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ORIGINAL

Generation Prediction in a Mini Hydroelectric Power Plant Using Machine Learning and Open-Source Software

Predicción de Generación en una Mini Central Hidroeléctrica usando Aprendizaje Automático y Software Libre

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ABSTRACT

Introduction: ecuadorian electric companies that own run-of-the-river hydroelectric plants with regulating reservoirs equal to or less than one day must submit the hourly generation curve planned for the following day to the National Electricity Operator of Ecuador (CENACE) before 10:00 am daily, in addition to having long-term estimates that allow for optimizing their operational planning.
Objective: to predict the behavior of electrical power generation at the Illuchi 1 run-of-river plant by applying machine learning methods, and then determine the most efficient method for each time scenario.
Method: for the development of this study, a historical database of electrical power generation from the Illuchi 1 mini hydroelectric plant was compiled, corresponding to a period of 3 years, 7 months, which was ordered chronologically and subsequently preprocessed. The open-source software Python was used, applying a methodology based on the model and evaluation of machine learning techniques such as Linear Regression, LSTM, GRU and XGBoost.
Results: the XGBoost algorithm showed better prediction performance for one and seven days, obtaining mean absolute error MAE values of 39,26 [W] and 25,60 [W] respectively and the coefficient of determination R^2 of 0,44 and 0,79. On the other hand, the GRU model showed greater prediction accuracy in the two-day horizon, reaching a mean absolute error MAE of 36,03 [W] and its coefficient of determination R^2 of 0,61.
Conclusions: XGBoost and GRU stand out from other prediction methods due to their ability to identify non-linear models, in order to optimize their forecast accuracy at different time intervals.

Keywords: Machine Learning; Generation; Prediction; Forecasting Models.

RESUMEN

Introducción: las empresas eléctricas del Ecuador propietarias de centrales hidroeléctricas de pasada con embalses de regulación igual o menor a un día, deben entregar diariamente antes de las 10:00 am la curva de generación horaria planificada para el día siguiente al Operador Nacional de Electricidad del Ecuador CENACE, además de contar con estimaciones a largo plazo que permitan optimizar la planificación operativa de las mismas.
Objetivo: predecir el comportamiento de la generación de potencia eléctrica en la central de pasada Illuchi 1 aplicando métodos de aprendizaje automático, para posteriormente determinar el método más eficiente para cada escenario temporal.
Método: para el desarrollo de este estudio, se recopiló una base de datos histórica de generación de potencia eléctrica de la mini central hidroeléctrica Illuchi 1, correspondiente a un periodo de 3 años,7 meses, la cual fue ordenada cronológicamente y posteriormente preprocesada. Se utilizó el software de código abierto

Python, aplicando una metodología basada en el modelo y evaluación de técnicas de aprendizaje automático como la Regresión Lineal, LSTM, GRU y XGBoost.
Resultados: el algoritmo XGBoost presentó un mejor desempeño de predicción para uno y siete días, obteniendo valores de error absoluto medio MAE de 39,26 [W] y 25,60 [W] respectivamente y el coeficiente de determinación R^2 de 0,44 y 0,79. Por otra parte, el modelo GRU mostro mayor precisión de predicción en el horizonte de dos días, alcanzando un error absoluto medio MAE 36,03 [W] y su coeficiente de determinación R^2 de 0,61.
Conclusiones: XGBoost y GRU destacan sobre otros métodos de predicción por su capacidad de identificar modelos no lineales, a fin de optimizar su precisión de pronóstico en distintos intervalos de tiempo.

Palabras clave: Aprendizaje Automático; Generación; Predicción; Modelos de Previsión.

INTRODUCTION

Ecuador's energy matrix is made up of renewable energy sources, the main source of which, at 80 %, comes from hydroelectric sources with a daily operating production of 86 500 MWh.[1] It must be taken into account that the generation capacity of these is affected by various types of factors such as variability in rainfall and dry seasons, which drastically reduces the generation capacity, causing blackouts and scheduled power outages. Given this background, it is necessary to implement electricity generation forecasting models, because an adequate forecast is essential for the operation and dispatch of the national interconnected system (SNI). This will guarantee the energy supply to users.[2]

Historical data, being the main input for predictions, can present a problem due to missing data or atypical deviations, which is why it is suggested to perform a preliminary analysis of the data for the development of forecasts since they can influence the accuracy of results.[3,4] Consequently, the success of prediction models will depend on the collection, processing and timing of historical data.[5]

In short-term generation forecasting, such as one-day, two-day, and seven-day forecasts, hourly production is predicted according to the requirements of the National Electricity Operator (CENACE). Therefore, short-term generation forecasting is essential for the planning and operation of the National Electricity Operator (SNI). Consequently, poor planning leads to poor electricity supply scheduling, resulting in losses by requiring more expensive generation units to meet hourly demand.[6]

