electronic and Computer Engineering, University of Catania, Viale A.Doria n.6, Catania, Italy*
[2]*EHT, Viale Africa n.31, Catania, Italy*

Keywords: Renewable Energy, Aggregators, Hydropower, Machine Learning, Sustainability, Water Distribution System, Forecasting.

Abstract: The global push for higher renewable energy production is driven by concerns about climate change, pollution, and diminishing fossil fuel reserves. Governments, businesses, and communities worldwide prioritize cleaner energy sources like solar, wind, and hydroelectric, over traditional fuels. Technological advancements enhancing efficiency and cost-effectiveness have made renewables more competitive, catalyzing their growing dominance in the energy market. In this context, renewable energy forecasting models are fundamental for both operators of the energy market called energy aggregators, and prosumers for different reasons like planning, decision-making, energy sales optimization, and investment evaluation. Therefore, the present work aimed to develop a machine learning model designed for multi-step hydropower forecasting of plants integrated into Water Distribution Systems (WDSs). The Alcantara 1 Hydroelectric Plant, situated in Italy, was utilized as the case study. This plant generates electricity from the water flow utilized for municipal water supply, which is then sold to the medium voltage network, resulting in substantial remuneration. This innovative approach utilizes previously unused architectures like TCN and N-Beats, to provide multi-step hydropower forecasting for WDS-integrated plants, a special category of systems for which models have not yet been developed. Results indicate TCN as the most accurate model for addressing the proposed task.

1 INTRODUCTION

In the last few years, the energy sector has been featured by an increasing need for renewables and energy supply diversification as well as for continuous technological progress (Borozan and Pekanov Starcevic, 2021); the current global trend is to increase the proportion of renewable energy production.

Worldwide, governments, companies, and communities are increasingly prioritizing cleaner and more sustainable energy sources—such as solar, wind, hydroelectric, geothermal, and biomass—over traditional fossil fuels. Climate change, pollution, and the depletion of finite fossil fuel reserves have prompted a shift toward cleaner energy sources that have a significantly lower impact on the environment. In response to these concerns, governments are implementing policies and regulations to incentivize and accelerate the adoption of renewable energy technologies (Kerscher and Arboleya, 2022). Additionally, there is a noticeable increase in investment, both public and private, in renewable energy infrastructure and research and development initiatives.

This transitional phase owes its feasibility to technological advancements that made renewable energy sources more efficient and cost-effective. This progress has contributed to their increased competitiveness in the energy market, further driving the shift toward renewables.

[a] https://orcid.org/0009-0008-8895-2175
[b] https://orcid.org/0009-0007-6564-704X
[c] https://orcid.org/0000-0001-9077-3688
[d] https://orcid.org/0000-0002-8014-0243

Di Grande, S., Berlotti, M., Cavalieri, S. and Gueli, R.
Optimizing Planning Strategies: A Machine Learning Forecasting Model for Energy Aggregators and Hydropower Producers.
DOI: 10.5220/0012626100003690

In *Proceedings of the 26th International Conference on Enterprise Information Systems (ICEIS 2024) - Volume 1*, pages 490-501
ISBN: 978-989-758-692-7; ISSN: 2184-4992

1.1 Energy Market

The traditional and modern energy markets differ significantly in various aspects, including their infrastructure, sources of energy, market dynamics, and technological advancements.

In the traditional energy market model, large centralized power plants (such as nuclear and coal-fired plants) typically monopolize energy production. Energy flows in a unidirectional manner from these centralized producers through the grid to consumers. The market is often regulated, with utilities playing a significant role in energy generation, transmission, and distribution. Notably, electricity customers do not actively participate in the electricity market (Kerscher and Arboleya, 2022).

Modern energy markets, however, embrace a more decentralized approach, incorporating multiple small-scale renewable energy sources like solar panels, wind turbines, and hydroelectric plants, alongside demand-response resources, to contribute to the energy mix. These advancements in renewable energy have facilitated a shift in energy generation capacity closer to consumption points. The coordination of generation and demand in the electric power system is crucial, especially in managing a greater number of active consumers and what are termed 'prosumers'—consumers who both consume and produce electricity within the grid (Hernandez-Matheus et al., 2022).

To facilitate this coordination, energy aggregators play a crucial role. These entities integrate different energy sources, allowing them to participate in energy trading and contribute to grid flexibility. Serving as intermediaries between prosumers and electricity markets, they offer competitive pricing and streamline the buying and selling of energy services (Iria and Soares, 2023; Kerscher and Arboleya, 2022; Khajeh et al., 2020; Marneris et al., 2023).

1.2 Paper Aim and Motivation

Aggregators engage directly in the modern wholesale electricity market through three primary foundations (Hernandez-Matheus et al., 2022):

- employing optimal bidding strategies and pertinent optimization techniques;
- utilizing advanced forecasting methods;
- leveraging spatial aggregation (known as the 'portfolio effect'), which inherently minimizes the variability and uncertainty in renewable energy sources production.

This paper specifically emphasizes the second point, particularly the development of renewable energy production forecasting models. The models employed are machine learning models focused on hydropower forecasting of plants inserted into a Water Distribution System (WDS).

A particular case of study is considered: Alcantara 1 Hydroelectric Plant, located in the region of Sicily, in Italy. The plant generates electricity from the flow of water used for municipal water supply. The electricity produced is sold to the medium voltage network, allowing for favorable remuneration and contributing significantly to reducing the high costs associated with electricity consumption in WDSs. In Section 3, a deeper description of the case study will be provided.

In this context, the forecasting models serve the interests of both aggregators and hydropower prosumers, catering to diverse purposes such as planning, decision-making, and optimizing energy sales in the market (Ahmad et al., 2020; Barzola-Monteses et al., 2022; Hernandez-Matheus et al., 2022). Accurate forecasts play a fundamental role in effectively planning energy sales within the market. This accuracy contributes to maximizing profits through informed decisions on the timing and quantity of energy to sell. Forecasting energy production facilitates resource allocation by aiding the management of maintenance schedules, optimizing water flow, and ensuring efficient resource utilization to meet energy demands. The reliability of these forecasts reduces risks associated with overestimating or underestimating energy production, enhancing risk management in trading operations and financial planning. Moreover, predicting energy generation supports grid management by providing insights into expected supply, assisting in the balancing of the grid supply and demand dynamics.

