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A Neural Network Model for Estimation of Maximum Next Day Energy Generation Capacity of a Hydropower Station: A Case Study from Turkey

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Abstract

Energy planning in a hydro power station (HPS) is essential for reservoir management, and to ensure efficient operation and financial usage. For robust energy planning, operators should estimate next day energy generation capacity correctly. This paper investigates use of a robust neural network model to estimate maximum next day energy generation capacity by using reservoir inflow rates for the previous four days, the current level of water in the reservoir, and the weather forecast for the Darıca-2 HPS in Ordu Province, Turkey. The generated energy in an HPS is directly dependent on the level of stored water in the reservoir, which depends on reservoir inflow. As the level of water in a reservoir varies during the year depending on climatic conditions, it is important to be able to estimate energy generation in an HPS to operate the HPS most effectively. This paper uses reservoir inflow data that has been collected daily during 2020 for the training phase of a neural network. The neural network is tested using a data set that has been collected daily during the first four months of 2021. Used neural network structure is called as LWNRBF (Linear Weighted Normalized Radial Basis Function) network, which is developed form of RBF network. In order to be able to be created valid model, LWNRBF network is trained with a two-pass hybrid training algorithm. After the training and testing stages, average training and testing error percentages have been obtained as 0.0012% and -0.0044% respectively

Keywords: Hydro-electric power generation, hydropower generation, neural network, reservoir inflow, renewable energy sources

1. Introduction

Although electrical energy is a clean form of energy, some electrical energy generation methods such as nuclear and thermoelectric plants have negative environmental effects. The most important negative effect in electrical energy generation is global warming due to the use of fossil fuels that cause unwanted CO_2 emission, especially in thermoelectric plants. Annual CO_2 emission due to use of fossil fuels is about 32.8 billion tons [1,2]. In order to reduce the effects of global warming, the most effective way is to use renewable energy sources such as hydro-electric, with hydropower stations being one of the most commonly used renewable energy sources. Globally, the hydropower industry meets about 17% of the world's electricity demand [3,4].

Today HPSs are among the most cost-effective means of generating electricity [5]. The general structure of an HPS is given in Fig.1 [6].

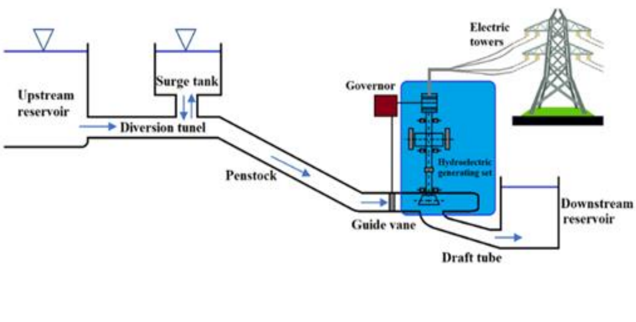

Figure 1. General structure of a hydropower station.

Generally, HPSs can be categorized into three groups depending on their function; storage, run-of-the-river, and pumped-storage technologies. HPSs can also be grouped by size; small, medium and large [7]. A small size HPS has a capacity less 10MW. Capacity of a medium size HPS is between 10 and 100MW for run-of-the river type and between 100 and 300MW for reservoir type HPS. A large-scale hydropower station capacity is greater than 300 MW [8].

Optimization of energy generation and planning processes depends on many parameters such as the technology, physical features, environmental features, losses (mechanic, electrical, hydraulic), and load demand. Optimization of several processes in an HPS using neural network structures and regression models have been investigated [9–11]. This includes predicting reservoir inflow and reservoir flow. Models include climatology of historical flow observations and pre-dam storage volumes [12–14].

Most HPSs have been established on rivers, as HPSs need a reliable water supply. This requires planning due to scarcity of water, population, and increasing energy demand [15]. Proper management and planning approaches are essential for efficient utilization of an HPS.

The paper is structured as follows: review of academic literature on studies of optimization of energy generation and planning; introduction of case study; methodology; conclusions and suggestions for further research.

