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Prediction of power output of solar-powered, waterwheel-based pumped hydroelectric storage system using ANN model

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***Abstract*—In this work, prediction of power output of solar-powered, waterwheel-based pumped hydroelectric storage system using ANN model is presented. The essence of this study is to use artificial neural network (ANN) to characterize the nonlinear relationship between the input features and power output of the solar-powered, waterwheel-based pumped hydroelectric storage (SPWWPHS) system. The following four parameters are considered for their impact on the SPWWPHS system power output; height (m), flow (m^3/s), tank discharge time (seconds) and rotational speed (rad/s). The SPWWPHS was modeled and simulated using ANSYS Mechanical software. The ANN was trained over 500 epochs using four key input parameters derived from the system's experimental dataset. Particularly, the results showed that the output power value ranges from 1500 W at the height of 15 m to 1800 W at the height of 17.438 m. The results also showed that the output power value ranges from 1500 W at flow rate of 0.00087260 m^3/s to 1800 W at flow rate of 0.00087775 m^3/s. The output power also increased linearly with power output from the Tank Discharge Time until the 4400.8 seconds at which point the power output begins to drop. In all, the ANN model gave good performance for both the training and validation cases. With the ANN model, the designer of the solar-powered, waterwheel-based pumped hydroelectric storage system can effectively predict the expected power output for any combination of the four input parameters.**

Keywords*— Solar Power, Waterwheel, ANSYS Mechanical Software, Pumped Hydroelectric Storage, Artificial Neural Network (ANN)

1. Introduction

Solar-powered, waterwheel-based pumped hydroelectric storage is used to generate electrical energy from solar power as the primary source and the waterwheel tribune as the hydro power segment to convert the pumped water to electrical energy [1,2,3]. Generally, solar hydroelectric power system is expensive to set up and proper understanding of the system using a model is key to minimizing wastage and enhance efficiency of the system [4,5,6]. Again, in practice, such systems are modelled to enable parametric analysis of the system under various conditions [7.8.9]. In such way, the system components dimensions are carefully selected based on the model output.

In some cases, analytical modelling is used, in another case simulation software is used to model the system [10,11,12]. Yet in another case, data driven model can be used to study a system, especially for application in the design of enhanced version of the existing system or the application of the data driven model in the design of new systems [13,14]. Specifically, in this study, the data driven approach is used. Notably, some key data records acquired from some monitoring sensors-based monitoring mechanism are used to evaluate the effect of selected parameters on the power output of a case study. Particularly, artificial neural network model is trained and used to predict the power output of the solar-powered, waterwheel-based pumped hydroelectric storage system [15,16,17]. The study will assist in the maintenance and enhancement of the performance of the system by identifying the key components parameters settings that will give the optimal power output.

2. Methodology

The essence of this study is to use artificial neural network (ANN) to characterize the nonlinear relationship between the input features and power output of the solar-powered, waterwheel-based pumped hydroelectric storage (SPWWPHS) system. The following four parameters are considered for their impact on the SPWWPHS system power output; height (m), flow (m^3/s), tank discharge time (seconds) and rotational speed (rad/s). The SPWWPHS was modeled and simulated using ANSYS Mechanical software.

2.1 Dataset Description

The dataset was originally derived from computational simulations of a solar-powered, waterwheel-based pumped hydroelectric storage (PHES) system, validated using ANSYS Mechanical software. The dataset includes the four input variables mentioned above and a single output variable, the power output in watts. Each record in the dataset includes values for the following input variables: height (m), flow (m^3/s), tank discharge time (seconds) and rotational speed (rad/s). The corresponding output variable is the power output and error measurements expressed in terms of Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE) and Mean Absolute Error (MAE). The simulations in ANSYS Mechanical software were automated to ensure consistency and broad coverage of various operational scenarios, resulting in a high-quality training dataset.

1. **Data Analysis:** Initial analysis was performed using Python's Pandas library. The data was consolidated into a structured format and visualized using box plots for each input and output variable to assess distributions, identify outliers, and evaluate value ranges. To enhance visual interpretability, data was normalized using `StandardScaler`, and the box plots were generated using the Seaborn library
2. **Data Pre-processing:** Data preprocessing conducted included:
   i. Conversion of all input and output columns to numeric types
   ii. Dropping rows containing non-numeric or missing values
   iii. Normalization of features using `StandardScaler`
   iv. Splitting of the data into training and testing sets using an 80/20 ratio with `train_test_split` from Scikit-learn

3.2.7 The Artificial Neural Network (ANN) Model Architecture and Configuration

The artificial neural network (ANN) was developed to approximate the nonlinear relationship between the input features and power output using the function:

$$\hat{y} = \mathrm{f}\,(x, \theta) \quad \text{for } x \in \mathbb{R}^4 \qquad (1)$$

Where: Input vector [Height (m), Flow (m^3/s), Tank Discharge Time (secs), Rotational Speed (rad/s),] $\hat{y}$: Predicted power output, errors and θ: Learnable parameters (weights and biases)

The ANN architecture:

The ANN model was implemented using TensorFlow's `Sequential` API. The ANN architecture (as shown in Figure 1) is composed of:

i. Input Layer: 4 input nodes (one for each feature)

ii. Hidden Layer 1: 64 neurons, ReLU activation

iii. Hidden Layer 2: 32 neurons, ReLU activation

iv. Output Layer: 1 neuron (regression output, linear activation)

The model's architecture was visualized using `networkx` as shown in Figure 1.