This paper presents an extended version of the work developed in (Di Grande et al., 2023a). The authors have enhanced the earlier research by providing a more accurate literature review and by testing the machine learning algorithms for multi-step-ahead forecasting.

According to the aim of the paper, just pointed out, the paper is structured as it follows. Section 2 gives an overview of the related work present in the current literature; Section 3 highlights the methods and algorithms utilized in this study; Section 4 details and deliberates upon the attained results; Section 5 will provide final remarks and prospects for future works.

2 RELATED WORKS

The main distinction between WDS-integrated and traditional plants lies in their purpose and location.

WDS-integrated plants produce electricity by utilizing water flow from sources serving other functions, like municipal water supply or irrigation. As a result, their primary role revolves around water distribution. On the contrary, traditional plants are primarily designed for power generation, often harnessing significant water flow from large reservoirs to generate substantial grid power. WDS-integrated facilities strategically position themselves within or near existing water distribution systems, while conventional hydroelectric plants are typically found in areas abundant in natural water resources, like rivers or large bodies of water, where dams can be constructed for water storage and subsequent power generation.

During the last years, the energy sector has featured an increasing digitalization, for example, in terms of the metering and control of energy, or the use of technologies such as big data applications and artificial intelligence (Hernandez-Matheus et al., 2022; Kezunovic et al., 2020; Weigel and Fischedick, 2019). In particular, (Mosavi et al., 2019) provided an overview of the use of artificial intelligence in the energy sector, demonstrating that machine learning can greatly increase the accuracy of energy production forecasting. For system operators of electrical grids, energy production forecasting is of great importance. Indeed, for daily operation tasks short-term time horizon of prediction is required, while for grid planning and investment evaluation, a medium-long-term horizon is preferred (Ahmad et al., 2020; Hernandez-Matheus et al., 2022).

In the same way, energy production forecasting is fundamental for prosumers, like companies operating in the WDS sector with the integration of renewable energy plants. In WDSs, the digitalization phase is quite recent. The Water 4.0 industrial revolution has introduced different features, such as automation, increased integration of sensors, the Internet of Things, Big Data analysis, and Artificial Intelligence (Adedeji et al., 2022). In literature, three of the most famous applications of artificial intelligence in WDSs are anomaly detection, water demand forecasting, and energy consumption forecasting (Adedeji et al., 2022; Berlotti et al., 2023; Di Grande et al., 2023b). The energy used by these systems to deliver water is high, indeed approximately 7%-8% of the total energy generated worldwide is used for the production and distribution of drinking water (Sharif et al., 2019). A great part of this energy comes from fossil fuels but driven by goals of sustainability, cost savings, and adherence to environmental regulations, companies today are motivated to reduce energy consumption. As reported in (Alhendi et al., 2022; Yi et al., 2022), energy consumption forecasting in WDSs is a consolidated field for different tasks, such as energy optimization, identification of anomalous consumption patterns, energy load plans for estimating anticipated costs and assessing the capacity of the system to meet the required demands. Therefore different works exist about the energy consumption forecasting in WDSs (Bagherzadeh et al., 2021; Di Grande et al., 2023b; Oliveira et al., 2021; Yi et al., 2022).

The forecasting of hydropower generated in WDSs, instead, is an unexplored topic, maybe because the construction of hydroelectric WDS-integrated plants is relatively recent (Sari et al., 2018).

The literature presents many works about forecasting models for traditional plants. Statistical and neural network models are the most used in this field. In (Barzola-Monteses et al., 2022), the authors employed artificial neural network (ANN) models, such as MLP (Multilayer Perceptron), LSTM (Long Short-Term Memory), and seq2seq LSTM (sequence-to-sequence Long Short-Term Memory), to forecast hydroelectric output in Ecuador over the short and medium term. They illustrated that ANN models exhibit enhanced accuracy in predicting hydropower generation, even when the dataset is not extensive. Moreover, they conducted an extensive literature review encompassing similar studies. Case studies from various regions worldwide, as cited in (Jung et al., 2021; Kostić et al., 2016; Lopes et al., 2019; Zhou et al., 2020), showcase the use of ANN models for hydropower prediction, highlighting their efficacy in addressing this specific task. The algorithms used are DeepHydro recurrent neural networks and MLP. These researchers underscored the superior performance of ANN models compared to statistical approaches in multivariate time series problems. Conversely, the studies outlined in (Mite and Barzola-Monteses, 2018; Polprasert et al., 2021) serve as instances demonstrating the application of statistical models, AutoRegressive Integrated Moving Average (ARIMA) model, to accomplish the same forecasting task.

To the best of the authors' knowledge, literatures features the absence of papers about multi-step ahead hydropower generation forecasting in WDSs-integrated plants. Furthermore, the authors would like to point out that, there is a dearth of similar studies in existing literature that have applied the Neural Basis Expansion Analysis for Time Series (N-Beats) and the Temporal Convolutional Network (TCN) algorithms within contexts related to hydropower forecasting, despite their strong performance in the broader field of water and energy forecasting (Di Grande et al., 2023b; Guo et al., 2022; Lin et al., 2020; Xu et al., 2022). Consequently, this paper aims to showcase the viability of employing these innovative architectures for the intended forecasting task. Furthermore, unlike prevailing literature that predominantly focuses on the general run-of-river or storage-reservoir-based systems (Barzola-Monteses et al., 2022), the proposed methodology is designed to apply to all WDSs-integrated plants.

3 EXPERIMENTAL SETUP

In this section, the case study will be described, including an outline of the project steps such as data collection, preprocessing, and model development and evaluation.

3.1 Case Study

This study utilizes data obtained from the Alcantara 1 Hydroelectric Plant, situated in Taormina, Sicily, Italy, and operated by Siciliacque S.p.A. (https://www.siciliacquespa.it/). This hydroelectric plant, with a maximum power of 1.1 megawatts, holds significance due to its integration within a WDS. The Alcantara aqueduct, spanning 65 kilometers, ensures a consistent flow rate of 600 liters per second.

