One-day ahead forecasting of energy production from run-of-river hydroelectric power plants with a deep learning approach

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Abstract. Accurate energy production forecasting is critical when planning energy for the economic development of a country. A deep learning approach based on Long Short-Term Memory (LSTM) to predict one-day-ahead energy production from the run-of-river hydroelectric power plants in Turkey was introduced in the present study. Furthermore, to compare the prediction accuracy, the methods of Adaptive Neuro-Fuzzy Inference System (ANFIS) with Fuzzy C-Means (FCM), ANFIS with Subtractive Clustering (SC), and ANFIS with Grid Partition (GP) were utilized. The predicted values obtained by the application of these four methods were evaluated with detected values. The correlation coefficient (R), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE) were used as quality metrics for prediction. The comparison showed that the LSTM neural network provided higher accuracy results in short-term energy production prediction than other ANFIS models used in the study.

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1. Introduction

Hydroelectric energy is the largest renewable energy source that is substantially critical to more than 160 countries in the world [1-3]. By the end of 2018, 15.9% of global electricity was generated by hydroelectric power, and hydroelectricity also represented more than 62% of electricity generated from renewable sources worldwide. Hydroelectric power generation reached approximately 4,200 TWh, making the highest ever contribution from renewable energy sources. Approximately, 22 GW hydropower capacity was commissioned and the world’s total installed power capacity increased to 1,292 GW [4].

Energy plant investments are incredibly high, especially in hydropower plants; besides, the cost and environmental effects should be carefully considered. To be able to decide on sustainable solutions in energy-related decisions, accurate estimation is a crucial subject. Accurate energy production estimation from run-of-river or small hydropower plants is essential in many decision-making areas. Meanwhile, network demand forecasting with a time series problem must also be made to realize that the provided power is fully consumed. Short-term forecasting is crucial to planning a backup power supply, providing the ongoing power supply, and performing energy operations between power stations [5]. The power generation of a small hydroelectric power plant refers to a dynamic

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process that shows the maximum production capacity under certain hydrological and meteorological conditions. It is also easily affected by climate, hydrology, and installation capacity. Therefore, estimating the power generation of a small hydroelectric system is a complex problem with non-linear and multi-factor dynamics [6].

The possibility of accurately predicting the fundamental trends in the energy production of renewable power plants supplies essential benefits to both the facility management and investors. For energy companies, reasonable estimates of future electricity generation are essential to planning resources to avoid shortfalls and maximize profits in the electricity trade. Policy-makers need to make an appropriate plan for hydroelectric power plant development and achieve this successfully. Policy-makers should constantly track the electricity load in the hydroelectric market and check if the target fits the actual condition. If the hydroelectric energy production is higher than consumer demand, the excess capacity of hydroelectric energy will arise. Conversely, a lower hydroelectric energy production than the demand for hydroelectric consumption will produce a shortage of hydroelectric supply. Also, climate change and natural variability of water flow in rivers where power plants are set up substantially affect the run-of-river hydroelectric power plants [7].

Related literature indicates that the importance of energy production, water inflow, and water level forecasting methods associated to hydropower plants is gradually increasing worldwide. However, forecasting energy production from the run-of-river hydroelectric power plants is not a simple task due to complex factors such as internal faults, scheduled plant closures, power grid faults, floods, extreme weather conditions, water inflow, etc. Since hydroelectric power is a type of electrical energy, run-of-river hydroelectricity consumption is forecasted, similar to the forecasting models for other energy consumption types [7]. The published prediction models are generally classified under four categories: statistical, physical, artificial intelligence, and hybrid models. However, many existing models typically require historical observations or complex independent variables such as atmospheric air temperature, reservoir inflow, and precipitation. Generally, two major categories are valid for classification: the regression model and the time-series approach [8]. The regression model must accurately determine certain descriptive or independent variables that may affect energy production in a plant to estimate the energy production efficiently. On the other hand, in the time series approach, energy production can be modeled as a function of the historical data [9].