There are different challenges when forecasting electricity generation, which can be addressed by applying machine learning methods based on artificial intelligence. These include models such as Linear Regression, LSTM, GRU, and XGBoost, implemented to achieve predictions with greater accuracy, in order to analyze highly complex patterns and forecast future scenarios, as argued by Mhlanga.[7]

Due to its ease of execution and its ability to structure the linear dependence between variables, Linear Regression is easy to implement. It has a limited capacity to capture nonlinear patterns; however, under conditions of relatively linear relationships between variables, it has been used to make successful short-term generation predictions. Generally, in predictions, linear regression is used to contrast with more complex models. It is also often used in studies on electricity demand prediction, as proposed by Gökçe et al.[8].

Another approach used in various studies for forecasting electric power generation, which seeks to achieve greater performance than conventional methods and solve time series problems, is the LSTM method. Thanks to its neural network layout and capture of long-term temporal dependencies, it has achieved 90 % effectiveness in short-term electric power predictions.[9]

GRUs provide excellent performance for processing statistical databases with missing or noisy data due to their accuracy and speed. They were designed to solve gradient problems using two gates: the update gate and the reset gate. These gates basically focus on determining what information is allowed to advance to the output, and they can be trained to store information from past time.[9,10]

The XGBoost prediction model is known as a high-performance algorithm for supervised learning, thanks to its high accuracy in predicting time series due to its high execution speed in the calculation. It uses a variety of methods to avoid overfitting, for this reason several studies such as Segovia et al.[11] They demonstrate that this model is generally used in the forecasting of electric power generation.

In addition to providing accurate predictions, more advanced models enable the implementation of strategies to optimize plant operations, thereby improving efficiency and enabling better real-time decision-making.

Python software was used in this research due to its ability to optimally handle robust databases thanks to its specialized libraries, widely available in this programming language. Python is also an important tool for data analysis due to its intuitive interface. Furthermore, it is freely available and does not entail any costs compared to other development environments specialized in forecasting.[11] On the other hand, in research proposed for the forecasting of electric power generation, the performance of the software to build complex regression models is evident, as in Gallo et al.[6]

In other countries in the region, research has also been carried out aimed at applying machine learning models within the electricity sector. For example, in Cuba, artificial neural networks were used to model the active power demand of a distribution circuit and in business buildings, achieving adjustment levels above 94 %, which demonstrates the efficiency of these techniques in improving energy planning.[12] However, in Ecuador, studies focused on the prediction of electricity generation, particularly in hydroelectric plants, are scarce. Therefore, this research seeks to contribute to the development of forecasting models applied to the national context, taking advantage of the potential of machine learning.

In this context, this study is justified by the need for tools that allow for anticipating the behavior of hydroelectric generation, thereby optimizing the operational planning of mini-power plants.

Finally, the objective of the research is to predict the behavior of electrical power generation at the Illuchi 1 run-of-river plant by applying machine learning models, which allow the identification of the appropriate model for each time horizon.

METHOD

This research is classified as longitudinal analytical observational, considering that it is based on the analysis of historical power generation data from the Illuchi 1 mini-power plant, during the period from January 2021 to July 2024.

The study universe consists of the mini-power plant's electrical power generation records for the indicated period, which correspond to 64 092 records. For the analysis, the entire dataset was used as a sample, forming two subsets: the first, corresponding to 80 % of the database, is used to train the models, and the remaining 20 % is used for validation.

The techniques designed, evaluated and tested are the following: Linear Regression, prediction model with LSTM neural networks, GRU Closed Recurrent Units and XGBoost.[11] To obtain the forecast of the variable, the design methodology presented in figure 1 is implemented.

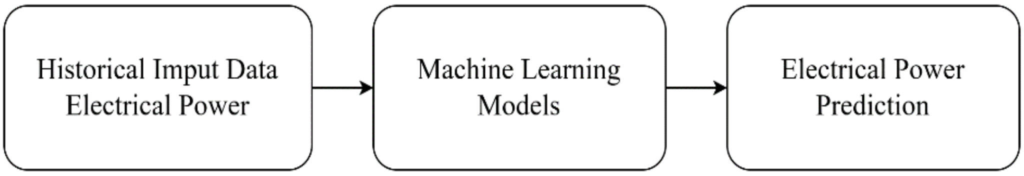

Figure 1. Process for determining the electrical power forecast

Input data for machine learning

For the purpose of this study, the electric power generation database of the Illuchi 1 mini hydroelectric plant located in Ecuador, Cotopaxi province, Latacunga, was used. This database covers the period from January 1, 2021 to July 31, 2024, representing 3 years and 7 months of historical information, which are taken by the operators of ELEPCO SA Consequently, this database represents a solid resource for analysis, providing significant value in terms of the accuracy of prediction models.[13]

