TEPES
TURKISH JOURNAL OF ELECTRICAL POWER AND ENERGY SYSTEMS

TEPES, Vol. 4, Issue. 3, 159-164, 2024 **DOI:** 10.5152/tepes.2024.24018

RESEARCH ARTICLE

Forecasting Model of Electricity Production from Hydroelectric Sources with Long Short-Term Memory (LSTM) Networks

İnayet Özge Aksu[1], Tuğçe Demirdelen[2]

[1]Department of Artificial Intelligence Engineering, Adana Science and Technology University, Adana, Türkiye
[2]Department of Electrical and Electronic Engineering, Adana Science and Technology University, Adana, Türkiye

Cite this article as: İ. Özge Aksu and T. Demirdelen, "Forecasting model of electricity production from hydroelectric sources with long short-term memory (LSTM) networks," *Turk J Electr Power Energy Syst.*, 2024; 4(3), 159-164.

ABSTRACT

Electricity is one of the most important elements for economic growth and development of societies in today's modern societies. The research of electricity generation, knowing the size of the electricity supply, and the methods developed to meet this supply are among the important subjects of study today. With the increase in electricity supply and the increasing importance of environmental pollution, the use of renewable energy sources in electricity generation is increasing. In this study, Long Short-Term Memory (LSTM), a type of recurrent neural network, is used to predict the energy production in a hydroelectric power plant. The LSTM method is one of the most popular recurrent neural network methods and is widely used in the field of deep learning. The graphical and numerical results obtained at the end of the study show the success and efficiency of the LSTM method.
C_t represents the updated cell state. With f_t, forgotten information is removed, with i_t, new information is added. In the last step, the output layer is obtained by using the equations given below.

Index Terms—Forecast, hydroelectric power, long short-term memory, renewable energy.

I. INTRODUCTION

Increasing in the world population, developments and expectations in social welfare and living standards, rapid developments in industry and technology also increase energy consumption and consequently energy demand. Environmental and economic damages in the production of fossil fuels, which are among the existing energy sources, have led countries to new energy production sources. The most important of these is renewable energy sources. Renewable energy is an inexhaustible, clean energy source that constantly renews itself. Some of these renewable energy sources are hydraulic energy, solar energy, wind energy, geothermal energy, and biomass energy.

Hydraulic energy is among the most widely used renewable energy sources. In order to benefit from this energy, dams are built and water is collected. Thanks to the motion energy of this accumulated water, electrical energy is produced in the turbine. Hydroelectric power plants (HEPPs) are also established for this purpose. The hydroelectric potential of the countries is determined according to the calculation of 100% efficiency of all-natural water flows within the borders of the country. Hydroelectric energy is renewable because of the natural cycle of water. The water evaporates, clouds form, and then it rains, and the water returns to the earth again. Because of this cycle, using water as an energy source is a safe and ideal choice.

About 71% of the electricity produced by renewable energy sources all over the world originates from hydroelectric energy [1]. Thanks to the hydraulic energy obtained depending on the precipitation regime, the high amount of electricity needed such as the operation of the factories and the lighting of the cities can be provided. In HEPPs, electricity is produced by utilizing the power of flowing water.

Hydroelectric Energy Production in Türkiye In 2019: the amount of energy produced only in HEPPs in Türkiye was 68 452 GWh. The installed capacity of HEPPs is increasing every year. As of 2020, there are 653 HEPPs across the country. However, the amount of hydroelectric energy production changes every year due to the climate. It still has a large share in energy production [2]. The use of

Corresponding author: İnayet Özge Aksu, oaksu@atu.edu.tr

Received: July 8, 2024
Revision Requested: August 1, 2024
Last Revision Received: August 5, 2024
Accepted: August 7, 2024
Publication Date: October 21, 2024

hydroelectric energy, which has an important place among renewable energy sources, is increasing in the world. Since 2018, the electricity produced by the hydroelectric energy method has reached an annual average of 4,200 TWh in the world. The country with the highest hydropower potential is China with 352 GW. China is followed by Brazil with 104 GW, America with 103 GWh, and Canada with 81 GW. These 4 countries produce approximately 50% of the world's HEPP installed power [3].

This research aims to develop and apply Long-Short Term Memory (LSTM) models to predict electricity production from hydroelectric sources. For this purpose, hydroelectric source data were configured, trained, and validated. The results show that the preferred model works successfully on hydropower-based energy forecast data. The model developed could be a useful tool for energy planning and decision-making for long-term hydropower generation.