Various studies examine energy production, water inflow, and water level forecasting methods related to the hydropower plants in the world. Artificial Neural Network (ANN) [10-15], Artificial Neural Network model with Artificial Bee Colony (ANN-ABC) algorithm [16], Numerical Weather Prediction (NWP) model [17-19], Autoregressive Integrated Moving Average (ARIMA) model [13,20,21], Seasonal Auto-Regressive Iterative Moving Average (SARIMA) model [21], a Model for Assessment of Energy Demand (MAED) [22], Grey Model (GM) [23,24], Correlation Analysis Method (CAM), Complementary Modeling Framework (CMF) [25], least squares Support Vector Regression (SVR) ensemble learning approach, Bayesian regularization with Echo State Network (BESN-ESN) [26], Regression Analysis (RA) [27], Support Vector Machines (SVMs) [28], Genetic Algorithm-Support Vector Machines (GA-SVM) [29], Grey Wolf Optimization method coupled with an Adaptive Neuro-Fuzzy Inference System (GWO-ANFIS) [30].

As can be understood from the literature studies mentioned above, various studies have been carried out in many countries to estimate energy production from hydroelectric power plants. Also, a reasonable estimate for energy consumption helps optimize plant operational planning and control operational management. Energy production in hydroelectric power plants is dynamic; however, a control system can record dynamic time-series data to establish a relationship between current and historical working conditions.

This study predicts energy production from run-of-river hydroelectric power plants with a time series approach. This is a time series problem since the current energy production from run-of-river hydroelectric power plants is directly related to previous operating conditions or data. As is known, the time series estimation technique is regression analysis. Traditional models usually cannot learn time series data as they cannot store previous information, leading to a limited ability to estimate long-term time-series data, e.g., energy production. Thus, a new method with the ability to process significant amounts of high-quality data is needed. Hence, the present study adopted
a Long-Short-Term Memory (LSTM) neural network that dynamically recalls historical information to estimate energy production from run-of-river hydroelectric power plants. Studies in which deep learning approaches based on the LSTM network are successfully applied are included in the literature. Refs. [31–42] can be examined for detailed information.

Within the scope of this study, the following subjects are at focus:

- A deep learning approach based on LSTM is presented to predict energy production from run-of-river hydroelectric power plants in Turkey. Studies on the deep learning-based LSTM neural network to predict electricity generation from river-type hydroelectric power plants are limited in the literature;

- As for forecast models published in the literature on hydropower, many studies have been carried out with the aim of predicting sizeable hydroelectric power plants and they have focused mainly on estimating river flows such as streamflow, reservoir inflow, precipitation, and runoff. However, the number of studies on estimating small hydropower generation is limited, especially in Turkey. In this paper, LSTM, a helpful attempt at deep learning, is applied to study energy production from Turkey’s run-of-river hydroelectric power plants;

- Additionally, within the scope of the research, the findings acquired from the LSTM method were correlated with those of the ANFIS models using the same data to prove the performance of the current approach used in the study and the differences between them were interpreted.

2. Material and methods

2.1. Adaptive neuro-fuzzy inference system

Adaptive Network Fuzzy Inference System (ANFIS) is a universal estimator. It can be used for any proper continuous function in a compact setup to any degree of accuracy. ANFIS is expressed as a network statement of Sugeno-type fuzzy systems equipped with neural learning capabilities and creates fuzzy if-then rules with appropriate Membership Functions (MF) from input-output by employing a neural network learning algorithm. FIS development procedure using the ANN framework is stated ANFIS [43,44]. In the working principle of an ANFIS model, the system is first trained similarly to ANN. After that, the system is conducted as a fuzzy inference system. In this sense, ANFIS’s integration of both ANN and FIS principles has led to integration of the advantages of both systems into a single system [45].

The neuro-fuzzy model contains a total of five layers as a multi-layered neural-network-based fuzzy system. The network structure contains input and output nodes representing input states and output response, respectively, and nodes in hidden layers acting as Membership Functions (MFs) and rules. Thus, the disadvantage of an observer’s difficulty in understanding or replacing a standard feedforward multi-layered network is avoided [46,47]. Figure 1 shows type-3 fuzzy reasoning and corresponding equivalent ANFIS architecture (Type-3 ANFIS), respectively. In the structure, a circle represents a fixed node, while a square represents an adaptive node. Two inputs, \( x \) and \( y \), and one output, \( f \), are considered, as it is a

![Figure 1](image-url)
simple structure. Thanks to its high interpretability, computational efficiency, and built-in optimal and adaptable techniques, the Sugeno model is the most widely applied fuzzy model found in the relevant literature.