Data pre-processing

First, a literature review was conducted to understand the state of the art related to electric power prediction. Next, the historical database corresponding to the generation variable of the Illuchi 1 mini-hydroelectric plant was compiled. To this end, the data were organized and reviewed using Microsoft Excel to verify their consistency and prepare the database for processing in Python software. Data preprocessing was then performed, which included converting temporal information to a unified date and time format, as well as numerically coding the categorical variable corresponding to the day of the week and checking for null values to ensure record quality. Finally, a new dataset was consolidated in which the temporal variable "date" was established as an index and the generated power variable remained as the main column, which allowed for a correct structure for time series analysis. It is worth noting that the data are collected hourly, in 30-minute intervals, providing 48 records per day, thus providing a sufficient level of detail for modeling and prediction.

Data division

In order to validate the performance of the models, the database is divided into three sections: the first section is the training data set which is used to train the forecast models, the second section is the test set which allows us to evaluate the test set and finally the validation set which helps to check the performance of the projection models implemented.[11]

After data preprocessing, a total of 64 092 electric power generation records were obtained, where 80 %

of the database (51274 data) is used to train the models and the remaining 20 % (12818 data) to evaluate the predictive performance. It is important to note that 1 day (48 data points), 2 days (96 data points), and 7 days (336 data points) were used for model validation.[14]

Programming

For programming, Python software was selected, which allows managing robust databases. It also has a wide variety of libraries such as Pandas that helps with data analysis. Sklearn was used to implement machine learning methods. Keras also allows building and modeling neural structure techniques.[14]

Nomenclature

Simple linear regression prediction model.

- Y: dependent variable.
- X: independent variable.
- B_0: intersection or point where the line cuts the Y axis.
- B_1: slope of the population line.
- *ε: random error.*
- Y ̂: estimated value of Y.

Prediction model with closed recurrent units GRU.

- ht: hidden state at time t.
- zt: upgrade Gate.
- rt: reset door.
- h˜t: candidate state.

Prediction model with LSTM neural networks.

- Ct: hidden state of the cell (memory).
- ht: hidden state cell exit.
- ft,it y ot: the activations of the doors of forgetting, entry and exit.
- C˜t: candidate information to be added to the cell.

Mean absolute error (MAE) and mean square error (MSE).

- n: sample size.
- Xi: value of the prediction.
- Yi: actual value.
- Y˜i: predictive value of observation i.
- R^2: coefficient of determination.

Machine learning models

Simple linear regression prediction model

In equation 1 the expressed model can be observed, said model presents two variables, the variable to be predicted is the dependent variable (Y), in addition to the independent variable (X) which is used as input to make the prediction. To make the predictions, equation 2 is applied, known as the prediction line.[15]

$$Y = \beta_0 + \beta_1 x + \varepsilon \qquad (1)$$

$$\hat{Y} = b_0 + b_1 x \qquad (2)$$

The method does not require hyperparameters, so the input variable's lag was adjusted. After identifying the impact of the different configurations, the selected configuration is predicted variable electric power and variable Inputs in electric power (5-step lag) and Hyperparameters are no tunable hyperparameters

Prediction model with LSTM neural networks

To address uncontrolled gradient fading and growth, the LSTM recurrent neural network model is ideal, as it facilitates capturing long-term temporal relationships in the data.

Equations 3 and 4 model the behavior of the method, the principle of the model consists of combining the previous information with the new input, in this way it manages to dynamically adapt to non-linear patterns present in the electrical power data.[16]

$$\mathrm{Ct} = \mathrm{ft} * \mathrm{Ct} - 1 + \mathrm{it} * \tilde{\mathrm{C}}\mathrm{t} \qquad (3)$$

$$\mathrm{ht} = \mathrm{ot} * \tanh(\mathrm{Ct}) \qquad (4)$$

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The configuration is predicted variable electric power and variable inputs is electric power (5-step lag) and neurons (50), Dropout (0,4/0,2), batch size (128), epochs (50).

Prediction model with closed recurrent units GRU

To reduce the computational demand without affecting the management of temporal dependencies, the GRU model is applied. This model is a simplification of the LSTM, since it only uses two gates, one for updating and one for restarting.[17]

For the prediction of electric power generation, the GRU model is adequate, because it discards information of low relevance and efficiently updates its internal state.[17] Equations 5 and 6 model the internal behavior of the method.

$$\tilde{h}t = \tanh(W * [rt * ht - 1, xt] + b) \quad (5)$$

$$ht = (1 - zt) * ht - 1 + zt * \tilde{h}t \quad (6)$$

The configuration is predicted variable electric power and variable inputs is electric power (5-step lag) and neurons (256), dropout (0,5/0,5), batch size (128), epochs (50).