2. Literature Review

Optimization of energy generation and planning processes in an HPS is an important and complex problem in terms of technological, economic, physical, and environmental aspects. This study focuses on the energy generation stage in a hydropower station. Most solutions for power optimization can be divided in two groups (i) optimization of reservoir operation and (ii) scheduling the water flow [16]. However, optimization in this field includes many uncertainties such as unpredictable future demand, water flow, climate conditions, and economic factors. However, the generated energy is directly related to the power produced at the turbine shaft by water pressure. This mechanical power, P can be estimated as (1) [17].

$$P = \eta t \rho w g Q h \qquad \textbf{(2.1)}$$

where

ηt = hydraulic efficiency of the turbine
ρw = density of water
g = acceleration due to gravity
Q = discharge of water acting on the turbine
h = head of water acting on the turbine

As seen in (1), the power produced at the generator shaft depends directly on the flow of the water. As the only energy input to the HPS is water flow, management of the water is essential for optimal operation of the HPS. Ren et al. investigated management of water resources and its impact on optimal hydropower generation [18]. They suggested an algorithm for resolving optimization problems in the management of the reservoir and hydropower generation. Huangpeng et al. used a neural network model to predict future hydropower generation under the influence of climate change [19]. Wang et al. developed a neural network model that includes water storage, water inflow, monthly water inventory, monthly reservoir level, and average water consumption for electricity generation as inputs to predict energy generation of an HPS [20].

Optimization of reservoir operation has been extensively studied in the literature; often referred as operating rules. Jia et al. used a Bayesian based method to determine the operating rules for hydropower reservoirs. They used 129-annual flow records as input to obtain the optimal operation trajectories [9]. Optimization of reservoir operation is also important for efficient use of the water supply. Li et al. redesigned the operating rules of a reservoir to satisfy the demand for lake water in a real-world case by using a form of genetic algorithm [21]. Their method reduced use of lake water by 5% and improved hydropower generation and hydropower reliability by 3.9% and 8.3%, respectively.

When hydropower stations are established on the same river, they act in a cascade, which requires more complex optimization strategies. Feng et al. proposed an adaptive sine cosine algorithm for optimization of multiple hydropower reservoirs [22], applying their proposed method to a hydropower system in China; claiming that their method would be suitable for similar problems in other research fields. Emami et al. used machine learning with a hybrid constrained coral reefs optimization algorithm to optimize operation of multi-reservoir systems [23]. Li et al. proposed a multi-objective tangent algorithm for optimization of the operation rules of cascade reservoirs, with the main objective to maximize hydropower generation, ecology and navigation [24].

Neural networks are a useful tool for optimization in many engineering problems, including extensive use in every stage of HPS optimization. For example, Cai et al. used an artificial neural network to evaluate soil and water resources in power generation at HPSs [25]. Shanga et al. used a back propagation neural network for real-time forecasting of downstream water levels in a case study from China.[26]

Recent studies have shown that, accurate reservoir inflow forecasting is also highly important for multi-purpose reservoir systems to improve on the economy of hydropower production. Olofintoyea et al. used a neural network model for real-time optimal water allocation in an HPS [27].

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Yang et al. used a neural network model to predict inflow for real-time reservoir operation [28]. Hadiyan et al. used neural network structures to predict reservoir inflow [29], using several different models of static and dynamic artificial neural network structures in their study. Ahmad et al. used a neural network model that used short-term weather forecasts, historic hydrological data, and reservoir inflow as inputs to maximize hydropower generation [12]. Karunanayake et al. used a neural network with well-known learning algorithms (Levenberg–Marquardt, quasi-Newton, scaled conjugate gradient) to estimate reservoir inflow in a real-world case investigating future climate scenarios [30].

Although reservoir inflow estimation is a popular field in the literature, estimation of reservoir inflow is not an easy task due to the changing climate and human activity. However, these factors do not change rapidly over a period of days or months and robust methods for estimation of reservoir inflow for short time periods can be very useful for hourly or daily energy generation of an HPS. For example, Cheng et al. developed an artificial neural network model to estimate daily reservoir runoff [31]. Xu et al. used an artificial neural network to estimate short term reservoir inflow, achieving estimates of reservoir inflow for the forthcoming 1-7 hours [32]. Dampage et al. used a convolutional neural network to estimate daily reservoir inflow for an HPS [33].

Most studies using neural network models have been applied to real-world applications as each HPS has unique geographic, physical and seasonal properties and uncertainties. Ahmad et al. developed a web-based decision support system for the Detroit dam (Oregon) using weather forecasts to generate the daily optimized release decisions [34]. Liu et al. developed a Bayesian deep learning-based model that considered multiple uncertainties to derive operation rules for the Three Gorges Project on the Yangtze River [35].