2.2. Long Short-Term Memory (LSTM)

neural network

LSTM is a repetitive neural network designed by Hochreiter and Schmidhuber [48]. The architecture allows LSTM networks to either carry information for the long term or forget the information. This process is controlled by gates that are some kind of activation function in this case. The decision of whether the information will be passed along or not falls on the activation function. Long-term dependencies of RNN are specific types of RNN, thus learning long-term dependencies and remembering data for a long time by default. They are used in processing, prediction, and classification of information based on time series data. Their use in speech recognition, machine translation, language modeling for tourism, and stock prediction has yielded successful results. Studies on LSTM have shown their successful applications including their possible application to energy forecasting.

LSTM networks address the issue of retaining information for the long term. Standard recurrent neural networks rely on a simple tan-hyperbolic layer. LSTM network has the same structure, but it also has additional layers that interact in a particular manner. Figure 2 shows the architecture of a typical LSTM block. This architecture gives LSTM networks the ability to carry information for the long term or forget it. This process is controlled by gates that are some kind of activation function in this case. The decision of whether the information will be passed along or not falls on the activation function. The chain structure of LTSM comprises four neural networks and different memory blocks, namely cells. The cells retain information and the gates manipulate memory. LTSM networks address the issue of retaining information for the long term. Standard recurrent neural networks rely on a simple tan-hyperbolic layer. LSTM network has the same structure, but also has additional layers that interact in a particular manner. An LSTM unit comprises a cell, an input gate, an output gate, and a forget gate. The forget gate was not initially included and was later proposed by Gers et al. [49] to allow a network to reset its state. LSTM architecture comprises a group of regularly reconnected sub-networks, i.e., memory blocks. The memory block maintains its state as time passes and regulates information flow through non-linear gating units. Input activation flow into the memory cell is controlled by the input gate. The output gate controls cell activations’ output flow into the remaining network. Finally, the forget gate was included in the memory block.

2.2.1. Forget gate

Forget gate (Figure 3) removes the now-redundant information in the cell state. The gate is fed with two inputs $x^{(t)}$ (input at a particular time) and $y^{(t-1)}$ (previous cell output), which are then multiplied by weight matrices and added to the bias term. An activation function processes the resultant, yielding a binary output. For a particular cell state, the information is forgotten if the output is zero; it is retained for future use if the output is 1.

$$f^{(t)} = \sigma \left( W_f x^{(t)} + R_f y^{(t-1)} + p_f \odot c^{(t-1)} + b_f \right),$$  

where $W_f$, $R_f$, and $p_f$ are the weights associated with $x^{(t)}$, $y^{(t-1)}$, and $c^{(t-1)}$ respectively, while $b_f$ is for the bias weight vector.

![Figure 2](image)

*Figure 2. The architecture of a typical LSTM block.*
2.2.2. Input gate
The input gate (Figure 4) adds helpful information to the cell state. The sigmoid function firstly regulates the information and similarly filters the values to that of forget gate with inputs \( y^{(t-1)} \) and \( x^{(t)} \). The tanh function, which yields an output of values ranging from \(-1\) to \(+1\), is used to create a vector containing all the possible values from \( y^{(t-1)} \) and \( x^{(t)} \). Finally, the vector values and regulated values are multiplied to obtain helpful information.

\[
i^{(t)} = \sigma \left( W_i x^{(t)} + R_i y^{(t-1)} + p_i \odot c^{(t-1)} + b_i \right),
\]

\[
z^{(t)} = g \left( W_z x^{(t)} + R_z y^{(t-1)} + b_z \right),
\]

where:
- \( \odot \) Point-wise multiplication of two vectors
- \( W_i, W_z \) Weights associated with \( x^{(t)} \)
- \( R_i, R_z \) Weights associated with \( y^{(t-1)} \)
- \( p_i \) Weight associated with \( c^{(t-1)} \)
- \( b_i \) Bias vector
- \( b_z \) Bias weight vector

2.2.3. Output gate
The output gate (Figure 5) extracts helpful information from the current cell state and presents it as an output.

\[
o^{(t)} = \sigma \left( W_o x^{(t)} + R_o y^{(t-1)} + p_o \odot c^{(t-1)} + b_o \right),
\]

where \( W_o, R_o, \) and \( p_o \) are the weights associated with \( x^{(t)} \), \( y^{(t-1)} \), and \( c^{(t-1)} \), respectively, while \( b_o \) is the bias weight vector.