One critical challenge faced by WDSs is the potential for excessive pressure, posing a risk to infrastructure integrity and leading to pipeline leaks or bursts. Previously, Siciliacque managed hydraulic jumps by dissipating them through tanks and valves. However, the implementation of integrated turbines now harnesses these hydraulic jumps to generate electricity. Another significant concern within WDSs is the considerable energy expenditure. Therefore, Siciliacque constructed this hydroelectric plant for electricity generation, which is then channeled into the medium voltage network and incentivized through a tariff scheme, effectively reducing their substantial electricity consumption expenses. Notably, integrating this hydropower plant into the WDS does not compromise the primary function of the system, which is to provide water to communities. Following electricity production, the water discharged from the plant is directed into a lower tank and subsequently conveyed through pipelines to 61 delivery points (tanks). These delivery points cater to the Municipalities of the Ionian Messina Strip, ensuring continued water supply.

The necessity for more meticulous and rational energy management, driven by the significance of electricity costs and environmental impacts, motivated Siciliacque to become one of the pioneering companies in Italy to attain the Energy Management System certification (ISO 50001).

3.2 Dataset

The paper aimed to predict the hydropower generated by the plant, necessitating access to hydropower-related information. In the dataset provided by Siciliacque, the hydropower variable was only partially available due to various missing values caused by malfunctions or maintenance of the plant. To derive a variable accounting for normal hydropower generation, excluding malfunctions or maintenance events, other dataset variables were utilized to calculate the target variable.

Modern hydroelectric plants harness mechanical potential energy within a water flow at a specific elevation relative to the turbine's position. Consequently, the power of the hydraulic system relies on three primary factors: the elevation difference between the water resource level and its level after passing through the turbine (head of water), the mass of water passing through the machine per unit time (inflow), and the efficiency of the hydroelectric system. The efficiency of the hydroelectric system is contingent upon factors such as turbine type and efficiency, alternator performance, mechanical transmissions, and electromechanical components contributing to energy production losses. Additionally, the Earth's gravitational acceleration value must be considered.

Therefore, as outlined in (1), the hydroelectric plant's power (P) in kilowatts (kW) is computed by multiplying four key input variables: Earth's gravitational acceleration (9.8 meters per second squared, m/s^2), inflow denoted as Q in cubic meters per second (m^3/s), the net head (H_n) in meters (m), and the efficiency (η).

The head and inflow information was derived from two time series collected from the plant's commissioning from January 2019 to May 2023, with a 5-minute timestep. The efficiency was set to 0.9, as suggested by the plant operators. As the head of water was measured in bars and the inflow in liters per second (l/s), a unit conversion was performed. Specifically, the head was converted into meters using the conversion factor where 1 bar equals

10.1974 meters of water, while the inflow was converted to cubic meters per second.

$$P[kW] = 9.8[m/s^2] \times Q[m^3/s] \times H_n[m] \times \eta \quad (1)$$

Then, noises were detected through a boxplot and were deleted from the dataset. A boxplot is a graphical method used to display the distribution, variation, and potential outliers within a dataset. It represents the quartiles (25th, 50th, and 75th percentiles) of the data, along with the minimum and maximum values or outliers. This method facilitated the identification of outliers or irregular data points that significantly deviated from the typical range of values within the dataset. Addressing these outliers was crucial as they could potentially distort the analysis or modeling outcomes (Arimie et al., 2020; Kolbaşı and Ünsal, 2021). Therefore, once these outliers were visually identified using the boxplot, they were deleted from the dataset to ensure the integrity and accuracy of subsequent procedures.

Finally, as the authors were focused on monthly hydropower forecasting, data were aggregated using the mean operator to create a monthly timestep. In particular, the 'resample('M')' Python function was applied to the hydropower time series to change the frequency of the data. In this case, data were resampled to a new frequency based on months ('M'), indeed the original 5-minute data were segmented into separate monthly groups. After resampling the data to a monthly frequency, the '.mean()' function calculated the average value for each month within the dataset. The result of this step was a new series where each data point corresponds to the average hydropower value within each month of the original dataset.

Since the authors aimed to solve a univariate time series problem by predicting the hydropower based solely on past hydropower values, the final dataset was composed of the time and the hydropower columns, and 53 rows containing hydropower data in each month from January 2019 to May 2023.

After the preprocessing steps, the dataset was split into a training set and a test set. The training set comprised the first 80% of the dataset, encompassing monthly observations from January 2019 to June 2022. Meanwhile, the remaining 20% of observations, covering the period from July 2022 to May 2023, constituted the test set.

3.3 Models Development

Several machine learning models were evaluated to identify the most suitable one for the current univariate time series problem. In univariate time series problems, only a single variable serves as both the input and output of the model. In this specific case, the variable of interest is the hydropower production.

To demonstrate the superior performance of the selected complex models compared to simpler ones, the seasonal AutoRegressive Integrated Moving Average (ARIMA) model was chosen as the baseline model. The models examined encompass the ARIMA, the Neural Basis Expansion Analysis for Time Series (N-Beats), and the Temporal Convolutional Network (TCN).

All machine learning models were performed through Darts (*ARIMA — Darts Documentation*, n.d.; *N-BEATS — Darts Documentation*, n.d.; *Temporal Convolutional Network — Darts Documentation*, n.d.), a Python machine learning library specific for time series analysis, in particular for time series forecasting (Herzen et al., 2023). The powerful feature of Darts is to provide modern machine learning functionalities with a user-friendly and easy-to-use API design (Herzen et al., 2023). Since hyperparameter optimization is crucial in machine learning model development, the best set of hyperparameters was found using the Optuna Python library (*Optuna: A Hyperparameter Optimization Framework — Optuna 3.5.0 Documentation*, n.d.), encompassing the exploration of 600 models.