II. LITERATURE SURVEY

In the field of sustainable energy production, hydroelectric power stands as a dominant and reliable source, contributing significantly to global electricity generation [4]. The accurate forecasting methods in hydroelectric power generation are very important for efficient grid management. This review examines the diverse array of predictive techniques employed in forecasting hydroelectric power generation, shedding light on their efficacy, limitations, and potential avenues for enhancement.

It is introduced that short-term prediction models designed specifically for estimating average electricity generation in hydropower plants [5–8]. The model relies on input data, including projected precipitation figures sourced from Numerical Weather Prediction tools, alongside historical records of hourly power output from these small-hydro plants. Covering a forecast horizon of seven days, the proposed model offers a practical solution for incorporating power production forecasts into Power System operations, electricity markets, and the scheduling of maintenance tasks within small-hydro power plants. The model's efficacy is evaluated through its application to aggregate hourly average power production forecasts for a real-world ensemble of 130 small-hydro power plants in Portugal. Impressively, the model yielded favorable outcomes, maintaining forecasting errors within a tight threshold and achieving consistently low values [9].

Main Points

- The aim of this study is to predict electricity generation from hydroelectric sources and long short-term memory (LSTM) networks method is used for the prediction process.
- Long short-term memory is a type of recurrent neural network and is used in this study to predict power generation in a hydroelectric power plant. The LSTM method is a popular recurrent neural network method that is widely used in the field of deep learning.
- The graphical and numerical results obtained at the end of the study show the success and efficiency of the LSTM method.

Ecuador's predominant electricity generation sources encompass hydroelectric and thermo-fossil types, with hydroelectric production intermittently surpassing the 50% mark of national output. This study's core objective centers around constructing a predictive model for monthly hydroelectric energy production [10]. The study conducted that five distinct stochastic process models are implemented, leveraging a historical dataset spanning 2000 to 2015, specifically focusing on Ecuador's monthly hydroelectric energy production. Employing this model, projections are made for the year 2020, revealing an anticipated uptick in monthly production. Impressively, the actual values align within the confidence interval of the Auto-Regressive Integrated Moving-Average (ARIMA) model, which incorporates annual seasonality for predictions. The resulting model serves as a valuable tool for characterizing and predicting Ecuador's hydroelectric energy generation, thereby holding promise for guiding prospective planning efforts within the electric sector. The results obtained for the data used in the study showed that the standard absolute deviation Mean Absolute Percentage Error (MAPE) value was 14.32% and the R2 value was 72.39%, indicating that the estimation was quite successful [11]. Also, it introduced a predictive analysis of hydroelectricity usage in Pakistan, utilizing 53 years' worth of historical data. The methodology employed involves the application of ARIMA modeling. The outcomes of this study include a forecasted equation, which enabled the projection of hydroelectricity consumption up until the year 2030. The forecast in the study shows an average annual increase of 1.65% in hydroelectric energy consumption. By 2030, there is a cumulative increase of 23.4% [12]. Using the three-parameter whitening grey prediction model as a foundation, a two-parameter optimized version is formulated by combining and optimizing the order of accumulating fractional order in real-world scenarios with the background value coefficients. This tailored model is then employed to forecast China's hydroelectric power generation. Impressively, the model demonstrates a high level of proficiency, with a mere 1.13% comprehensive error rate. The outcomes underscore that the model's effectiveness is substantial, suggesting a viable pathway to reaching the carbon peak target by the year 2030 [13].

The hydroelectricity consumption of China is estimated using a novel approach based on grey modeling techniques. The forecasting process aimed in the study was performed with the gray-based models GM(1,1), DGM(1,1), and NGBM(1,1) and the non-gray-based time series forecasting models PR, ARIMA, and artificial neural networks (ANN). When the results obtained at the end of the study are analyzed, it is seen that the experimental results obtained by the unbiased NGBM(1,1) model are more accurate [14]. The study delved into twenty distinctive input combinations, encompassing factors like dam inflow, rainfall data, and preceding months' hydropower output. In each scenario, the anticipated output was a one-month projection of hydropower generation. Subsequently, the GWO-ANFIS hybrid model was leveraged to anticipate forthcoming hydropower production levels. The GWO-ANFIS demonstrated impressive capabilities in forecasting hydropower generation, effectively meeting satisfactory benchmarks [15]. In [16], the study centers on a reservoir situated in China and spans the data range from 1979 to 2016. These include the utilization of ANN, ARIMA, and support vector machines. The resultant findings illuminate the promising potential of these models in effectively predicting hydropower generation, thus offering a valuable avenue for energy decision-makers to explore.