Finally, the block output combining the current cell value \( c^{(t)} \) with the current output gate value is calculated through the following equation:

\[
y^{(t)} = g (c^{(t)}) \odot o^{(t)},
\]

where \( \sigma, g, \) and \( h \) in the above steps represent point-wise non-linear activation functions.

\[
\sigma(x) = \frac{1}{1 + e^{-x}} \quad \text{(logistic sigmoid)}.
\]

The logistic sigmoid is the gate activation function and the hyperbolic tangent \( g(x) = h(x) = \tanh(x) \) is often the block input and output activation function [50].

2.3. Error analysis
In our study, four statistical error criteria including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and correlation coefficient (R) are used for assessing the goodness of a model to estimate an observed output variable. Their calculation methods are given as follows [51–53]:

Mean absolute error:

\[
MAE = \frac{1}{N} \sum_{i=1}^{N} |p(i) - o(i)|.
\]

Root mean square error:
\[ RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} [p(i) - o(i)]^2}. \]  

Mean absolute percentage error:

\[ MAPE = \frac{1}{N} \sum_{i=1}^{N} \frac{|p(i) - o(i)|}{o(i)} \times 100. \]

The correlation coefficient:

\[ R = \left( \frac{\sum_{i=1}^{N} [p(i) - \bar{p}] [o(i) - \bar{o}]}{\sqrt{\sum_{i=1}^{N} [p(i) - \bar{p}]^2 \sum_{i=1}^{N} [o(i) - \bar{o}]^2}} \right). \]

where \( p(i) \) and \( o(i) \) are the predicted and observed values at time \( i \), respectively; \( \bar{p} \) and \( \bar{o} \) are the means of the predicted and actual values, respectively, and the total number of data is represented by \( N \).

3. Results and discussion

3.1. Data analysis and model structure

Since topographical conditions make small power plant development more convenient in Turkey, run-of-river hydroelectric power plants have shown significant development in recent years. As of the end of 2020, the total installed power value of these power plants was approximately 8 GW. This is equivalent to 8.4% of Turkey’s total installed power capacity. Therefore, forecasting studies over energy production from the run-of-river hydroelectric power plants have become very important, especially for Turkey. Moreover, since Turkey is mainly dependent on foreign sources of electricity generation, accurate and precise forecasting of energy production is very important. Therefore, this study aims to predict short-term energy generation from the run-of-river hydroelectric power plants for Turkey. The data used for this objective in this study cover daily energy production from run-of-river hydroelectric power plants in Turkey. These data were obtained by the Turkish Electricity Transmission Corporation (TEİAŞ) by collecting an energy generation of 576 run-of-river power plants in 25 river basins of Turkey. The location of Turkey’s 25 river basins is presented in Figure 6.

In this study, a time-series analysis-based LSTM neural network was proposed and applied to predict the energy production of run-of-river hydroelectric power plants in Turkey. In the LSTM neural network simulation, the measurement inputs were divided into two datasets. The first one, the training dataset, was employed for the model’s training, while the second one, the testing dataset, was employed for over-fitting model validation. The evaluation criteria comprised RMSE, MAPE, MAE, and \( R \). In addition to the LSTM neural network, three different approaches including ANFIS-FCM, ANFIS-SC, and ANFIS-GP were used. Then, the ANFIS models were analyzed. The results

![Figure 6. Location of Turkey’s 25 river basins.](image-url)
were compared using performance statistics. The number of MFs varied between 2 and 10, and the number of iterations varied between 30 and 300.