XGBoost model

Is a scalable machine learning algorithm that can be used for both classification and regression tasks. It performs a second-order Taylor expansion on the loss function and can automatically utilize multiple central processing unit (CPU) threads for parallel computing. Additionally, XGBoost uses a variety of methods to prevent overfitting.[11]

The XGBoost algorithm works, where decision trees are built sequentially. Each tree attempts to correct the errors of the previous one by adjusting the weights of the variables that were poorly predicted. These variables with the greatest errors are prioritized in subsequent trees. Finally, the individual results from all the trees are combined, usually by averaging, to generate a more accurate and robust prediction.[11]

Hyperparameter combinations were explored using heuristic tests, also incorporating relevant variables such as water level. The configuration is predicted variable electric power and variable inputs is electric power (5-step lag) and toilet level and objective (mistake), estimators (100), learning rate (0,3), max depth.[6]

Estimated behavior of electricity production in the mini hydroelectric plant

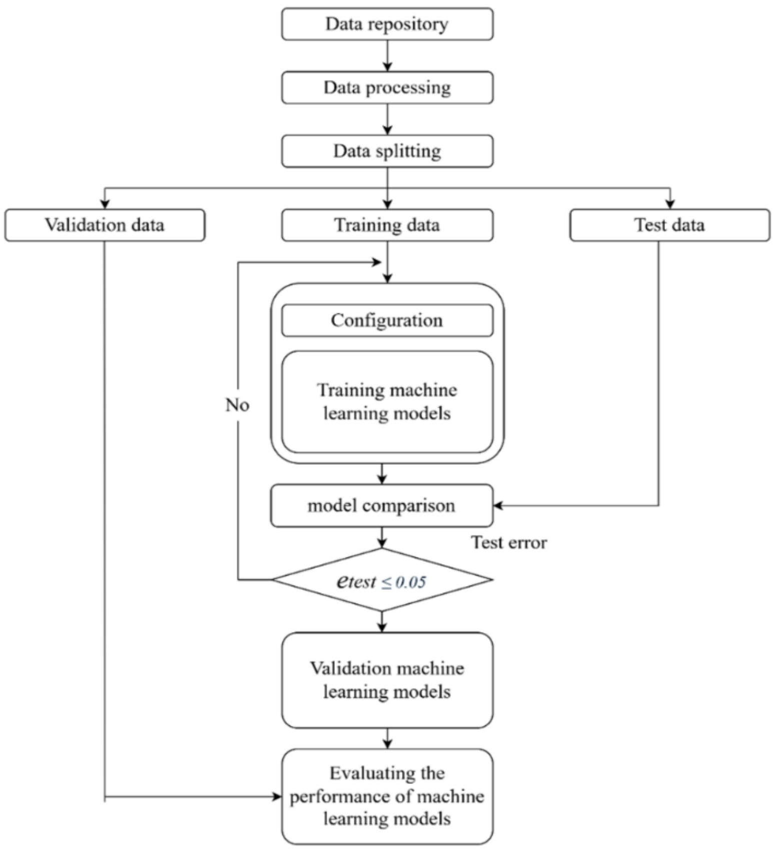

Figure 2. Generation prediction flowchart

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Evaluating the performance of machine learning models

In order to identify the discrepancy between projected and actual values, it is proposed to use error metrics that allow evaluating the performance of the implemented models, which are detailed below:

Mean absolute error (MAE)

It is a metric that allows evaluating machine learning models, which consists of averaging the absolute errors between the real value and the predicted value, thus allowing the quantification of the average magnitude of the errors generated in the prediction.[11] Therefore, it becomes a valuable resource when making projections of electric power generation and is described by equation 7.

$$MAE = \frac{\sum_{i=0}^{n} |yi - xi|}{n} \qquad (7)$$

The mean square error (MSE)

It is a performance metric that consists of obtaining the difference between the predicted and actual data, then squaring it and subsequently performing an average.[13] According to the mathematical expression represented in equation 8.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (yi - \widetilde{yi})^2 \qquad (8)$$