The LSTM method has started to be used in the field of energy in Türkiye. M. Bilgili et al. valuated the success of LSTM on energy consumption data in Türkiye. The results showed that LSTM can be used effectively in energy consumption forecasting [17]. In another study, the use of LSTM networks to forecast Gross electricity consumption in Türkiye is discussed [18]. Cobaner et al. introduce a pragmatic approach that employs ANNs to forecast the potential of hydropower energy, specifically tailored to assess the viability of integrating a hydropower plant unit into an existing irrigation dam. At the end of the study, mean square error (MSE) and R2 results obtained using ANN and MLR models are given. For Bahçelik dam, the MSE result obtained with ANN is 1.006E+11, and the MSE result obtained with multiple linear regression (MLR) is 1.637E+11. For Sarimsakli Dam, the MSE result obtained with ANN is 5.986E+9, and the MSE result obtained with MLR is 1.143E+11. When these results are examined, it becomes clear that the accuracy of ANN is better than MLR [19]. Accurate prediction of photovoltaic power generation (PV power) is an area of interest today. Hu et al. [20] used the LSTM network for PV power estimation in their study. In this study, the method is applied to real PV power data of a building in Japan. At the end of the study, successful results were obtained with the LSTM model. In another study, a bidirectional long short-term memory network (Bi-LSTM) based method was used for accurate short-term prediction of wind power [21]. In the optimization phase of the parameters of the Bi-LSTM model, the grey wolf optimization (GWO) method was used. With this method, high-accuracy results were obtained for short-term wind power forecasting. Wind power forecasting is also a challenging process, as it often has nonlinear and non-stationary characteristics. Liu et al. [22] used a hybrid deep learning model based on parallel architecture by using a tensor concatenate module to combine a temporal convolution network and a LSTM neural network to improve the prediction performance. In their study, they used wind turbine data from Türkiye. They obtained successful results with the proposed model.

Studies in the literature show that LSTM is an effective method and that deep learning techniques are becoming increasingly popular in time series forecasting. Traces of this trend can also be seen in energy research in Türkiye. In this study, the choice of the LSTM method for electricity generation from Türkiye's hydroelectric resources is a reflection of this trend. It is observed that the use of LSTM in Türkiye's energy sector is increasing. This study, like other studies on hydroelectric power generation in Türkiye, aims to obtain more accurate forecasts using the LSTM method.

III. LONG SHORT-TERM MEMORY (LSTM)

LSTM was developed in the late 1990s as a subset of Recurrent Neural Network (RNN) for modeling sequential data. The RNN technique examines each piece of information in the input data iteratively, taking into consideration the value of the preceding output. Although it is claimed that this architecture executes learning that takes past time periods into account, it has been shown that this is not viable due to the gradient disappearance/explosion problem. To solve this problem, the LSTM architecture, which can remember

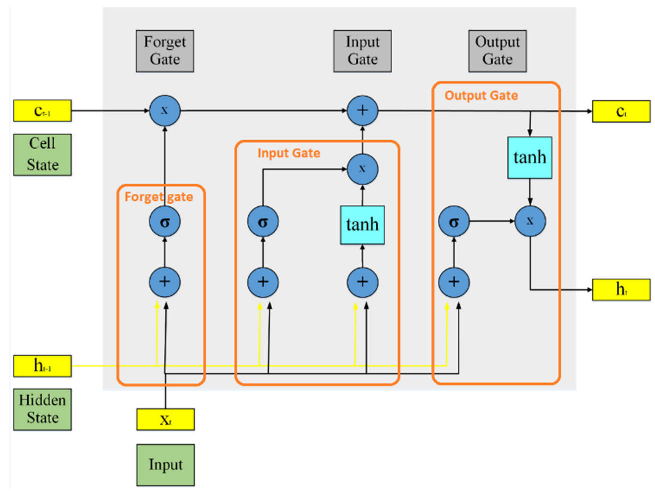

Fig. 1. Block diagram of the long-short tem memory prediction model.

long-term information, has been developed. The most prominent feature that distinguishes LSTM networks from other RNN structures is the gate mechanisms and cell state. With these structures, gradient fading and bursting problems are reduced. The cell state in the network structure uses the chain rule. This preserves the gradients and allows the gradients to remain large enough to learn long-term dependencies. As a result, the problem of gradient decay is reduced by this structure. At the same time, gate mechanisms prevent gradient explosion by controlling the size of the gradients. A block diagram of the LSTM prediction model is given in Fig. 1.