Figure 7 shows the energy production data used in the present work. They were obtained from the TETC in Turkey as a daily dataset from January 01, 2016 to April 19, 2020 [54]. Turkey’s daily energy production from the run-of-river hydroelectric power plants ranged from 13.87 GWh to 142.11 GWh between January 01, 2016 and April 19, 2020. The minimum daily energy production was realized on September 17, 2017, while the maximum daily energy production was on May 09, 2019. During these five years, the average daily energy production was calculated to be approximately 54 GWh. A total of 1571 samples were partitioned into two sections as the first 80% section was the train set and the last 20% section was the test.

The water carried by the rivers may vary in amount every year or every season of the year. Some rivers may dry out entirely in some arid years, or rivers may overflow by not fitting in their beds in some rainy years. Similarly, different amounts of water streams may increase in different seasons of the year. Given that energy production is a dynamic process depending on river water flow and many independent variables, energy production throughout the year exhibits a significant change daily and monthly. As shown in Figure 7, energy production increases upon increasing the amount of water flow in river water due to excessive rainfall, especially in March, April, and May. Although energy production in hydroelectric power plants is dynamic, a control system can record dynamic data to establish a time-series relationship between current and historical working conditions. This study predicts the energy production from the run-of-river hydroelectric power plants using a time series approach. The proposed method processes the previous load series data instead of various factors such as time, water stream, climate, and socio-economic activities that affect energy production because it is not always easy to obtain and measure these independent variables.

3.2. Results of the LSTM network
Table 1 gives the prediction performances for the LSTM neural network with different accuracy criteria. The values shown in bold indicate the best results.

| Model  | Number of hidden layers | MAE (GWh) | MAPE (%) | RMSE (GWh) | R    |
|--------|-------------------------|-----------|----------|------------|------|
| LSTM-1 | 5                       | 2.71      | 5.98     | 3.62       | 0.9914|
| LSTM-2 | 10                      | 2.73      | 6.03     | 3.62       | 0.9914|
| LSTM-3 | 15                      | 2.74      | 6.04     | 3.62       | 0.9914|
| LSTM-4 | 20                      | 2.76      | 6.07     | 3.63       | 0.9914|
| LSTM-5 | 25                      | 2.78      | 6.12     | 3.65       | 0.9913|
| LSTM-6 | 30                      | 2.77      | 6.12     | 3.66       | 0.9913|
| LSTM-7 | 50                      | 2.79      | 6.12     | 3.63       | 0.9914|
| LSTM-8 | 75                      | 2.77      | 6.10     | 3.64       | 0.9914|
| LSTM-9 | 100                     | 2.80      | 6.15     | 3.66       | 0.9913|
| LSTM-10| 125                     | 2.77      | 6.06     | 3.65       | 0.9913|
| LSTM-11| 150                     | 2.81      | 6.17     | 3.65       | 0.9913|
| LSTM-12| 175                     | 2.84      | 6.16     | 3.72       | 0.9910|
| LSTM-13| 200                     | 2.81      | 6.15     | 3.68       | 0.9911|
in all tables. The evaluation criteria in this table were considered according to the forecasting values obtained from the test process results. A total of 13 LSTM neural network models ranging from 5 to 200 hidden layers were tried and tested. According to this table, the performance values obtained using different hidden layer numbers are quite close to each other. For example, MAPE values for all the models were calculated to be between 5.98% and 6.17%, while $R$ values were obtained to be between 0.9910 and 0.9914. However, the best result was observed when the number of the hidden layers was equal to 5 with the values of 2.71 GWh MAE, 5.98% MAPE, 3.62 GWh RMSE, and 0.9914 $R$. The results demonstrated that the LSTM models performed satisfactorily in forecasting daily energy production.

Observe and predicted daily energy production data for the LSTM network are shown in Figure 8(a). The daily production variations could be observed in the energy production time series. As seen from Figure 8, the prediction of the energy production time series is quite consistent with the actual values in the testing. The testing values were presented in Figure 8(b) in more detail. In addition to Figure 8(a) and (b), Figure 8(c) shows the regression plots of actual and predicted values of the energy production data from the LSTM neural network. This figure shows that good estimation results are obtained due to the formation of data points closer to the 45° line.