Before performing hyperparameter optimization for ARIMA, the 'statsmodels' library was utilized to conduct seasonal decomposition of the time series data, followed by visualization of the decomposed components. Subsequently, an optimization process was carried out for each hyperparameter of the model, searching for optimal values within the range of 0 to 2 for all parameters.

For both N-Beats and TCN, some hyperparameters that were used for training were set as constants. The batch size was set to 1, and the max n epochs were set to 30. The output length was set to 3 because the purpose of the paper is to do a multi-step ahead forecast producing the forecasting for the subsequent three months. Finally, the objective function to optimize hyperparameters was to minimize the Symmetric Mean Absolute Percentage Error (SMAPE).

For N-Beats, the range of values to search for each hyperparameter is as follows: input chunk length ranging from 10 to 12, number of stacks from 25 to 35, number of blocks from 1 to 3, number of layers from 2 to 6, and dropout from 0.0 to 0.5 with step of 0.05.

For TCN, the range of values includes input chunk length ranging from 10 to 12, kernel size from 2 to 9, number of filters from 16 to 512, number of layers from 2 to 10, dilation base from 2 to 8, weight normalization as either True or False, and dropout ranging from 0.0 to 0.5 with an increment of 0.05.

3.4 Models Evaluation

A total of 600 distinct models were created and validated; they were achieved considering the three models described before, tuning the relevant parameters.

Considering the time series nature of the data, a specific validation method was adopted. Time series data possess autocorrelation, signifying that observations close in time are correlated. Traditional cross-validation techniques (e.g., K-fold, Shuffle split) are not suitable as they assume sample independence and identical distribution. Since temporal relationship in time series data needs to be preserved during testing, a viable solution is employing Walk Forward Validation (WFV), a rolling basis cross-validation technique (Barzola-Monteses et al., 2022; Bergmeir and Benítez, 2012; Ngoc et al., 2021).

Darts offers two functions catering to this need: ‘historical_forecasts()’ and ‘backtest()’. ‘historical_forecasts()’ generates iterative training sets by extending from the series beginning or maintaining a fixed length (‘train_length’). The model trains on this set, forecasts a length equal to ‘forecast_horizon’, and shifts the end of the training set forward by 'stride' time steps. The 'start' parameter was set to '2022-07', marking the initial date of the test set. The 'forecast_horizon' was set to 3 for the multi-step-ahead forecasts, and 'stride' was set to 1 ensuring consecutive predictions and validations. With 'retrain' set to True, the model updates and retrains with new data after each forecast. Therefore, the validation works by training the model with the first x observations, and testing it with the next x + 1, x + 2, and x + 3 observations. The 'backtest()' directly returns the average error metric post-forecasting. The principal evaluation metric used was the SMAPE. Additional metrics supported the decision-making process: Mean Absolute Percentage Error (MAPE), Root Mean Squared Scaled Error (RMSSE), and Mean Absolute Scaled Error (MASE) (Botchkarev, 2019; Koutsandreas et al., 2022). Lower values across these metrics signify better model performance.

4 RESULTS AND DISCUSSION

The aim of this section is the presentation and discussion of the main results achieved in the research carried out by the authors. A two-step evaluation procedure has been considered, made up of a statistical analysis of the data set and the analysis of forecasts achieved by the models described in the previous section.

The statistical analysis was aimed at understanding the underlying patterns and structures within the time series data; the study of the behavior of the time series during the years to see if there are specific patterns was performed; a time series seasonal decomposition was performed to reach this goal.

The seasonal decomposition was applied to break down the hydropower generation time series into its constituent components trend and seasonal. Figure 1 represents the observed time series, the detected trend, and the seasonal pattern.

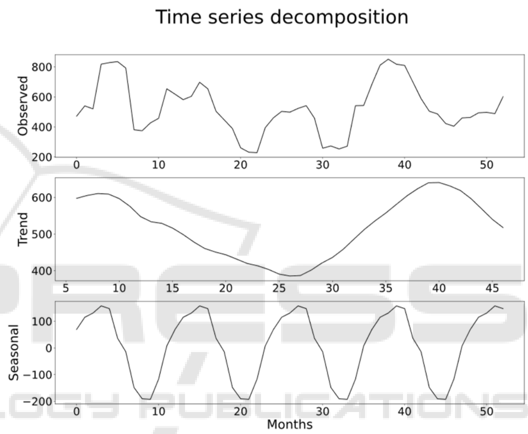

Figure 1: Decomposition of hydropower production time series.

The trend component within a time series offers a comprehensive view of the underlying behavior or trajectory observed in the dataset over an extended period. It reflects the long-term movement, identifying whether the data generally display an upward, downward, or relatively stable pattern over time. An upward trend signifies consistent growth or increase in the time series, while a downward trend indicates a decline or decrease.

Upon close inspection of the dataset spanning from 2019 to 2021, an evident declining trend emerges, suggesting a consistent decrease in the observed values over this timeframe. However, an intriguing shift occurs thereafter, marking a reversal in the trend. From 2021 to 2022, the dataset reflects an increasing pattern, signifying a notable rise in values. Subsequently, the trend reverts to a declining trajectory, indicating a return to decreasing values.

The behavior of seasonality and trend is contingent upon the variability of power, which in turn relies on the fluctuating flow rate, a variable attribute owing to its source. The flow rate fluctuates due to its origin from the slopes of Mount Etna and is subject to the influence of rainfall and the melting of snow. As a result, not only does the behavior differ each month but also across years distinguished by varying levels of rainfall and temperatures. These factors impact the creation and melting of snow, thereby contributing to the variability observed over time.

Shifting the focus to the seasonal component, it captures the recurring, periodic patterns or seasonality inherent within the time series data. This component reveals cyclicality or periodic fluctuations that occur regularly within specific timeframes, such as daily, weekly, monthly, or yearly cycles. Peaks and troughs within the seasonal component correspond to the high and low points recurring within each seasonal cycle.

Notably, the seasonal pattern within this dataset exhibits a yearly recurrence, wherein the identified patterns tend to replicate themselves, presenting similar characteristics and fluctuations within each annual cycle. This seasonality can be particularly valuable for understanding and forecasting trends tied to specific time periods or seasons, aiding in better predictions or analysis within seasonal contexts.