In the LSTM structure, information flow occurs in a certain flow order. The basic structure of LSTM consists of a memory unit called the cell state and three main gates designed to update, delete or read this memory. The gate is used to add and update new information to the cell state. First, a sigmoid activation function determines which values will be updated. Then, a new candidate cell state is created with a *tan*h activation function. These two values are multiplied and the current cell state is updated. Forget gate is used to remove unnecessary information from the cell state. Values calculated with a sigmoid activation function determine how much of the information in the cell state is forgotten. Values between 0 and 1 determine which information will be preserved and which information will be forgotten. After old information is removed with the forgetting gate, new information is added with the entry gate. This allows the cell state to be updated and long-term dependencies to be learned. The output gate is used to produce output from the updated cell state. By activating a sigmoid on the cell state, it is determined which information will be used as output. Additionally, the values derived from the cell state are normalized with the *tan*h activation function.

As seen in Fig. 1, the LSTM design is made up of multiple sections that repeat themselves. In general, the LSTM structure is formed up of three layers: forget, input, and output. The information to be erased is initially determined in the LSTM architecture by using the X_t and h_{t-1} information as inputs. These actions are carried out in the forget layer (*ft*) and the activation function is sigmoid.

$$f_t = \sigma(W_f, x \times X_t + W_f, h \times h_t - 1 + b_f) \quad (1)$$

In this equation, f_t is the output of the forgetting gate. $W_{f,x}$ and $W_{f,h}$ represent the weight matrices, h_{t-1} represents the hidden state of the previous time step, and X_t represents the input of the current time step. b_f is the bias term and σ represents the sigmoid activation function.

In the second step, the input layer (i_t) to calculate the new information is updated using the sigmoid function. In the next step, the candidate information that will become the new information is then determined by the *tan*h function.

$$it = \sigma\ (W_{i,x} \times X_t + W_{i,h} + h_{t-1} + bi) \quad (2)$$

here *it* is the output of the input gate. $W_{i,h}$ and b_i are the weight matrix and relevant bias terms, respectively.

$$Ct = tan\text{h}\ (W_{c,x} \times X_t + W_{c,h} \times h_{t-1} + b_c) \quad (3)$$

C_t represents the candidate cell state information. $W_{c,h}$ is the weight matrix and b_c is the bias term. *tan*h represents the hyperbolic tangent activation function. Next step is cell status update operations. New information is obtained using with this equation:

$$C_t = C_{t-1} \times f_t + i_t + C_t \quad (4)$$

$$o_t = \sigma(W_{o,x} \times X_t + W_{o,h} \times h_{t-1} + b_o) \quad (5)$$

o_t represents the output of the output gate and h_{t-1} represents the hidden state of the previous time step. $W_{o,h}$ represents the weight matrix and σ represents the sigmoid activation function.

$$h_t = o_t \times tan\text{h}\ (C_t) \quad (6)$$

here h_t represents the hidden state of the current time step and *tan*h represents the hyperbolic tangent activation function. In Fig. 1, the gates of the LSTM model, including the input, forget and output gates, are detailed in the figure.

In the working logic of the algorithm, the process, whose steps are given, continues iteratively. The weight parameters (*W*) and bias parameters (*b*) are updated by the model to minimize the error value between the actual training values and the LSTM output values. Thus, the learning process is performed.

IV. RESULT AND DISCUSSION

Electricity production from hydroelectric sources data were used in this study. The data set covers the period between 1960 and 2013 [23]. The data set consists of annual data. The data between 1960 and 2009 is used as training data and the data for the last 4 years are used as test data. In the study, data on the ratio of the amount of electricity production from hydroelectric resources to the total electricity production between 1960 and 2013 were used [23]. These data are given in the Fig. 2 [23].