### 3.3. Results of the ANFIS-FCM model

Table 2 shows different evaluation criteria values for the ANFIS-FCM model. A total of 9 ANFIS-FCM models ranging from 2 to 10 MFs were tried and tested. In terms of a general evaluation, it was observed that the performance values obtained from all ANFIS-FCM models gave very close results to each other. However, a small number of the MFs did not yield satisfactory results due to the non-good partitioning of the inputs. In addition, a large number of MFs did not give good results, as this led to the use of a large number of nodes and fuzzy rules that add to the computation.

### Table 2. The prediction performances for the ANFIS-FCM models.

| Model       | Number of MFs | MAE (GWh) | MAPE (%) | RMSE (GWh) | $R$     |
|-------------|---------------|-----------|----------|------------|---------|
| ANFIS-FCM-1 | 2             | 2.82      | 6.23     | 3.72       | 0.9910  |
| ANFIS-FCM-2 | 3             | 2.82      | 6.20     | 3.72       | 0.9909  |
| ANFIS-FCM-3 | 4             | 2.80      | 6.16     | 3.66       | 0.9912  |
| ANFIS-FCM-4 | 5             | 2.79      | 6.14     | 3.67       | 0.9912  |
| ANFIS-FCM-5 | 6             | 2.82      | 6.15     | 3.69       | 0.9911  |
| ANFIS-FCM-6 | 7             | 2.88      | 6.31     | 3.77       | 0.9907  |
| ANFIS-FCM-7 | 8             | 2.86      | 6.27     | 3.75       | 0.9908  |
| ANFIS-FCM-8 | 9             | 2.84      | 6.22     | 3.74       | 0.9909  |
| ANFIS-FCM-9 | 10            | 2.87      | 6.28     | 3.79       | 0.9906  |
time. According to the test process results, the best performance was obtained from MFs = 5 with 2.79 GWh MAE, 6.14% MAPE, 3.67 GWh RMSE, and 0.9912 $R$.

The daily time series energy production data with actual and predicted values for the ANFIS-FCM method are presented in Figure 9(a). As revealed in Figure 9, the energy production time series estimates agree with the actual values in the test part. Figure 9(b) shows the test values so as to take a closer look at prediction results. In addition to Figure 9(a) and (b), Figure 9(c) shows the regression plots of the actual and predicted values of the energy production data from the ANFIS-FCM method. This graph presents the distribution of actual and predicted values and shows how consistent the model results are with the actual data. A strong linear relationship between actual and predicted values in this figure shows that the ANFIS-FCM method predicts daily energy production from run-of-river hydroelectric power plants with remarkable accuracy (99%).

### 3.4. Results of the ANFIS-SC model

Similarly, the prediction methodology was applied to the ANFIS-SC model. Different cluster radius sets were analyzed in the range of 0.1 to 0.9. Table 3 gives the results obtained from the testing process. According to the table, all models of ANFIS-SC have given accuracy values very close to each other. However, the ANFIS-SC-4 and 5 models gave better RMSE and $R$ estimates. The MAE, MAPE, RMSE, and $R$ values were obtained for these models as 2.81 GWh, 6.16%, 3.70 GWh, and 0.9911, respectively. Results showed that low values of the cluster radius did not allow good mapping of the ANFIS-SC model. However, the high values of the cluster radius made the training more difficult and led to overfitting or memorization of undesirable inputs.

The actual and predicted daily energy production data are shown in Figure 10(a) for the ANFIS-SC method. Figure 10(b) shows the testing values for the last 20% of the dataset. Figure 10(c) shows the

![Figure 9](image_url)

**Figure 9.** (a) The daily time series energy production data with actual values (blue) and predicted values (red) for the ANFIS-FCM method. (b) Actual values (blue) and predicted values (red) of the testing of energy production data for the ANFIS-FCM method. (c) Regression plots of the actual values and predicted values of the energy production data for ANFIS-FCM method.