Turkey is a developing country. Increasing energy demand and environmental considerations are making renewable energy sources popular in Turkey. Currently, HPSs provide 18.4% of energy generation in Turkey [36]. However, for HPSs to be more efficient, Turkey needs to adopt technological and scientific innovations in HPS operation and water management. Cobaner et al. developed an artificial neural network-based model to evaluate the feasibility of installing a hydropower plant at an existing irrigation dam [37]. Kucukali et al. developed a Fuzzy logic-based model to identify suitable existing irrigation dams where small HPSs could be developed [38]. Koç investigated the problems of the operation of hydropower plants that were integrated with irrigation schemes in Turkey and, by analyzing technical, environmental, social and structural problems occurring during the operation of an HPS, determined solutions for these problems [39].

In this study, we develop a neural network model that is used in energy planning for the Darıca-2 HPS established in Ordu Province, Turkey.

3. Material and Methods

The Darıca-2 HPS (Fig.2 and Fig.3) is on the Melet River in Ordu Province, Turkey.

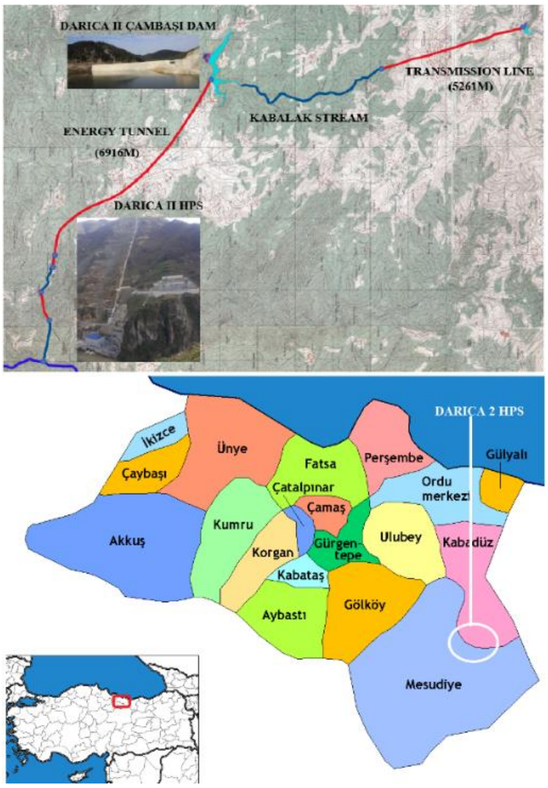

Figure 2. Location of Darıca-2 HPS.

Figure 3. Location Darıca-2 hydropower station, Ordu, Turkey.

The HPS is fed by the Çambaşı Dam, which is at an altitude of 1395 m. The Darıca-2 HPS is at 330 m, giving a hydraulic head of 1064 m, the second highest in Turkey. Its reservoir size is 4 million m3. The Darıca-2 HPS, with a capacity of 75 MW, is a medium scale HPS, and has an average annual electrical energy generation capacity of 207 GWh.

3.1 Data Acquisition

This study uses a neural network structure called LWNRBF to estimate the maximum possible next day energy generation capacity of the HPS. The inputs to the neural network are the reservoir inflow rates from the previous four days, the current level of water in the reservoir, and weather forecast data.