The aim of the study is to make forward-looking forecasts. At this stage, The LSTM method, which is popular among the RNN methods, is preferred. At the end of the prediction phase, the prediction results obtained for the years 2009–2013 are given in Fig. 3. The aim of the study is to provide training of the LSTM network with the available data for the years 1960–2009 [23]. At the end of the training phase, predictions were made for the years 2009–2013 [23]. Electricity production from hydroelectric sources values obtained as a result of the estimation were compared with the real values for the years 2009–2013 [23]. The graphs of the results obtained at this stage are shown in the Fig. 3.

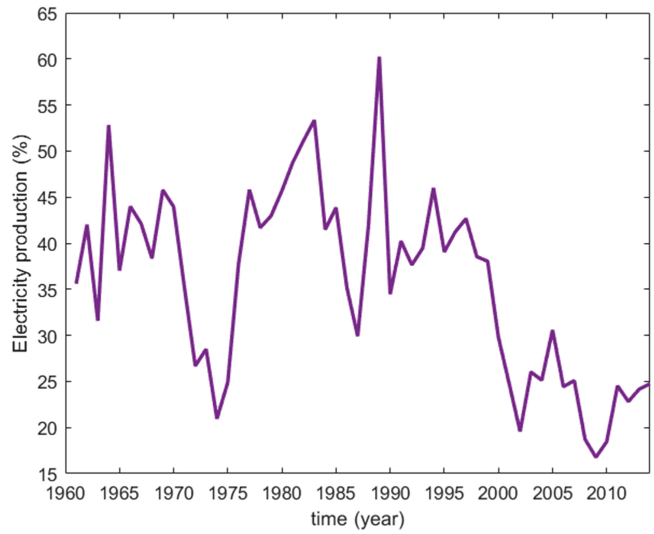

Fig. 2. Real electricity production from hydroelectric sources data (% of total) for the years 1960–2013 [23].

Root Mean Square Error (RMSE) error criterion is used to show the relationship between the actual values and the values obtained as a result of the estimation process. The RMSE error criterion is calculated as follows:

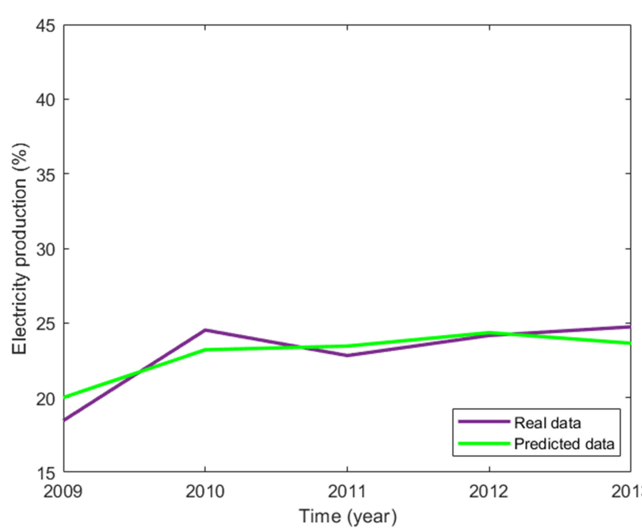

Fig. 3. Real electricity production from hydroelectric sources data [23] against predicted values by long-short term memory.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i^{'}\right)^2} \tag{6}$$

where i and n are the index and the data number, respectively. y_i represents the real data and $y_i^{'}$ represents the result obtained. The RMSE value of the obtained results is 1.0753 and the regression result is 0.93306. The regression graph of the results is given in Fig. 4. The regression value of 0.93306 obtained as a result of the estimation study shows that the regression model used explains the data well. In this case, the higher the regression value, the better the model fits the actual data. This high regression value indicates that the prediction model for the electricity generation rate from hydroelectric sources strongly captures the relationship between the data and explains this relationship well. The regression graph of the results obtained at the end of the study is shown in Fig. 4.

V. CONCLUSION

Hydroelectric resources are one of the preferred energy sources to meet the ever-increasing electricity supply. In this study, a prediction study has been carried out for the utilization of hydroelectric resources used in electricity generation. When the studies in the literature are examined, it is seen that recurrence-based methods are preferred in the prediction studies carried out in recent years. In the prediction phase of the study, the LSTM algorithm, which is a recurrent method, is preferred. At the end of the study, the estimation process is completed with an error value of 1.0753 according to the RMSE error criterion. The results obtained at the end of the study show that the preferred method can be used successfully in the prediction studies to be carried out in the field of utilization of hydroelectric resources.