The R^2 metric

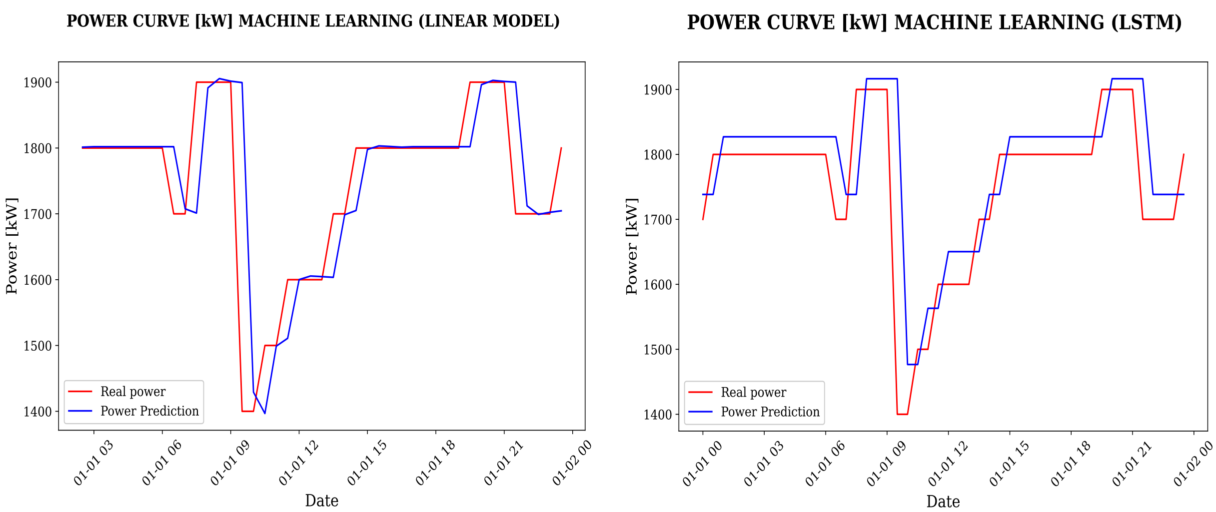
In addition to quantifying the error, it is necessary to determine the performance of the prediction models, for which the metric is applied R2. Which indicates that the results will be in the range of 0 to 1, if the value is close to 1 the method presents a good fit and if the value is close to 0 it is indicative of poor performance.[13] This metric is calculated by taking the quotient of the sum of squared errors and the total sum of deviations from the mean, as shown in equation 9.

$$R^2 = 1 - \frac{\sum (y_i - xi)^2}{\sum (yi - \mu y)} \qquad (9)$$

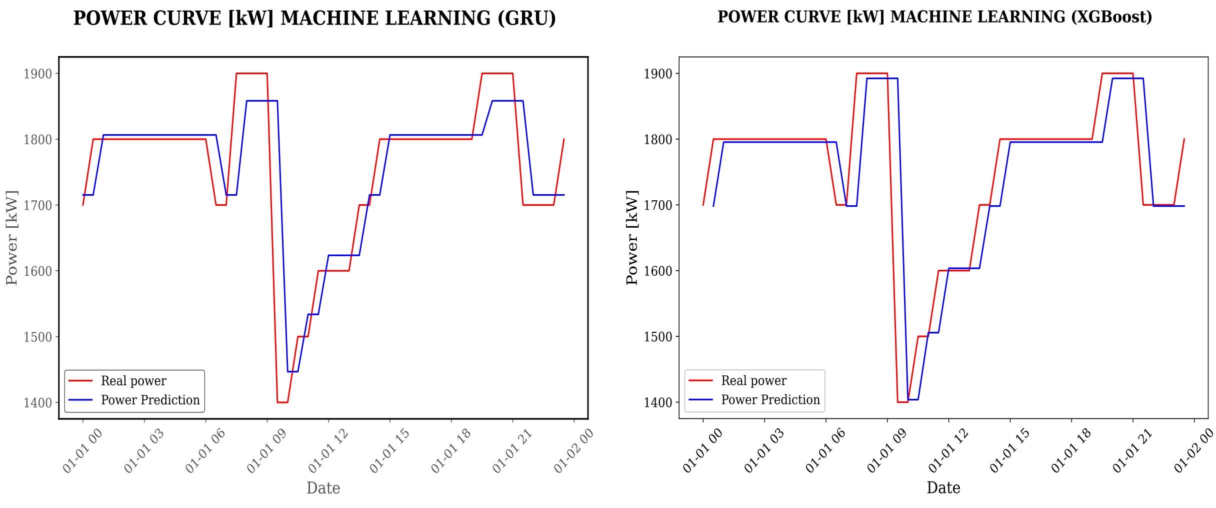
RESULTS AND DISCUSSION

The following section describes the technical contributions of the machine learning models used, such as Linear Regression, LSTM, GRU, and XGBoost, for one day, two days, and one week. Their predictive performance is subsequently evaluated by applying the MAE and MSE error metrics, in addition to assessing their performance with the coefficient of determination R^2. In this way, the ideal model is determined for each power generation prediction scenario at the mini-power plant.