Domain experts working at Siciliacque validated the existence of a noticeable seasonal pattern, providing and confirming detailed insights into the variations observed in the flow rate directed in input to the hydropower plant. The flow rate exhibits variability ranging from 200 l/s to 1000 l/s, peaking typically in May or June. Subsequently, from June onward, it steadily declines, reaching its lowest production of 200 liters in months such as September or October, before gradually rising again toward the peak.

After the statistical analysis results, models described in Section 3 were considered, testing various combinations of algorithms and hyperparameters. For each algorithm, the best-performing model was detected. The average performance metrics of the three models are reported in Table 1.

The best TCN model obtained operates with the following hyperparameters: in_len = 11, kernel_size = 7, num_filters = 255, num_layers = 3, dilation_base = 7, weight_norm = True, dropout = 0.4. The hyperparameters of the best N-Beats model are in_len = 11, num_stacks = 27, num_blocks = 2, num_layers = 3, and dropout = 0.0. Instead, the parameters of the top ARIMA model are p = 0, d = 0, q = 0, P = 1, D = 0, and Q = 2, with a seasonal period equal to 12.

Table 1: Average performance metrics of the three best-performing models for each algorithm.

Metrics	TCN	NBEATS	ARIMA
SMAPE	5.913	11.763	11.614
MAPE	5.911	11.733	11.484
RMSSE	0.674	0.737	0.805
MASE	0.896	1.034	1.12

As reported in Table 1, TCN achieved the lowest SMAPE of 5.913, indicating better accuracy in forecasting compared to N-Beats (11.763) and ARIMA (11.614). Lower SMAPE values signify better accuracy and closeness of predicted values to the actual values. Similarly, TCN has the lowest MAPE (5.911), showcasing superior accuracy compared to N-Beats (11.733) and ARIMA (11.484). TCN once again displays the lowest RMSSE (0.674), indicating better performance in capturing both the magnitude and relative variations in the forecasted values compared to the actual values. N-Beats follows with an RMSSE of 0.737, and ARIMA with 0.805. TCN demonstrates the lowest MASE (0.896), indicating better forecasting performance concerning the scale of the errors compared to N-Beats (1.034) and ARIMA (1.12).

Across all four metrics, TCN consistently outperforms N-Beats and ARIMA, showcasing superior accuracy and precision in its predictions for the given dataset. With regards to N-Beats and ARIMA, the former has higher SMAPE (11.763) and MAPE (11.733) compared to the latter (SMAPE: 11.614, MAPE: 11.484), indicating that ARIMA performs slightly better in terms of predicting closer values to the actual ones. At the same time, N-Beats demonstrates a lower RMSSE (0.737) and MASE (1.034) compared to ARIMA (RMSSE: 0.805, MASE: 1.12), implying that N-Beats performs slightly better in capturing the magnitude and relative variations between forecasted and actual values.

As explained before in Section 3.4, after training the model with a certain number of observations, the model was tested multiple times by making predictions for subsequent time periods while incrementally updating the training dataset. During each test iteration, the model generates forecasts for the future.

In this particular case, for every step forward in the dataset, the model produces three forecasts for the subsequent three months. Based on the length of the test dataset, each multi-step forecasting model was tested nine times, each time producing three forecasts for subsequent months, resulting in a total of 27 individual forecasts (9 test iterations multiplied by 3 forecasts per iteration).

Table 2 will report more precise results regarding the performance of the TCN model.

Table 2: SMAPE of TCN model for each test iteration.

1st month	2nd month	3rd month	SMAPE
2022-07	2022-08	2022-09	5.333
2022-08	2022-09	2022-10	6.084
2022-09	2022-10	2022-11	5.483
2022-10	2022-11	2022-12	4.638
2022-11	2022-12	2023-01	8.196
2022-12	2023-01	2023-02	6.207
2023-01	2023-02	2023-03	3.239
2023-02	2023-03	2023-04	6.17
2023-03	2023-04	2023-05	7.974

As reported in Table 2, The SMAPE values range between 3 and 8, indicating the percentage of error between the predicted and actual values for each forecasted three-month period. Lower SMAPE values, such as 3.239 and 4.638, suggest higher accuracy in prediction for those particular forecasted periods. Most SMAPE values are below 8, suggesting a very good overall performance in predicting hydropower generation. Conversely, higher SMAPE values, for instance, 8.196 and 7.974, indicate relatively larger discrepancies between the model predictions and the actual hydropower generation for those periods. These occasional spikes in SMAPE highlight potential challenges or outliers where the model struggled to accurately predict hydropower generation.

Therefore, the model appears to perform relatively well in some forecasted periods, showcasing lower SMAPE values, and indicating higher prediction accuracy. However, certain time intervals demonstrate higher error percentages, suggesting challenges or limitations in accurately forecasting hydropower generation during those periods. Further analysis will be done to understand the specific factors contributing to the discrepancies observed during certain forecasted periods and to potentially refine the model for improved accuracy across all forecast intervals.

Table 3 and Table 4 will report more precise results regarding the performance of the N-Beats and the ARIMA model.

As reported in Table 3, for N-Beats moderate SMAPE values range from 8 to 16, indicating varying levels of forecasting accuracy across different periods. In Table 4, SMAPE values range from 4 to 19, showing higher and lower accuracy with respect to N-Beats in certain periods.

Table 3: SMAPE of N-Beats model for each test iteration.

1st month	2nd month	3rd month	SMAPE
2022-07	2022-08	2022-09	13.717
2022-08	2022-09	2022-10	8.576
2022-09	2022-10	2022-11	10.555
2022-10	2022-11	2022-12	13.817
2022-11	2022-12	2023-01	15.810
2022-12	2023-01	2023-02	11.650
2023-01	2023-02	2023-03	15.433
2023-02	2023-03	2023-04	7.905
2023-03	2023-04	2023-05	8.401

Table 4: SMAPE of ARIMA model for each test iteration.