### Table 3. The prediction performances for the ANFIS-SC models.

| Model     | Radius of the cluster | MAE (GWh) | MAPE (%) | RMSE (GWh) | $R$     |
|-----------|-----------------------|-----------|----------|------------|---------|
| ANFIS-SC-1| 0.1                   | 2.84      | 6.25     | 3.74       | 0.9909  |
| ANFIS-SC-2| 0.2                   | 2.85      | 6.26     | 3.75       | 0.9908  |
| ANFIS-SC-3| 0.3                   | 2.82      | 6.16     | 3.72       | 0.9909  |
| ANFIS-SC-4| 0.4                   | 2.81      | 6.16     | 3.70       | 0.9911  |
| ANFIS-SC-5| 0.5                   | 2.81      | 6.16     | 3.70       | 0.9911  |
| ANFIS-SC-6| 0.6                   | 2.81      | 6.18     | 3.70       | 0.9910  |
| ANFIS-SC-7| 0.7                   | 2.81      | 6.18     | 3.71       | 0.9910  |
| ANFIS-SC-8| 0.8                   | 2.81      | 6.20     | 3.71       | 0.9910  |
| ANFIS-SC-9| 0.9                   | 2.81      | 6.19     | 3.71       | 0.9910  |
regression plots of the actual predicted values of the energy production. The $R$-value was calculated to be 0.9911 for the ANFIS-SC method.

3.5. Results of the ANFIS-GP model

Similarly, the prediction methodology was applied to the ANFIS-GP model. This model used the Gaussian membership function and linear membership function as the input and output, respectively. The number of MFs received was 2 and 3. Table 4 gives the results obtained from the testing process. With a review of the table, it is understood that the model obtained using the ANFIS-GP approach predicts the energy production from run-of-river hydroelectric power plants with an accuracy rate of 98.81% according to the performance evaluation criterion, $R$. The daily time series energy production data with actual and predicted values for the ANFIS-GP method are presented in Figure 11(a). As seen in the figure, all ANFIS-SC

| Model     | Number of MFs | MAE (GWh) | MAPE (%) | RMSE (GWh) | $R$     |
|-----------|---------------|-----------|----------|------------|---------|
| ANFIS-GP-1| 2             | 2.99      | 6.40     | 4.26       | 0.9881  |
| ANFIS-GP-2| 3             | 6.21      | 10.41    | 16.18      | 0.8574  |

Table 4. The prediction performances for the ANFIS-GP models. Best results are shown in bold.
models have produced almost similar results in terms of accuracy measures. Figure 11(b) and (c) show a close look at test data and the regression plots of the dataset, respectively. For this model, the MAE, MAPE, RMSE, and $R$ values were calculated as 2.99 GWh, 6.40%, 4.26 GWh, and 0.9881, respectively.

3.6. Comparison of the models

LSTM neural network is one of the approaches that enjoys good prediction performance among deep learning methods. Therefore, this study compares the prediction performances of machine learning algorithms including ANFIS-FCM, ANFIS-SC, and ANFIS-GP with the performance of the deep learning method. The LSTM model can decide on the relationships between features while optimizing their network. Thanks to its memory structure, features can be forgotten or remembered. On the other hand, ANFIS is one of the most important machine learning approaches that combines the advantages of both neural and fuzzy systems in a single model. Besides, having a very high learning speed, the ANFIS algorithm provides high accuracy in the testing phase. In addition, it is easy to perform and can be used to predict different application areas. In Figure 12, the best evaluation criteria resulting from all the models used in the study were represented. As revealed by the table, the LSTM neural network model yielded the best result with the values of 2.71 GWh MAE, 5.98% MAPE, 3.62 GWh RMSE, and 0.9914 $R$. The ANFIS-FCM and ANFIS-SC models showed relatively similar results in terms of accuracy measures. However, the ANFIS-GP model resulted in slightly better MAE, MAPE, RMSE, and $R$. For this model, the MAE, MAPE, RMSE, and $R$ values were calculated as 2.79 GWh, 6.14%, 3.62 GWh, and 0.9912, respectively. Figure 12 shows that the ANFIS-GP model yielded less accurate results in comparison with other models. In summation, the results of the statistical indexes are shown in Figure 12; accordingly, the LSTM neural network achieved more good accuracy than the other models.

In Table 5, typical studies on energy production and water flow estimation methods related to hydroelectric power plants and the results within the scope of this study are presented for comparison purposes. In related studies, it is seen that the $R$ value varies between 0.7230 and 0.9999. However, the $R$ value achieved in this study was 0.9914, which was found to be very close to those found by similar studies in the literature.