1-day forecast



a) b)

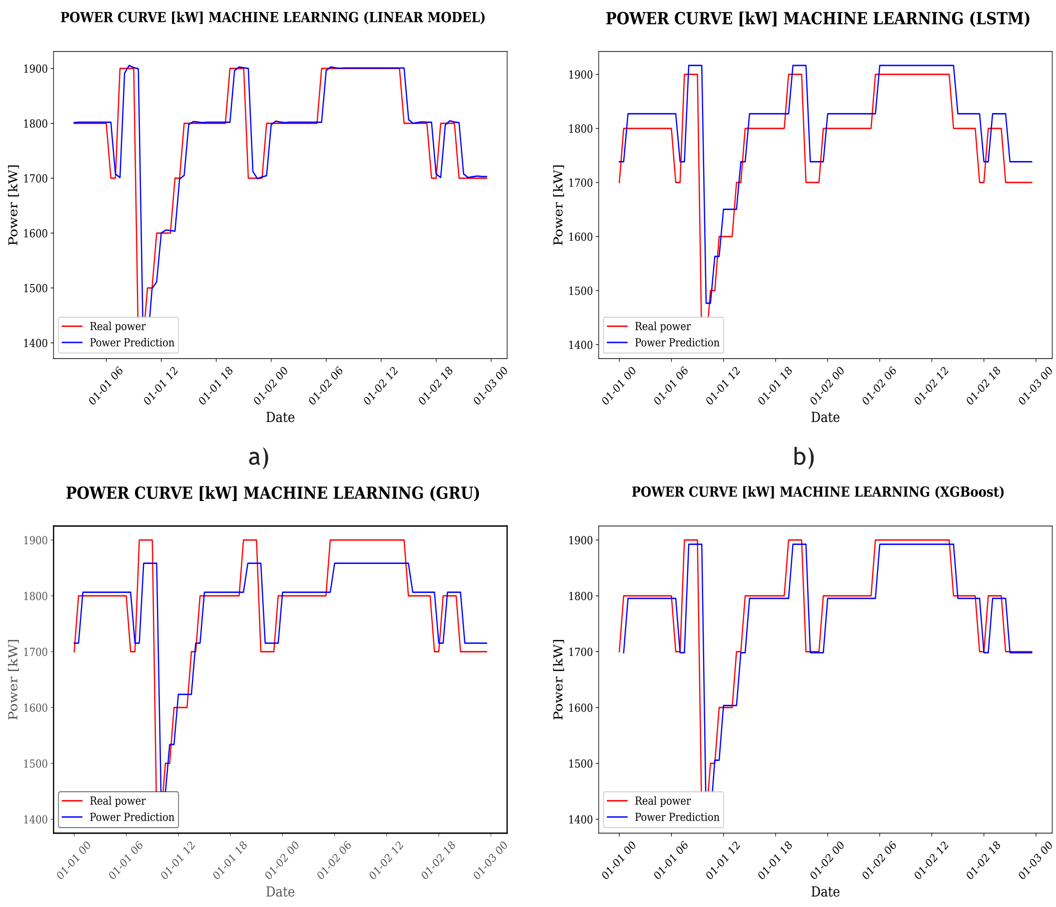


c) d)

Figure 3. Power Curve [kW] for one day: (a) Linear Regression, (b) LSTM, (c) GRU, (d) XGBoost

Figure 3 below shows a comparison between actual power generation on January 1, 2024, and predictions made using the Linear Regression, LSTM, GRU, and XGBoost models. The red curve represents actual performance recorded in the database, while the blue curve represents estimates generated by each model. This analysis is aligned with the requirements established by CENACE (National Energy Control Center) in Ecuador, which requires all generating plants to submit a 24-hour power generation forecast daily by 10:00 a.m.[18] Therefore, precision assessment over short-term horizons (one day) is essential to ensure the operational reliability of the national electricity system.

2-day forecast



c) d)

Figure 4. Power Curve [kW] for two days: (a) Linear Regression, (b) LSTM, (c) GRU, (d) XGBoost

Figure 4 shows the actual power generation for January 1 and 2, 2024, along with the predictions made by the Linear Regression, LSTM, GRU, and XGBoost models. The red line represents the actual behavior of the system, while the blue line reflects the generated predictions. This 48-hour horizon allows evaluating the models' ability to capture more complex temporal dynamics, such as daily cycles and variations due to operating or weather conditions. Although CENACE requires daily forecast reports, having projections of at least two days provides operators with a proactive tool that can improve decision-making in operational planning, reserve management, and coordination with projected demand.

