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Research Article

Energy Production Prediction In Hydroelectric Power Plants With Multi-Layer Perceptron Algorithm, Menzelet Dam Example

Ezgi Öztürk İSPİR [a], ***Hasan Erdinç KOÇER*** [b,*], ***Şerife Yurdagül KUMCU*** [c]

[a] *Department of Civil Engineering, Faculty of Engineering, Necmettin Erbakan University, Konya, Türkiye*
[b] *Electrical Electronic Engineering Department, Selcuk University, Konya, Türkiye*
[c] *Department of Civil Engineering, Faculty of Engineering, Necmettin Erbakan University, Konya, Türkiye*

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ABSTRACT

Hydroelectric energy is connected to clean and extractable energy produced by electric generators that convert the movement of water falling into dams into energy. From the perspective of life cycle planning of energy production systems, estimating the energy to be produced from hydroelectric power plants is very important in terms of energy production efficiency management, but it is quite difficult to do. Because the flow of such energy production data depends on factors such as precipitation-flow, flow, temperature and evaporation. This causes energy changes and fluctuations in variables. In this paper, long-term energy production planning was made using Multi-Layer Perceptron (MLP) from Artificial Neural Network architectures for Menzelet Dam and HEPP located in Ceyhan Basin of Kahramanmaraş province. The activation functions used in this study are sigmoid and tanh and the models used for learning are quick propagation and conjugate gradient descent. In the study, the energy production data between (1999-2020) is used for the experiment. The training and test parts were run. The results of the prediction values were compared by looking at CCR and R2 values. According to the tests, the highest prediction value for energy is 0.9891.

1. Introduction

Energy plays an important role in economic and social development as well as in improving living standards. Today, the need for electricity has increased with the intensive use of electrical devices. Fossil fuels are generally used to meet this need. However, governments offer various incentives for renewable energy sources to reduce the damage that fossil fuels cause to the environment. Clean and sustainable renewable energy is one of the most important energy sources for developed and sustainable societies today. When it comes to renewable energy, hydroelectric power plants are the first to come to mind and are one of the most important energy sources in the world.

Hydroelectricity represents more than 92.0% of the electricity produced from renewable sources worldwide [21]. Hydroelectric energy has zero emissions and low operating costs [4]. Moreover, hydroelectric energy is preferred by many countries due to its technical, economic and environmental benefits [5].

Turkey has many hydroelectric power plants that can meet its energy largely demands (Yüksel, 2008). Estimating the energy production to be obtained from hydroelectric power plants will shed light on planning for domestic and industrial uses as well as irrigation and other uses. In fact, Abdulkadir et al. (2012) carried out the management of hydroelectric reservoirs along the Niger River by estimating the future storage area using the Artificial Neural Network (ANN) model [1]. The network model was trained with monthly historical data of the inflow, outflow (release), storage and evaporation losses of the Jebba and Kainji hydroelectric reservoirs. The test success for Jebba was 97% and the test success for Kainji was 75%. In another energy production estimation study,

* Corresponding author. E-mail address: *ekocer@selcuk.edu.tr*
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Çetin and Işık (2022) estimated the energy data that could be produced in the future using deep learning algorithms using real solar energy data obtained from solar power plants belonging to Humartaş Energy [3]. In the study, analyzes and estimates were made using the LSTM (Long Short-Term Memory) method, which is used intensively in time series algorithms.

Another issue that is being worked on is the estimation of energy consumption. In this regard, Berus and Yakut (2024) aimed to estimate the energy consumption change using machine learning methods using the total 2027-day (5 years, 6 months, 19 days) active consumption data of a shopping mall located in the city center of Diyarbakir [2]. The amount of active consumption used in the study was measured hourly and a data set of 2027x24 = 48648 was obtained, and the necessary approvals were obtained from Dicle Electricity Distribution Inc. Four different deep network models, namely 1D-CNN, RNN, LSTM and BiLSTM, were developed for the estimation of energy active consumption. The models in question, especially the models in the recurrent neural network structure, were trained on the same criteria and the performance values between them were compared. Various studies have also been conducted on the demand for energy.