4. Conclusion

Short-term estimations of daily hydroelectric production for the day ahead are essential for power system representatives to program system operations and decision-making on the electricity market considering the hydroelectric power generation in real electric power plants and electricity market environments. A prediction of energy production that provided data on how much energy can be effectively generated by a particular energy plant in a given period can
Table 5. Some of the typical studies on energy production and water flow forecasting methods related to the hydropower plants in the world.

| Ref. | Method   | Prediction       | Study area | Data time          | Data term | Performance criteria |
|------|----------|------------------|------------|--------------------|-----------|----------------------|
| [6]  | CAM      | Energy production| China      | November, 2012 - July, 2015 | Monthly   | $R = 0.9400$         |
| [12] | ANN      | Energy production| Nigeria    | 1970-2011 and 1984-2011 | Monthly   | $R = 0.8900$         |
| [14] | ANN      | Energy production| Turkey     | 35-year-long recorded data | Monthly   | $R^2 = 0.9820$       |
| [15] | ANN      | Energy production| Iraq       | 2005-2015          | Daily     | $R = 0.9600$         |
| [30] | ARIMA    | Energy production| Ecuador    | 2000-2015          | Monthly   | $R = 0.7239$         |
| [23] | GM       | Energy production| China      | 2012-2015          | Monthly   | $R^2 = 0.9730$       |
| [55] | DNN      | Energy production| Turkey     | April-September of 2019 | Hourly    | $R^2 = 0.9999$       |
| [56] | LSTM     | Water flow       | Brazil     | January, 2016-September, 2019 | Daily     | $R^2 = 0.8519$       |
| [57] | HYPE and ANN | Energy production | Slovenia   | January, 2010-December, 2017 | Daily     | $R^2 = 0.7400$       |
| [58] | ANN-DCSA | Energy production| China      | 1990-2020          | Yearly    | $R^2 = 0.8827$       |
|      | LSTM     | Energy production| Turkey     | January, 2016-April, 2020 | Daily     | $R = 0.9914$         |

become advantageous for optimizing renewable energy marketing. In this study, an LSTM neural network was applied to develop a short-term forecasting model that could forecast daily energy production from Turkey's run-of-river hydroelectric power plants. Forecasting consists of predicting the future situation according to previous or past values. Comparison of the results obtained using the LSTM neural network with those obtained by the traditional ANFIS model showed that LSTM neural network model had a better performance than the ANFIS model under the same model structure and parameters. For example, the LSTM neural network model yielded the best result with 2.71 GWh MAE, 5.98% MAPE, 3.62 GWh RMSE, and 0.9914 $R$. In addition, the results demonstrated the higher predictive accuracy of the proposed LSTM neural network model and that the model enjoyed a more robust generalization capability, a faster response speed, and greater competitive power in modeling energy production. The time series method based on the LSTM neural network proposed in this study performed modeling by considering the hidden periodicities in the data. The most crucial advantage of univariate modeling is
that there is no need to obtain independent variables. Consequently, if the energy data contained a periodic fluctuation, an LSTM model based on time series and deep learning could be considered to calculate prediction values. For the future work, different deep learning architectures and functions will be used with hybrid models to improve the accuracy and precision of prediction results.

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Nomenclature

- ANFIS: Adaptive Neuro-Fuzzy Inference System
- FCM: Fuzzy c-Means
- GP: Grid Partition
- LSTM: Long Short-Term Memory
- MAE: Mean Absolute Error
- MAPE: Mean Absolute Percentage Error
- R: Correlation coefficient
- RMSE: Root Mean Square Error
- SC: Subtractive Clustering
- $b_1$: Bias vector
- $b_2$: Bias weight vector
- $c^{(t)}$: Current cell value
- $f$: Output
- $g$: Nonlinear activation function
- $\sigma$: Nonlinear activation function
- $\alpha(i)$: Observed value
- $p(i)$: Predicted value
- $R_1, R_2$: Weight associated with $c^{(t-1)}$
- $x$: Input
- $x^{(t)}$: Input at a particular time
- $y^{(t)}$: Block output
- $y^{(t-1)}$: Previous cell output
- $w$: Weight
- $W_1, W_2$: Weight associated with $x^t$
- $\odot$: Point-wise multiplication of two vectors

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