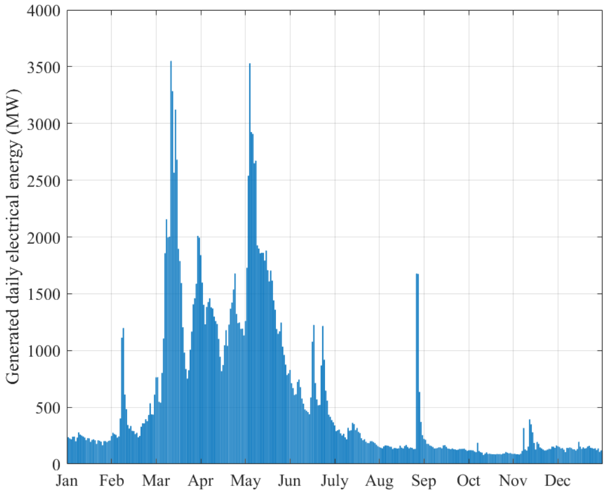

Figure 4. Daily generated electrical energy during 2020

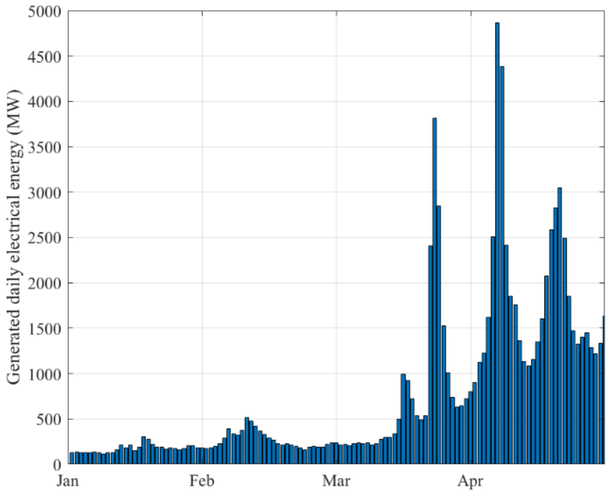

Figure 5. Daily generated electrical energy during first four months of 2021.

Data collected daily during 2020 were used in the training and testing stages of neural network and data collected daily from the first four months of 2021 were used for testing. The daily generated energy, shown in Fig.4 and Fig.5, were used in the training and testing stages.

2.1. Modelling

Many artificial neural network structures for pattern recognition, classification or modelling are described in the literature. Well-known forms include; multilayer perceptron network [40], radial basis neural network [41] and adaptive neuro fuzzy inference system (ANFIS) [42]. Learning methods include; gradient descent [43], back propagation [44], Levenberg–Marquardt [45], and orthogonal least squares [46]. Hybrid learning algorithms have also been used in the training stage of a neural network [47].

This study uses a new type neural network structure called LWNRBF with a two-pass hybrid learning algorithm which was developed by Özdemir [47], [48]. As known, classic RBF networks use widely in literature. RBF network structure is given with Fig. 6.

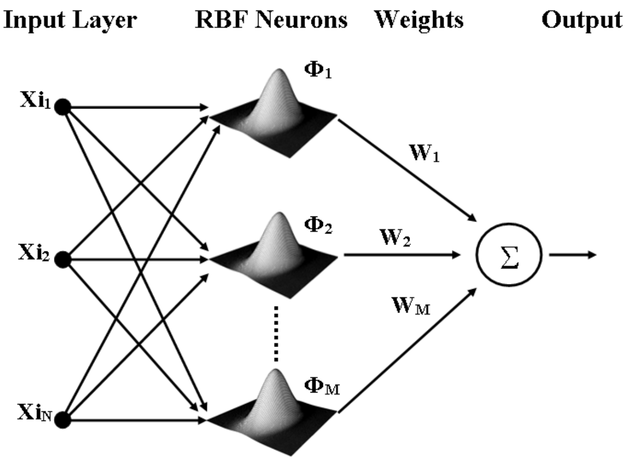

Figure 6. RBF Neural network structure.

RBF network structure is very suitable tool in system modelling. Training stage of RBFN needs to find two set of parameters. In the training stage of RBFN needs to find three set of parameters. These are centres, widths and weights of RBF neurons. In this study, an improved version of RBF network called LWNRBF is used with a two-pass hybrid learning algorithm. LWNRBF network structure is given with Fig. 7.

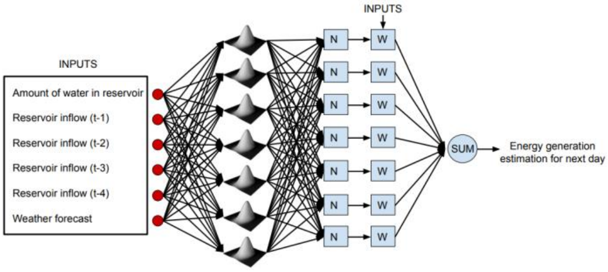

Figure 7. LWNRBF Neural network structure used.

The LWNRBF network has better modelling performance than the classical RBF network. But its structure is more complex than classic RBF network. Therefore, it needs more sophisticated training algorithm. Used training algorithm is given with Fig. 8.

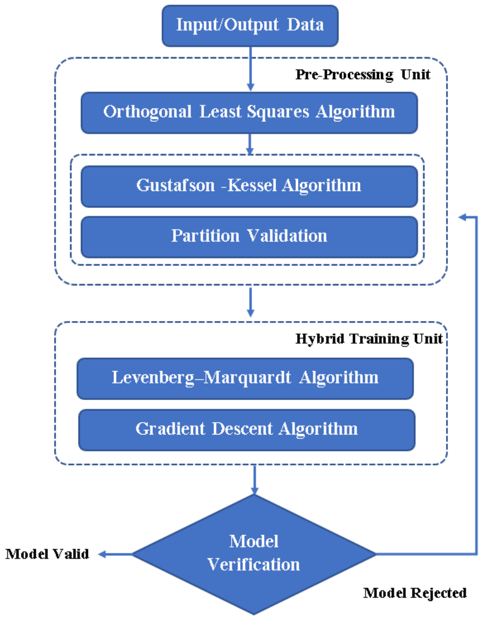

Figure 8. General framework of used two two-pass hybrid learning algorithm.