Toker and Korkmaz (2011) estimated short-term (hourly and daily) energy demand based on electricity consumption, temperature and radiation (daily sunlight duration) factors using artificial neural networks [9]. In another study, long-term electrical energy forecasting was made on a Turkish scale using machine learning and optimization algorithms. In this study, past population, export, import, GDP between 1980-2019 were taken as input data and energy demand was estimated with Linear Regression, Gaussian Process Regression and Particle Swarm Optimization algorithms [7].

The impact of climate change on hydroelectric power plants around the world has been examined in many studies. In the study conducted by Guo et al. (2021), the effects of climate change on hydroelectric production, electricity demand and greenhouse gas emissions were tried to be estimated [6]. The complexity of the nonlinear relationship required the use of Artificial Neural Networks (ANN) to estimate energy demand. To estimate the energy demand, an ANN model was used together with Improved Electromagnetic Field Optimization (IEFO) algorithms. The study by Ramião et al. (2023) evaluated how climate change will affect hydropower production by changing river flow and increasing reservoir evaporation [8].

The study emphasizes that predicting the effects of climate change on hydropower production is vital for effectively planning the renewable energy transition and developing adaptation strategies. In this study, the Multilayer Perception learning algorithm, which is a feedforward backpropagation model of Artificial Neural Networks, which is frequently preferred in research, was used to.

2. Material and Methods

The Ceyhan River Basin, including the Upper Ceyhan River Basin, is located in the Eastern Mediterranean between 36° 33' - 38° 43' north latitude and 35° 36' - 37° 47' east longitude (Figure 1). The basin is adjacent to the Seyhan Basin to the west, the Euphrates Basin to the north and east, and the Asi Basin to the south. The drainage area of the basin is approximately 21,487 km2, and the length of the river is 425 km. 190 km of the river can continue from the provincial borders of Kahramanmaraş, and its length in Osmaniye is 75 km. The basin covers 2.74% of the total area of Türkiye [10].

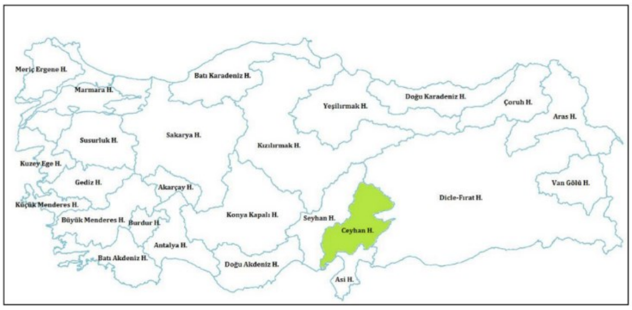


Figure 1. The Ceyhan River basin area

The Upper Ceyhan River Basin covers the mountainous regions of the Ceyhan River Basin and has a drainage area of approximately 9,239 km2; the length of the river is 183 km. The basin covers 1.18% of the total area of Türkiye. The basin covers a large part of Kahramanmaraş province and parts of Kayseri, Sivas and Malatya provinces (Figure 2).

Figure 2. The upper Ceyhan River basin area

The basin generally shows the characteristics of the Mediterranean climate. In line with the planned process in the research, since the majority of the basin is within the province of Kahramanmaraş, the hydrometeorological data belonging to the province of Kahramanmaraş were primarily evaluated. Kahramanmaraş has strategic importance in terms of understanding the possible effects of regional climate changes.

In this study, an attempt was made to make future predictions regarding energy production based on daily data from Menzelet Dam and Hydroelectric Power Plant between 1999-2020. These data can be listed as energy production (MWh), total precipitation in the region (mm), temperature of the region (°C), evaporation (mm), flow rate (m3/s) and net head (m). In order to analyze the relationship between energy production from the hydroelectric power plant and climate variables (temperature, precipitation, evaporation) and to make future energy production projections, the Artificial Neural Networks (ANN) model, which is an effective method in the analysis of nonlinear data within the artificial intelligence universe, was used.