1st month	2nd month	3rd month	SMAPE
2022-07	2022-08	2022-09	16.834
2022-08	2022-09	2022-10	19.083
2022-09	2022-10	2022-11	14.399
2022-10	2022-11	2022-12	8.733
2022-11	2022-12	2023-01	8.806
2022-12	2023-01	2023-02	7.319
2023-01	2023-02	2023-03	4.077
2023-02	2023-03	2023-04	12.191
2023-03	2023-04	2023-05	13.085

Comparing the performance results of the three models, for the TCN model, although mostly stable, there are minor fluctuations in SMAPE values across different forecast intervals. Overall, this model demonstrates relatively stable and comparatively accurate forecasting across the periods. In N-Beats models, while some periods exhibit higher accuracy (e.g., the 2023-02 to 2023-04 interval), others display comparatively higher forecasting errors (e.g., 2022-11 to 2023-01). The accuracy of this model varies more than the one of the TCN model, showing fluctuations in forecasting precision. For which regards the ARIMA model, it demonstrates higher SMAPE values across some forecast intervals (e.g., the 2022-07 to 2022-10 interval), implying less accurate predictions compared to the others. Furthermore, it shows significant variations in error rates among the different three-month periods.

In conclusion, this is the last ranking of models in terms of forecasting accuracy:

- TCN, with the most consistent and accurate predictions;
- N-Beats, showing moderate accuracy with varying performance across different intervals;
- ARIMA, displaying higher errors.

Figure 2, Figure 3, and Figure 4 depict segments of the observed time series spanning from September

2021 to December 2022, alongside the predictions generated by three forecasting models in their second, third, and fourth step iterations. Specifically, the top section of each image showcases predictions for a three-month period spanning from August 2022 to October 2022; the middle section displays predictions from September 2022 to November 2022; and the bottom section exhibits predictions from October 2022 to December 2023.

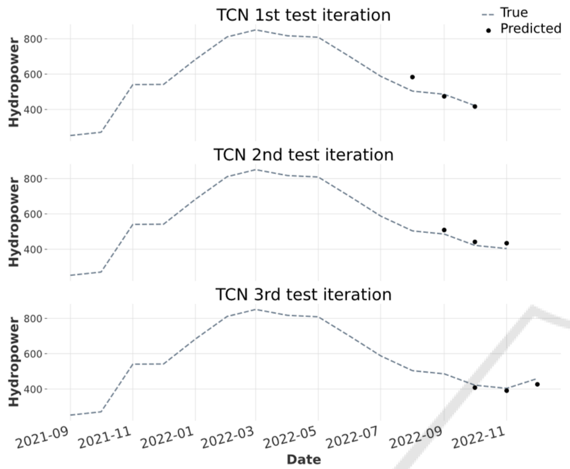

Figure 2: Observed hydropower time series and forecasts of TCN model for the second, third, and fourth test iteration.

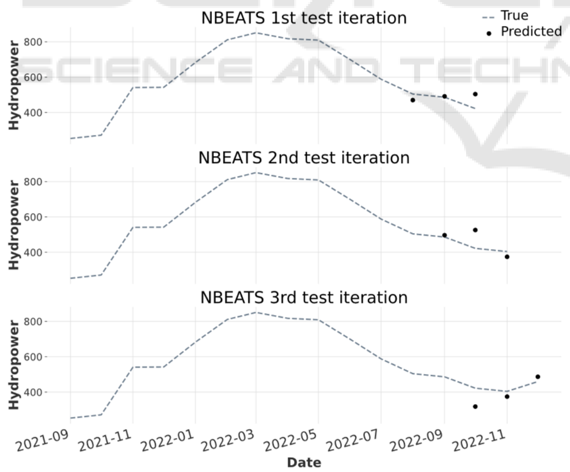

Figure 3: Observed hydropower time series and forecasts of N-Beats model for the second, third, and fourth test iteration.

Due to lack of space, a portion of the results is displayed through images. Anyway, it is evident that the TCN forecasts are more accurate than those of the other models within the same time period.

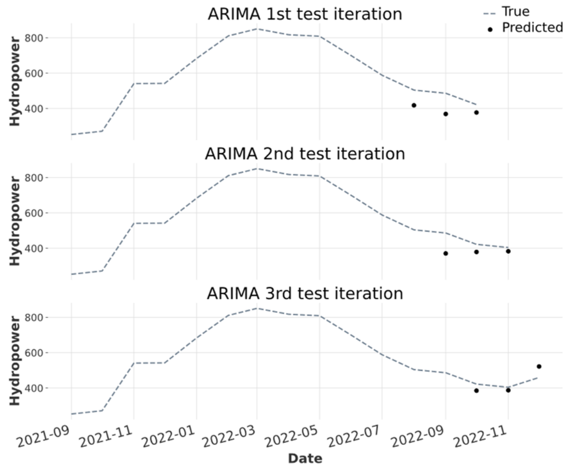

Figure 4: Observed hydropower time series and forecasts of ARIMA model for the second, third, and fourth test iteration.

5 CONCLUSIONS

Hydropower forecasting models are fundamental for energy aggregators and hydropower prosumers for planning, decision-making, energy sales optimization, and investment evaluation. Accurate forecasts are vital for planning energy sales, maximizing profits, and optimizing resource allocation. They reduce risks in trading and aid grid management by providing insights into expected supply and demand dynamics.

This paper introduces a multi-step univariate time-series model designed for hydropower forecasting. The novelty of this approach lies in employing previously unused models, such as TCN and N-Beats, within the field of hydropower forecasting, specifically tailored for a distinct category of hydropower plants integrated into Water Distribution Systems (WDSs).

To illustrate the viability of this method, the study focuses on the Alcantara 1 Hydroelectric plant situated in Sicily, Italy. This plant operates within a WDS, utilizing water flow from the municipal supply for electricity generation. The generated electricity is then sold to the medium voltage network, securing a favorable remuneration. This revenue significantly mitigates the substantial costs of WDSs associated with electricity consumption.

Following comparisons among various models, involving a mix of complex and baseline algorithms along with different sets of hyperparameters using a walk-forward validation process, performance metrics confirmed the viability of employing the TCN algorithm. Its notably high accuracy underscores its feasibility for multi-step hydropower forecasting.