In first step, centres of RBF neurons are selected by OLS Algorithm from input data. However, these centers may not be fully suitable. They need to be optimized by Gustafson – Kessel (GK) algorithm with partition validation. First step is started by selecting an εOLS parameter between 0 and 1. A small value of εOLS causes finding more centres. Centres found by OLS are optimized by GK Algorithm. After determining of the centres, a two-pass hybrid training algorithm uses to fine tuning of the network parameters. In first pass (Forward computation) RBF weights are calculated by LM algorithm and other parameters is fixed. In second pass (Backward computation) fine tuning of centres and widths of RBF is made by Gradient Descent (GD) algorithm.

Table 1. Two-pass hybrid training procedure for LWNRBF networks.

	Forward computation	Backward computation
RBF weights	LM algorithm	Fixed
RBF centers and widths	Fixed	GD algorithm
Signal	Node outputs	Error rates

Thanks to complex structure of LWNRBF network can be used for modelling very complex data. However, LWNRBF network needs more sophisticated training algorithm as mentioned above than classic RBF network.

Another important issue is to select input parameters of the network to create acceptable model. In this study, amount of water in reservoir, past four days reservoir inflow rates and weather forecast are used as inputs of the network. Output of the network is selected as possible energy generation capacity of the HPS for the next day (W).

In experiments, a set of past reservoir inflow rates were used. The best model performance is obtained for past four days reservoir inflow rates.

Training stage starts with selection only three parameters: OLS training parameter (εOLS) and learning parameters (µGD and µLM) for GD and LM algorithms. After the training process, if model is rejected user selects new parameter set until a valid model is created.

Table 2: Some parameter values used in OLS Algorithm.

Used learning parameter values			Number of Selected Centers by OLS
εOLS	µGD	µLM	
0.1	0.005	0.005	1
0.09	0.005	0.005	3
0.04	0.005	0.005	6
0.01	0.005	0.005	8

For the valid model creating, in the training stage εOLS parameter was selected as 0.01 and 8 RBF neuron centres were selected by OLS algorithm. These centers were optimized and reduced as 7 by GK algorithm. Learning parameters µGD and µLM were selected as 0.005. It has been observed that in order to be able to reach best training and testing values of error, values of µGD and µLM should be selected as 0.005 experimentally.

Due to structure of OLS algorithm, theses two parameters have not any effect on number of calculated values of centers by OLS algorithm.

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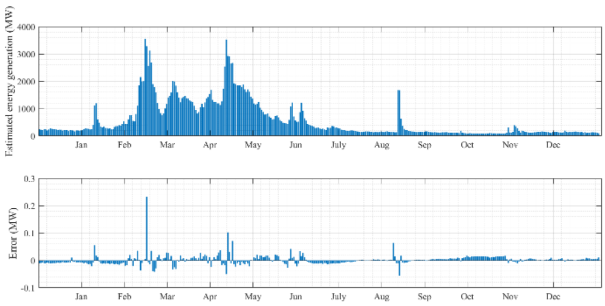

Figure 9. Estimated daily electrical energy generation and modelling error for months of 2020.

In the training process, average training error is calculated as 0.0012%. Outcomes of the testing process for first 4 days of 2021 is shown in Fig.10 – Fig.13.

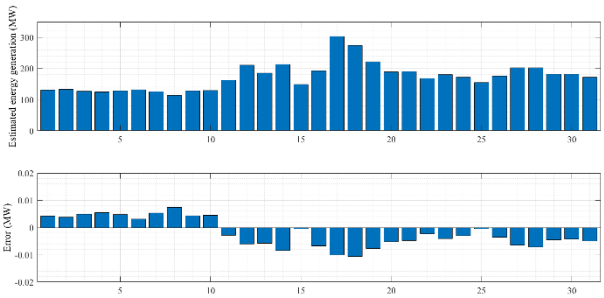

Figure 10. Estimated daily electrical energy generation and modelling error for January of 2021.