ANN is basically a machine learning model and with its layered structure, it calculates the data given to the input within the framework of the weighting approach and transmits it to the output layer via the hidden layer. The difference between the calculated value and the expected value at the output gives us an error of the network. If the error is higher than expected, the backpropagation algorithm is run, and the weights are updated based on a certain function and this process is called iteration. The weight update process continues until the error is lower than the specified value and the training of the network is thus completed. The Multilayer Perceptron, which is a feedforward recyclable model of ANN, which has many types and is frequently used in research, was also preferred in this study. This model uses more than one layer (input-hidden-output layers) to process the input data and obtain the output. MLP uses an activation function in each neuron to learn nonlinear relationships. These are usually Sigmoid and Tanh functions. Artificial neural networks are a computing system inspired by the structure and learning characteristics of biological neuron cells. It has many interconnected processing elements. It stores information with the weights in the connections. Each processing element responds dynamically to input stimuli. It gains the ability to learn, remember and generalize thanks to the connection weights adjusted with the training data [11].

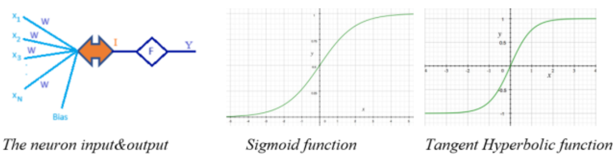


Figure 3. The neuron model and the activation functions [12]

The output of each neuron is calculated by the following equation.

$$I = \sum_{i=1}^{N} X_i W_i \quad (1)$$

Activation functions are calculated with the following equations.

$$F(I)=\begin{Bmatrix} Y = \frac{1}{1+e^{-\sum X_i W_i}}, Sigmoid \\ \\ Y = \frac{e^{\sum X_i W_i} - e^{-\sum X_i W_i}}{e^{\sum X_i W_i} + e^{-\sum X_i W_i}}, Tanh \end{Bmatrix} \quad (2)$$

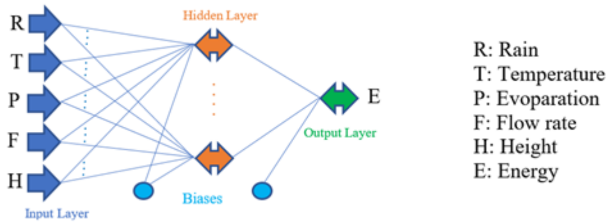


Figure 3. The MLP model and the input parameters

The process of training the network is changing the weights between the connections.

Initially, the weights are taken randomly. The output of each neuron is calculated as given above with the sum symbol. The output of the neurons in the output layer gives the output of the network. After the outputs are calculated according to the inputs, the error between the original output and the calculated output is calculated.

$$Error_{output\ neuron} = Calculated_{output\ neuron} - Predicted_{output\ neuron} \quad (3)$$

Then the total error of the network is calculated using all output neuron errors.

$$Total\ Error = \frac{1}{2}\sum(Error_{output\ neuron})^2 \quad (4)$$

If it is higher than the desired error value, the weights are changed, and the calculations are repeated. This is called the backpropagation algorithm and is a basic algorithm used to train artificial neural networks. This algorithm allows neural networks to learn from their errors and reach the correct results.

Iterations continue until an error value lower than the specified error value is obtained. The stopping criterion can also be the number of iterations. When the training is completed, the testing phase is started.

In artificial neural networks, the term bias is a parameter used to adjust the activation threshold of neurons. This helps the model learn better and recognize complex patterns.

3. Results and Discussion

A total of 7668 daily data (Energy, temperature, rain, evaporation, flow rate and height) was included in the study, and 68% of this data, i.e. 5216 rows, were used for training. 16% of the total data, i.e. 1216 rows, were used for validation, and 16% of the total data, i.e. 1236 rows, were used for testing. The results of this experiment are given in Table 1.

As we will see from this table, the Correct Classification Rates (CCR) and R^2 are used as metrics for showing the success of this experiment. These metrics give the performance of the neural network model to the researchers and can be seen highly in the literature. The success rates divided into two considering the activation functions (Sigmoid and Tanh) and learning models (quick propagation and conjugate gradient descent). Since the basic ANN model is applied in this study, sigmoid and Tanh activation functions were preferred instead of the ReLU activation function used in deep learning models.

The stopping criteria is mean square error (MSE) rate and taken as 0,0001. So, when the network error reaches to stopping criteria value, the learning process is done. If the network doesn't achieve the MSE criteria, the iteration process is limited to 300 epochs.

No cleaning process was performed on the data. However, a normalization process was applied to the data. While the data was normalized to the range of 0-1 when using the Sigmoid activation function, the data was normalized to the range of -1 to +1 when using the Tanh activation function. In the developed ANN model, the number of hidden layers was taken as 1 and the number of hidden layer neurons was determined by using the heuristic approach between 3 and 99, with an increment of 3, and the best result was obtained with the number of 69 neurons.