1 week forecast

Figure 5 shows the comparison between actual power generation and the seven-day predictions made by the evaluated models. In this case, the red line corresponds to the actual data from January 1 to 7, 2024, while the blue line shows the projected behavior of each model. This forecast horizon, considered medium to long term, is key for planning the economic dispatch of generation, anticipating scheduled maintenance, and analyzing energy management scenarios in the face of critical events. It should be noted that CENACE requests daily forecasts, which, together with robust weekly estimates, will allow the power plants and the national operator to visualize trends, identify potential imbalances, and make strategic decisions for the proper operation of the hydroelectric plant. Consequently, the model's ability to maintain accuracy over several consecutive days becomes a crucial indicator of its performance.

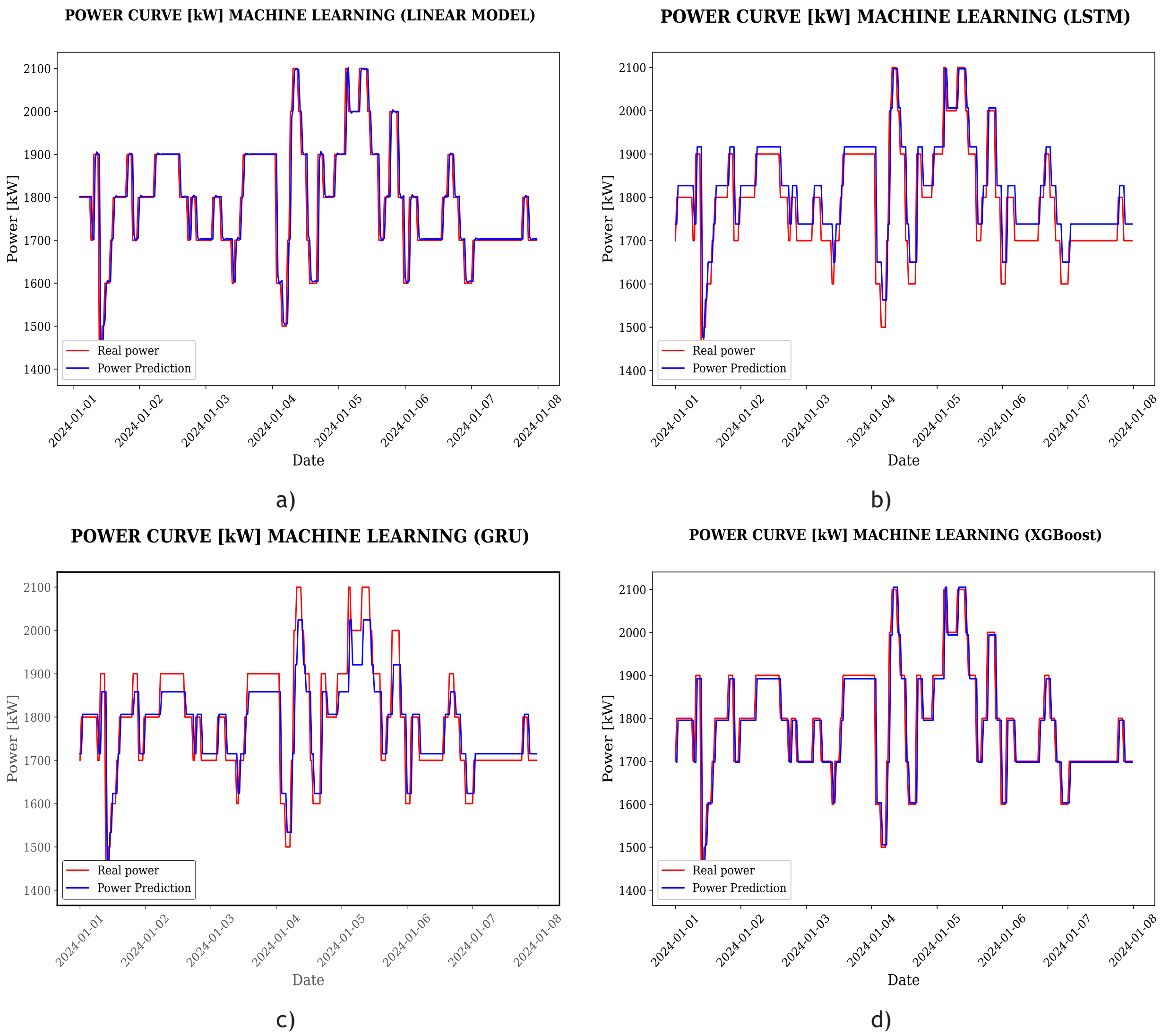


Figure 5. Power Curve [kW] for seven days: (a) Linear Regression, (b) LSTM, (c) GRU, (d) XGBoost

Table 1 presents the results of the error metrics for the comparison between the machine learning models for one, two, and seven days, which are the mean absolute error (MAE), the mean square error (MSE), and the coefficient of determination R^2, used to measure the effectiveness of the models.