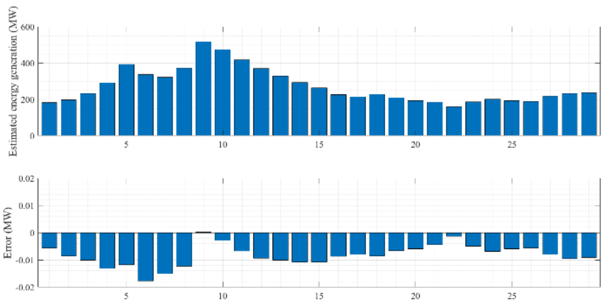

Figure 11. Estimated daily electrical energy generation and modelling error for February of 2021.

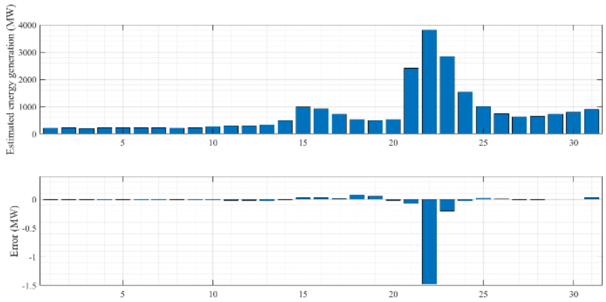

Figure 12. Estimated daily electrical energy generation and modelling error for March of 2021.

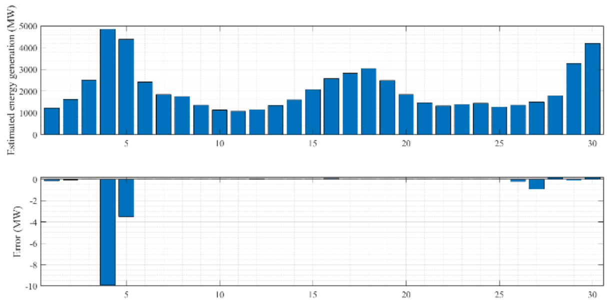

Figure 13. Estimated daily electrical energy generation and modelling error for April of 2021.

In the training process, average training error is calculated as -0.044%.

This study has developed a neural network model to be used in planning the daily energy generation of an HPS that has been shown to be accurate and reliable for estimation of daily energy generation. However, sudden rain and unpredictable seasonal change will affect the accuracy of the model. It was seen that when there was a sudden change in reservoir inflow, the model could adapt to the new condition within a few days.

4. Conclusion

The most important and principal criterion for determining the energy generation of an HPS is the water flow into the basin where the plant is located and energy planning in an HPS is generally made according to the expected water level in the reservoir. Efficient operation of an HPS depends on robust planning of its energy generation. Energy planning for an HPS can be summarized in three main points:

1. The energy generation of an HPS to be made on the next day is announced to the authorized body. It is mandatory for the HPS to fulfil its announced energy generation otherwise the HPS will face fines and sanctions.

2. Maximum efficiency of use of the water in the reservoir depends directly on energy planning and estimation. During a flood period, the entire volume of water cannot be used for electrical energy generation because the excess water must be drained. Outside a flood period, most of the water in the reservoir can be used for energy generation through robust estimation of energy generation.

3. Incorrect planning will cause unwanted stop-start operations and this will increase maintenance costs. This study uses a neural network model to estimate next day energy generation of an HPS and has shown that the neural network can provide accurate prediction of next day energy generation.

The study shows that unforeseen weather events will cause errors in the estimations. Although sudden rainfall causes deviations in the output of the model, it was seen that model would adapt to the new situation within a short period.

The model works most accurately with hourly data and for very short-term estimation. However, to be most useful for energy planning, the model needs to provide accurate estimation of next day energy generation. Although the neural network model made some incorrect estimates in the testing stage, with the main reason due to unpredictable conditions such as faults, sudden rain, and incorrect stop-start operations, the overall error was small and, as a result, the presented neural network is considered useful for energy planning.

Our aim in future work is to use a recursive neural network structure that can adapt itself to new conditions and new data coming and can make more reliable estimations for energy planning.

Author's Contributions

Serkan Inal and Ali Ekber Özdemir: Designed and developed the models and methods, analyzed the data, and drafted the manuscript.
Sibel Akkaya Oy: Guided and supervised the whole process.
S. Inal., S. Akkaya Oy and A.E. Ozdemir revised the manuscript; and all authors read and approved the fnal manuscript.

Ethics

There are no ethical issues after the publication of this manuscript.

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