The hardware configuration of the workstation is given below:

CPU: 3.0 Ghz

RAM: 16 Gb

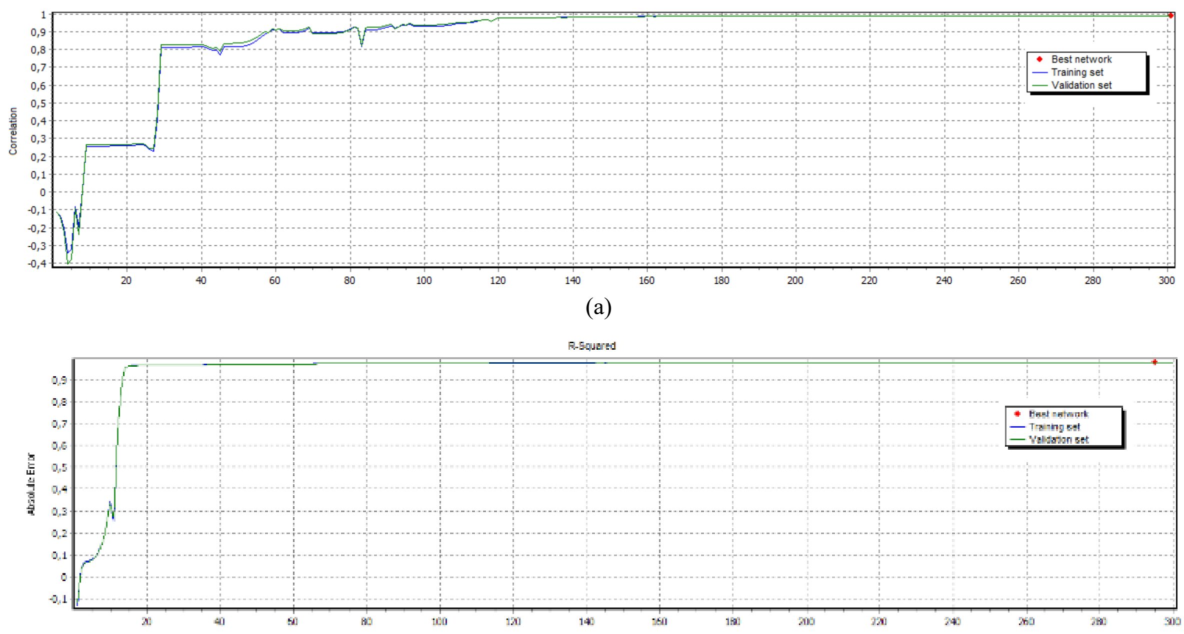
GPU: NVIDIA RTX 2060 (6 GB GDDR6 VRAM)

Table 1. Experimental Results

		Sigmoid Activation Function		Tanh Activation Function	
Metrics		Quick Propagation	Conjugate Gradient Descent	Quick Propagation	Conjugate Gradient Descent
Training	CCR (%)	98,9337	98,3261	98,8312	96,9435
	R^2	0,978251	0,964434	0,976229	0,932210
	Duration Time (mm:ss)	04:23	11:08	05:19	13:39
	MSE				
Testing	CCR (%)	98,9102	98,1958	98,7622	96,6504
	R^2	0,977819	0,962192	0,974970	0,928356

As we can see from the table above, the quick propagation learning method with Sigmoid activation function has the best testing result according to CCR (98,9102%) and R^2 (0,977819). The time duration for training process is also shortest in that model. The correlation vs epochs graphic for the training phase and R-Squared graphic between absolute error and epochs of the best model (Quick propagation with Sigmoid activation function) are shown in Fig.4a and 4b respectively.

In this study, many experimental applications were carried out for the training of the model. The graphs obtained from these experimental studies basically show a similar structure regarding the changes. Therefore, only the graphs related to the best result are given in this part of the article.