Future works involve testing and comparing alternative machine learning algorithms while developing different forecasting models utilizing varied data aggregation frequencies—hourly, daily, and weekly. Additionally, there will be evaluations of multi-variate time series forecasting models incorporating factors like weather measurements. Moreover, acknowledging the existence of additional hydroelectric plants integrated into WDSs across various areas of Sicily, another study will be conducted to create and compare global and local models.

ACKNOWLEDGEMENTS

Data and support were provided by Siciliacque S.p.A. and EHT S.C.p.A. The research results presented in this paper have been achieved inside the Water 4.0 project, named 'Technologies for the convergence between industry 4.0 and the integrated water cycle'. Water 4.0 is currently running and is funded by the Ministry of Enterprises and Made in Italy (https://www.mimit.gov.it/en/).

REFERENCES

Adedeji, K. B., Ponnle, A. A., Abu-Mahfouz, A. M., and Kurien, A. M. (2022). Towards Digitalization of Water Supply Systems for Sustainable Smart City Development—Water 4.0. Applied Sciences, 12(18), Article 18. https://doi.org/10.3390/app12189174

Ahmad, T., Zhang, H., and Yan, B. (2020). A review on renewable energy and electricity requirement forecasting models for smart grid and buildings. Sustainable Cities and Society, 55, 102052. https://doi.org/10.1016/j.scs.2020.102052

Alhendi, A. A., Al-Sumaiti, A. S., Elmay, F. K., Wescaot, J., Kavousi-Fard, A., Heydarian-Forushani, E., and Alhelou, H. H. (2022). Artificial intelligence for water–energy nexus demand forecasting: A review. International Journal of Low-Carbon Technologies, 17, 730–744. https://doi.org/10.1093/ijlct/ctac043

ARIMA — darts documentation. (n.d.). Retrieved 16 October 2023, from https://unit8co.github.io/darts/generated_api/darts.models.forecasting.arima.html

Arimie, C. O., Biu, E. O., and Ijomah, M. A. (2020). Outlier Detection and Effects on Modeling. Open Access Library Journal, 7(9), Article 9. https://doi.org/10.4236/oalib.1106619

Bagherzadeh, F., Nouri, A. S., Mehrani, M.-J., and Thennadil, S. (2021). Prediction of energy consumption and evaluation of affecting factors in a full-scale WWTP using a machine learning approach. Process Safety and Environmental Protection, 154, 458–466. https://doi.org/10.1016/j.psep.2021.08.040

Barzola-Monteses, J., Gómez-Romero, J., Espinoza-Andaluz, M., and Fajardo, W. (2022). Hydropower production prediction using artificial neural networks: An Ecuadorian application case. Neural Computing and Applications, 34(16), 13253–13266. https://doi.org/10.1007/s00521-021-06746-5

Bergmeir, C., and Benítez, J. M. (2012). On the use of cross-validation for time series predictor evaluation. Information Sciences, 191, 192–213. https://doi.org/10.1016/j.ins.2011.12.028

Berlotti, M., Di Grande, S., Cavalieri, S., and Gueli, R. (2023). Detection and Prediction of Leakages in Water Distribution Networks: Proceedings of the 12th International Conference on Data Science, Technology and Applications, 436–443. https://doi.org/10.5220/0012122000003541

Borozan, D., and Pekanov Starcevic, D. (2021). Analysing the Pattern of Productivity Change in the European Energy Industry. Sustainability, 13(21), Article 21. https://doi.org/10.3390/su132111742

Botchkarev, A. (2019). Performance Metrics (Error Measures) in Machine Learning Regression, Forecasting and Prognostics: Properties and Typology. Interdisciplinary Journal of Information, Knowledge, and Management, 14, 045–076. https://doi.org/10.28945/4184

Di Grande, S., Berlotti, M., Cavalieri, S., and Gueli, R. (2023a). A Machine Learning Approach for Hydroelectric Power Forecasting. 2023 14th International Renewable Energy Congress (IREC), 1–6. https://doi.org/10.1109/IREC59750.2023.10389561

Di Grande, S., Berlotti, M., Cavalieri, S., and Gueli, R. (2023b). A Proactive Approach for the Sustainable Management of Water Distribution Systems: Proceedings of the 12th International Conference on Data Science, Technology and Applications, 115–125. https://doi.org/10.5220/0012121200003541

Guo, J., Sun, H., and Du, B. (2022). Multivariable Time Series Forecasting for Urban Water Demand Based on Temporal Convolutional Network Combining Random Forest Feature Selection and Discrete Wavelet Transform. Water Resources Management, 36(9), 3385–3400. https://doi.org/10.1007/s11269-022-03207-z

Hernandez-Matheus, A., Löschenbrand, M., Berg, K., Fuchs, I., Aragüés-Peñalba, M., Bullich-Massagué, E., and Sumper, A. (2022). A systematic review of machine learning techniques related to local energy communities. Renewable and Sustainable Energy Reviews, 170, 112651. https://doi.org/10.1016/j.rser.2022.112651

Herzen, J., Lässig, F., Piazzetta, S. G., Neuer, T., Tafti, L., Raille, G., Van Pottelbergh, T., Pasieka, M., Skrodzki, A., Huguenin, N., Dumonal, M., Kościsz, J., Bader, D., Gusset, F., Benheddi, M., Williamson, C., Kosinski, M., Petrik, M., and Grosch, G. (2023). Darts: User-friendly modern machine learning for time series. The