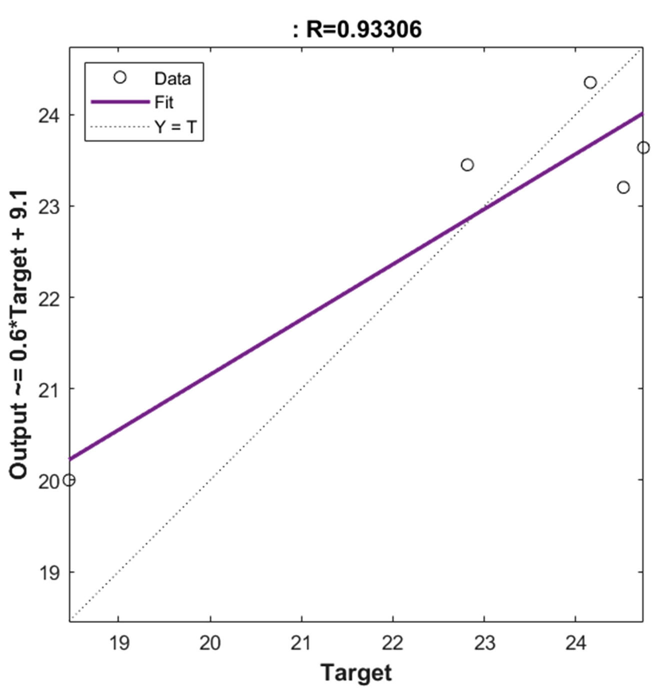

Fig. 4. Regression graph based on long-short term memory neural network architecture.

Availability of Data and Materials: The data that support the findings of this study are available on request from the corresponding author.

Peer-review: Externally peer-reviewed.

Author Contributions: Concept – İ.Ö.A., T.D.; Design – T.D.; Supervision – İ.Ö.A.; Resources – İ.Ö.A., T.D.; Materials – İ.Ö.A., T.D.; Data Collection and/or Processing – İ.Ö.A., T.D.; Analysis and/or Interpretation – İ.Ö.A.; Literature Search – T.D.; Writing – İ.Ö.A., T.D.; Critical Review – İ.Ö.A., T.D.

Declaration of Interests: Tuğçe Demirdelen is a member of Advisory Board of Turkish Journal of Electrical Power and Energy Systems, however, her involvement in the peer review process was solely as an author. İnayet Özge Aksu has no conflicts of interest to declare.

Funding: This study received no funding.

REFERENCES

1. E. F. Moran, M. C. Lopez, N. Moore, N. Müller, and D. W. Hyndman, “Sustainable hydropower in the 21st century,” *Proc. Natl Acad. Sci. U. S. A.*, vol. 115, no. 47, pp. 11891–11898, 2018. [CrossRef]
2. R. Uddin, A. J. Shaikh, H. R. Khan, M. A. Shirazi, A. Rashid, and S. A. Qazi, “Renewable energy perspectives of Pakistan and Turkey: Current analysis and policy recommendations,” *Sustainability*, vol. 13, no. 6, p. 3349, 2021. [CrossRef]
3. D. Bin, “Discussion on the development direction of hydropower in China,” *Clean Energy*, vol. 5, no. 1, pp. 10–18, 2021. [CrossRef]
4. G. Shahgholian, M. Moazzami, S. M. Zanjani, A. Mosavi, and A. Fathollahi, “A hydroelectric power plant brief: Classification and application of artificial intelligence,” in 17th International Symposium on Applied Computational Intelligence and Informatics (SACI), May 2023. IEEE Publications, 2023, pp. 000141–000146. [CrossRef]
5. S. K. Ahmad, and F. Hossain, “Maximizing energy production from hydropower dams using short-term weather forecasts,” *Renew. Energy*, vol. 146, pp. 1560–1577, 2020. [CrossRef]
6. S. Camal, F. Teng, A. Michiorri, G. Kariniotakis, and L. Badesa, “Scenario generation of aggregated Wind, Photovoltaics and small Hydro production for power systems applications,” *Appl. Energy*, vol. 242, pp. 1396–1406, 2019. [CrossRef]
7. Z. Ding et al., “A forecast-driven decision-making model for long-term operation of a hydro-wind-photovoltaic hybrid system,” *Appl. Energy*, vol. 291, p. 116820, 2021. [CrossRef]
8. J. Jurasz, A. Kies, and P. Zajac, “Synergetic operation of photovoltaic and hydro power stations on a day-ahead energy market,” *Energy*, vol. 212, p. 118686, 2020. [CrossRef]
9. C. Monteiro, I. J. Ramirez-Rosado, and L. A. Fernandez-Jimenez, “Short-term forecasting model for electric power production of small-hydro power plants,” *Renew. Energy*, vol. 50, pp. 387–394, 2013. [CrossRef]
10. J. Barzola-Monteses, M. Mite-León, M. Espinoza-Andaluz, J. Gómez-Romero, and W. Fajardo, “Time series analysis for predicting hydroelectric power production: The Ecuador case,” *Sustainability*, vol. 11, no. 23, Art. no. 23, 2019. [CrossRef]
11. M. Mite-León, and J. Barzola-Monteses, “‘Statistical Model for the Forecast of Hydropower Production in Ecuador’, *IJRER*,” *IJRER*, vol. 10, no. v8i2, pp. 1130–1137, 2018. [CrossRef]