(a)

(b)

Figure 4. a)The correlation vs epochs graphic for the training phase b)R-Squared graphic

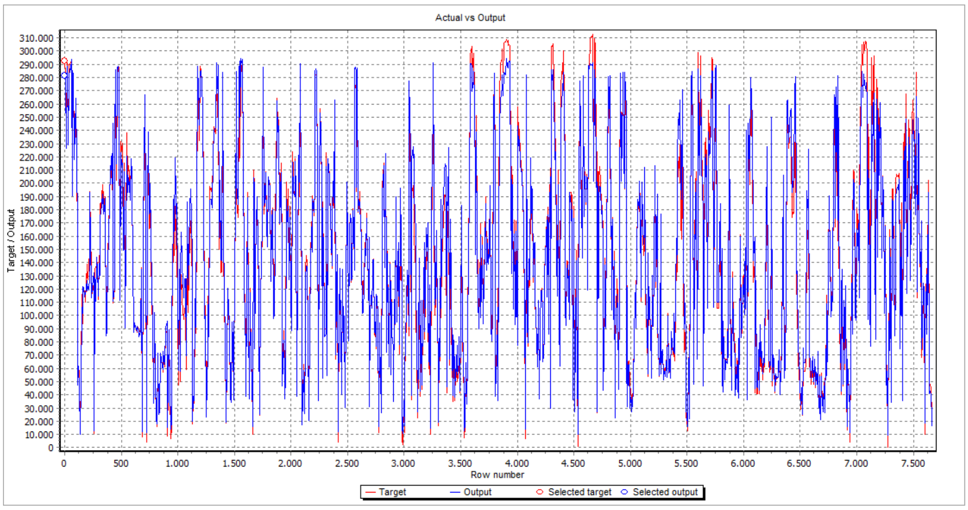


Figure 5. The actual vs predicted output graphic for the best success rate.

The predicted energy in testing process is obtained with a best success rate of 98,9102% and the actual vs predicted output graphic is given in Fig.5. Results show us that the basic ANN method approximation is adequate for predicting energy production for hydroelectric power plants.

4. Conclusions

This study successfully demonstrated the efficacy of a Multi-Layer Perceptron (MLP) Artificial Neural Network (ANN) model for long-term energy production forecasting at the Menzelet Dam and Hydroelectric Power Plant (HEPP) in the Ceyhan Basin, Kahramanmaraş. Recognizing the inherent complexities and variable dependencies (e.g., precipitation-flow, temperature, evaporation) in hydroelectric energy generation, accurate prediction is crucial for efficient energy production management and strategic life cycle planning within the renewable energy transition. Utilizing a comprehensive dataset of 7668 daily observations spanning from 1999 to 2020, which included energy output, temperature, rainfall, evaporation, flow rate, and height, the MLP model was trained, validated, and tested with a data split of 68%, 16%, and 16% respectively. The investigation systematically compared the performance of sigmoid and tanh activation functions in conjunction with quick propagation and conjugate gradient descent learning algorithms. Performance was evaluated using Correct Classification Rate (CCR) and R^2 values, with a mean square error (MSE) stopping criterion of 0.0001 or a maximum of 300 epochs. The results unequivocally indicate that the quick propagation learning method combined with the sigmoid activation function yielded the most superior predictive performance, achieving a remarkable CCR of 98.9102% and an R^2 value of 0.977819 during the testing phase. This optimal model also exhibited the shortest training duration, highlighting its computational efficiency. The high correlation observed during the training phase and the strong agreement between actual and predicted energy outputs affirm the model's robustness.

In conclusion, this research underscores that even a fundamental ANN methodology, specifically the Multilayer Perceptron, can provide highly accurate approximations for predicting energy production in hydroelectric power plants. Such predictive capabilities are vital for effective planning, developing robust adaptation strategies against climate change impacts, and ensuring a smooth and efficient transition to renewable energy systems.

Declaration of Ethical Standards

The article does not contain any studies with human or animal subjects.

Credit Authorship Contribution Statement

All authors contributed to the design and execution of the study. Ezgi Öztürk İspir was responsible for the conceptualization of the study, literature review, data preparation, and drafting of the manuscript. Hasan Erdinç Koçer supervised the research process, contributed to the critical revision of the content, and supported the project's methodology and overall structure. Şerife Yurdagül Kumcu contributed to the analysis and interpretation of data, and assisted in editing and finalizing the manuscript. All authors reviewed and approved the final version of the article.

Declaration of Competing Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Data Availability

The dataset used in this study was obtained from Adana DSİ.

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