Journal of Machine Learning Research, 23(1), 124:5442-124:5447.
Iria, J., and Soares, F. (2023). An energy-as-a-service business model for aggregators of prosumers. Applied Energy, 347, 121487. https://doi.org/10.1016/j.apenergy.2023.121487
Jung, J., Han, H., Kim, K., and Kim, H. S. (2021). Machine Learning-Based Small Hydropower Potential Prediction under Climate Change. Energies, 14(12), Article 12. https://doi.org/10.3390/en14123643
Kerscher, S., and Arboleya, P. (2022). The key role of aggregators in the energy transition under the latest European regulatory framework. International Journal of Electrical Power & Energy Systems, 134, 107361. https://doi.org/10.1016/j.ijepes.2021.107361
Kezunovic, M., Pinson, P., Obradovic, Z., Grijalva, S., Hong, T., and Bessa, R. (2020). Big data analytics for future electricity grids. Electric Power Systems Research, 189, 106788. https://doi.org/10.1016/j.epsr.2020.106788
Khajeh, H., Laaksonen, H., Gazafroudi, A. S., and Shafie-khah, M. (2020). Towards Flexibility Trading at TSO-DSO-Customer Levels: A Review. Energies, 13(1), Article 1. https://doi.org/10.3390/en13010165
Kolbaşı, A., and Ünsal, A. (2021). A Comparison of the Outlier Detecting Methods: An Application on Turkish Foreign Trade Data. Journal of Mathematical Sciences, 5, 213–234.
Kostić, S., Stojković, M., and Prohaska, S. (2016). Hydrological flow rate estimation using artificial neural networks: Model development and potential applications. Applied Mathematics and Computation, 291(C), 373–385.
Koutsandreas, D., Spiliotis, E., Petropoulos, F., and Assimakopoulos, V. (2022). On the selection of forecasting accuracy measures. Journal of the Operational Research Society, 73(5), 937–954. https://doi.org/10.1080/01605682.2021.1892464
Lin, K., Sheng, S., Zhou, Y., Liu, F., Li, Z., Chen, H., Xu, C.-Y., Chen, J., and Guo, S. (2020). The exploration of a Temporal Convolutional Network combined with Encoder-Decoder framework for runoff forecasting. Hydrology Research, 51(5), 1136–1149. https://doi.org/10.2166/nh.2020.100
Lopes, M., Rocha, B., Vieira, A., Sá, J., Rolim, P., and Silva, A. (2019). Artificial neural networks approaches for predicting the potential for hydropower generation: A case study for Amazon region. Journal of Intelligent & Fuzzy Systems, 36, 5757–5772. https://doi.org/10.3233/JIFS-181604
Marneris, I. G., Ntomaris, A. V., Biskas, P. N., Baslis, C. G., Chatzigiannis, D. I., Demoulias, C. S., Oureilidis, K. O., and Bakirtzis, A. G. (2023). Optimal Participation of RES Aggregators in Energy and Ancillary Services Markets. IEEE Transactions on Industry Applications, 59(1), 232–243. https://doi.org/10.1109/TIA.2022.3204863
Mite, M., and Barzola-Monteses, J. (2018). Statistical Model for the Forecast of Hydropower Production in Ecuador. International Journal of Renewable Energy Research, 8.
Mosavi, A., Salimi, M., Faizollahzadeh Ardabili, S., Rabczuk, T., Shamshirband, S., and Varkonyi-Koczy, A. R. (2019). State of the Art of Machine Learning Models in Energy Systems, a Systematic Review. Energies, 12(7), Article 7. https://doi.org/10.3390/en12071301
N-BEATS — darts documentation. (n.d.). Retrieved 16 October 2023, from https://unit8co.github.io/darts/generated_api/darts.models.forecasting.nbeats.html
Ngoc, T. T., Dai, L. V., and Phuc, D. T. (2021). Grid search of multilayer perceptron based on the walk-forward validation methodology. International Journal of Electrical and Computer Engineering (IJECE), 11(2), 1742. https://doi.org/10.11591/ijece.v11i2.pp1742-1751
Oliveira, P., Fernandes, B., Analide, C., and Novais, P. (2021). Forecasting Energy Consumption of Wastewater Treatment Plants with a Transfer Learning Approach for Sustainable Cities. Electronics, 10(10), Article 10. https://doi.org/10.3390/electronics10101149
Optuna: A hyperparameter optimization framework—Optuna 3.5.0 documentation. (n.d.). Retrieved 12 December 2023, from https://optuna.readthedocs.io/en/stable/index.html
Polprasert, J., Hanh Nguyên, V. A., and Nathanael Charoensook, S. (2021). Forecasting Models for Hydropower Production Using ARIMA Method. 2021 9th International Electrical Engineering Congress (iEECON), 197–200. https://doi.org/10.1109/iEECON51072.2021.9440293
Sari, M. A., Badruzzaman, M., Cherchi, C., Swindle, M., Ajami, N., and Jacangelo, J. G. (2018). Recent innovations and trends in in-conduit hydropower technologies and their applications in water distribution systems. Journal of Environmental Management, 228, 416–428. https://doi.org/10.1016/j.jenvman.2018.08.078
Sharif, M. N., Haider, H., Farahat, A., Hewage, K., and Sadiq, R. (2019). Water–energy nexus for water distribution systems: A literature review. Environmental Reviews, 27(4), 519–544. https://doi.org/10.1139/er-2018-0106
Temporal Convolutional Network—Darts documentation. (n.d.). Retrieved 16 October 2023, from https://unit8co.github.io/darts/generated_api/darts.models.forecasting.tcn_model.html
Weigel, P., and Fischedick, M. (2019). Review and Categorization of Digital Applications in the Energy Sector. Applied Sciences, 9(24), Article 24. https://doi.org/10.3390/app9245350
Xu, Z., Lv, Z., Li, J., and Shi, A. (2022). A Novel Approach for Predicting Water Demand with Complex Patterns Based on Ensemble Learning. Water Resources Management, 36(11), 4293–4312. https://doi.org/10.1007/s11269-022-03255-5
Yi, S., Kondolf, G. M., Sandoval-Solis, S., and Dale, L. (2022). Application of Machine Learning-based Energy Use Forecasting for Inter-basin Water Transfer Project.

Water Resources Management, 36(14), 5675–5694. https://doi.org/10.1007/s11269-022-03326-7
Zhou, F., Li, L., Zhang, K., Trajcevski, G., Yao, F., Huang, Y., Zhong, T., Wang, J., and Liu, Q. (2020). Forecasting the Evolution of Hydropower Generation. Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2861–2870. https://doi.org/10.1145/3394486.3403337