12. R. Jamil, “Hydroelectricity consumption forecast for Pakistan using Arima modeling and supply-demand analysis for the year 2030,” *Renew. Energy*, vol. 154, pp. 1–10, 2020. [CrossRef]
13. S. Li, N. Song, K. Gong, B. Zeng, and Y. Yang, “Forecasting China’s hydroelectric power generation under the New Era based on grey combination model,” *J. Grey Syst.*, vol. 35, no. 2, pp. 149–166, 2023.
14. C. Zheng, W.-Z. Wu, W. Xie, Q. Li, and T. Zhang, “Forecasting the hydroelectricity consumption of China by using a novel unbiased nonlinear grey Bernoulli model,” *J. Cleaner Prod.*, vol. 278, p. 123903, 2021. [CrossRef]
15. M. Dehghani et al., “Prediction of hydropower generation using grey wolf optimization adaptive neuro-fuzzy inference system,” *Energies*, vol. 12, no. 2, p. 289, 2019. [CrossRef]
16. M. Sattar Hanoon et al., “Prediction of hydropower generation via machine learning algorithms at three Gorges Dam, China,” *Ain Shams Eng. J.*, vol. 14, no. 4, p. 101919, 2023. [CrossRef]
17. M. Bilgili, N. Arslan, A. Şekertekin, and A. Yaşar, “Application of long short-term memory (LSTM) neural network based on deeplearning for electricity energy consumption forecasting,” *Turk. J. Electr. Eng. Comput. Sci.*, vol. 30, no. 1, pp. 140–157, 2022. [CrossRef]
18. M. Bilgili, and E. Pinar, “Gross electricity consumption forecasting using LSTM and SARIMA approaches: A case study of Türkiye,” *Energy*, vol. 284, p. 128575, 2023. [CrossRef]
19. M. Cobaner, T. Haktanir, and O. Kisi, “Prediction of hydropower energy using ANN for the feasibility of hydropower plant installation to an existing irrigation dam,” *Water Resour. Manag.*, vol. 22, no. 6, pp. 757–774, 2008. [CrossRef]
20. Z. Hu, Y. Gao, S. Ji, M. Mae, and T. Imaizumi, “Improved multistep ahead photovoltaic power prediction model based on LSTM and self-attention with weather forecast data,” *Appl. Energy*, vol. 359, p. 122709, 2024. [CrossRef]
21. H. Sun, Q. Cui, J. Wen, L. Kou, and W. Ke, “Short-term wind power prediction method based on CEEMDAN-GWO-Bi-LSTM,” *Energy Rep.*, vol. 11, pp. 1487–1502, 2024. [CrossRef]
22. S. Liu, T. Xu, X. Du, Y. Zhang, and J. Wu, “A hybrid deep learning model based on parallel architecture TCN-LSTM with Savitzky-Golay filter for wind power prediction,” *Energy Convers. Manag.*, vol. 302, p. 118122, 2024. [CrossRef]
23. Available: https://data.worldbank.org/indicator/EG.ELC.HYRO.ZS.