Table 1. Comparison with error metrics between models

Model/Days	1			2			7		
	MAE [W]	MSE [W]	R^2	MAE [W]	MSE [W]	R^2	MAE [W]	MSE [W]	R^2
Linear Regression	39,50	9216,42	0,43	25,19	4910,26	0,58	24,47	3918,22	0,76
LSTM	53,14	8741,21	0,41	42,91	5244,13	0,53	44,57	4518,24	0,72
GRU	43,18	7117,35	0,52	36,03	4328,30	0,61	40,76	4183,02	0,74
XGBoost	39,26	8502,67	0,44	27,00	4727,24	0,58	25,60	3878,06	0,79

For one-day forecasting, the XGBoost model performed best in terms of MAE of 39,26 [W] and R^2 of 0,44, reflecting good accuracy for short-term forecasts. In contrast, the GRU model achieved an R^2 of 0,52, the highest among all models at this horizon, and an MSE of 7117,35 [W], demonstrating a greater capacity to adjust to the variability of the time series, despite having a slightly higher MAE of 43,18 [W]. It is worth noting that LSTM and linear regression showed more modest performances, with R^2 of 0,41 and 0,43 respectively.

GRU demonstrated good prediction capability over the two-day horizon, obtaining an R2 of 0,61 and a mean square error MSE of 4328,30 [W]. Despite having an MAE of 36,03 [W], higher than the XGBoost model with 27 [W] and the linear regression model with 25,19 [W], its high capacity to interpret data trends makes it a suitable option for conditions where general performance takes priority over individual accuracy.

On the other hand, the model for making predictions over the seven-day horizon was the XGBoost model, achieving an R2 of 0,79, in addition to obtaining an MSE of 3878,06 [W] corresponding to the lowest mean square error of all the implemented models, demonstrating its effectiveness over long horizons. However, the linear model obtained an R2 of 0,76 with an MAE of 24,47 [W], followed by the GRU model with an R2 of 0,74 with an MAE of 40,76 [W], which is why they are consolidated as competitive models with respect to LSTM.

The results show that the performance of the models depends on the chosen prediction horizon, so the method to be applied will be chosen according to the corresponding requirement, if you want to have an immediate short-term prediction, the XGBoost model provides greater point precision compared to the other models, to obtain an intermediate prediction the GRU model has a great capacity to interpret the dynamics of the series, finally to obtain a long-term forecast the XGBoost model is consolidated as the most robust model due to its learning characteristics and management of data variability thanks to its regularization mechanisms and assembly of decision trees. The results obtained agree with what has been reported in previous studies on power projection, in which the use of GRUs is highlighted when there are medium-sequence training samples and a fast and decent precision is desired as proposed by Freire et al.[19] In addition, it is verified that models based on decision trees usually show better performance over long horizons. In the research proposed by Gallo et al.[6] the Random Forest model obtained the lowest absolute percentage errors, consolidating itself as the technique with the best projection performance. This finding is consistent with the results of the present study, where the XGBoost model was positioned as the most optimal model in the seven-day horizon.

Although the evaluated models demonstrated efficiency in predicting electric power generation, there are limitations that must be considered. First, the data analyzed correspond only to the Illuchi 1 mini-hydroelectric plant, which limits the generalization of the findings to other hydroelectric plants with different hydrological or operational conditions. Furthermore, the models considered only active power and water level, without incorporating external variables such as climatic parameters, which could improve the models' accuracy.

CONCLUSIONS

The research was proposed with the objective of predicting the behavior of the electrical power generation of the Illuchi 1 mini-power plant by applying machine learning models, which concludes that the choice of model must be adapted to the prediction time horizon, since each model offers different advantages with respect to the time scale.

Based on the results obtained, the XGBoost model was established as an effective alternative for short- and long-term projections, demonstrating high accuracy for immediate estimates and robustness for weekly estimates. This highlights the importance of selecting appropriate prediction techniques to strengthen operational planning.

In conclusion, the XGBoost model presents adequate results for the prediction of a day in advance, with which the hourly curve presented before 10:00 am of the following day can be adjusted to the National Electricity Operator of Ecuador CENACE.

Finally, it is concluded that each prediction horizon can be used, such as the XGBoost model for the short and long term, while in the medium term the GRU model allows for a visualization of the plant's behavior, thus facilitating strategic generation decision-making at the plant both for CENACE's immediate requirements and for estimates of energy production in the following days. It is recommended to continue feeding the models with data on a daily basis, as well as implementing other machine learning algorithms.

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The authors declare that there is no conflict of interest.

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