The ANN Model configuration:

The ANN Model configuration is as follows;

i. Optimizer: RMSprop

ii. Loss Function: Mean Squared Error (MSE)

iii. Evaluation Metrics: MAE, MSE, and custom-defined MAPE

The ANN Model Training and Evaluation

The ANN model was trained over a maximum of 500 epochs with a batch size of 20. A validation split of 20% was used to monitor generalization. Early stopping was set at 20 epochs. Additionally, a custom callback was defined to compute and monitor Mean Absolute Percentage Error (MAPE) during each epoch. Model performance during training and validation was plotted over time.

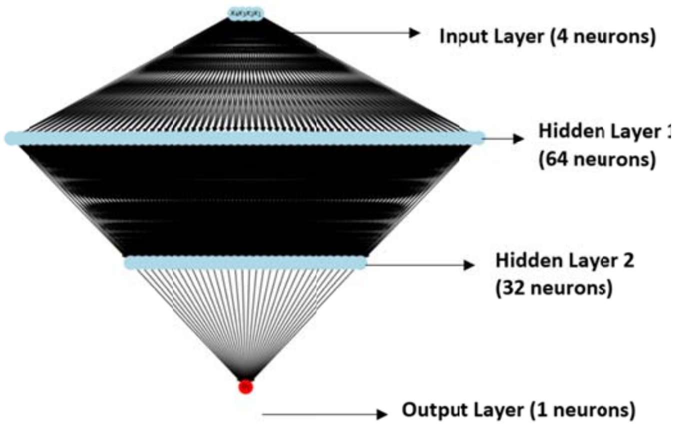

Figure 1 Artificial Neural Network (ANN) Model Architecture

The ANN Model Performance Metrics

The performance metrics used to assess the ANN model are as follows;

i. Mean Absolute Percentage Error (MAPE)

The MAPE with respect to the actual (A_t) and forecasted value (F_t) is defined as;

$$\text{MAPE} = \frac{100\,\%}{N}\sum_{t=1}^{N}\left(\frac{|A_t - F_t|}{0.5 \times (|A_t| + |F_t|)}\right) \quad (2)$$

Where number of observations is N.

ii. Mean Squared Error (MSE)

The MSE with respect to the actual value (y_t) and predicted value ($\hat{y}_t$) is defined as;

$$\text{MSE} = \frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2 \quad (3)$$

iii. Mean Absolute Error (MAE)

$$\text{MAE} = \text{mean}(|e_i|) = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \quad (4)$$

Where e_i = error between model prediction and observed value.

3. Results and discussion

The boxplot for the five parameters are presented in Figure 1 to Figure 6. Also, the graph of the power output versus each of the four input parameters are presented in Figure 7 to Figure 10. The trend line analytical models fitted to the graphs in Figure 7 to Figure 10 show that the power output is linearly related to the height and flow rate whereas the power output is related to the Tank Discharge Time and Rotational Speed based on logarithmic expressions.

Power output = 123.05(Height) - 345.78 (5)

Power output = 6E+07 (Flow Rate) - 49296 (6)

Power output = 12454 ln (Tank Discharge Time) - 102726 (7)

Power output = 378.08ln(Rotational Speed) + 660.6 (8)

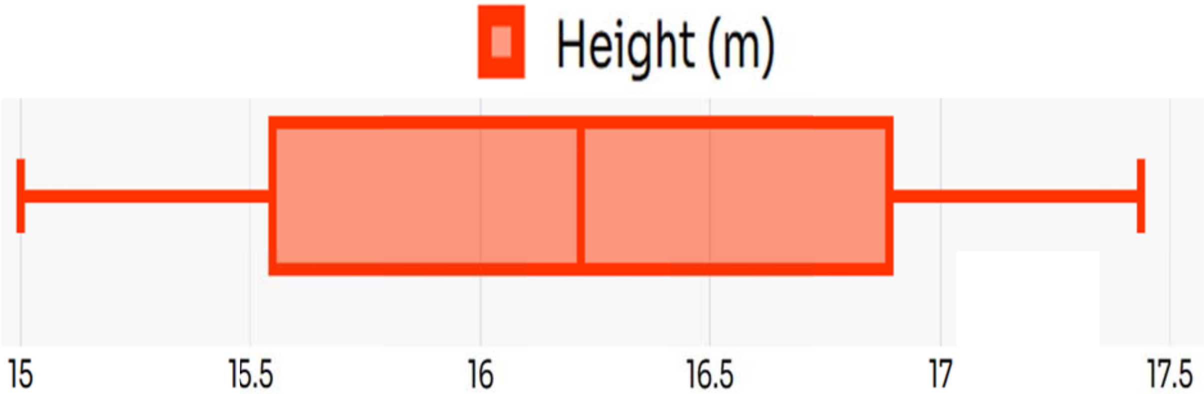

Figure 2 The Boxplot for the dataset on Height of the tank

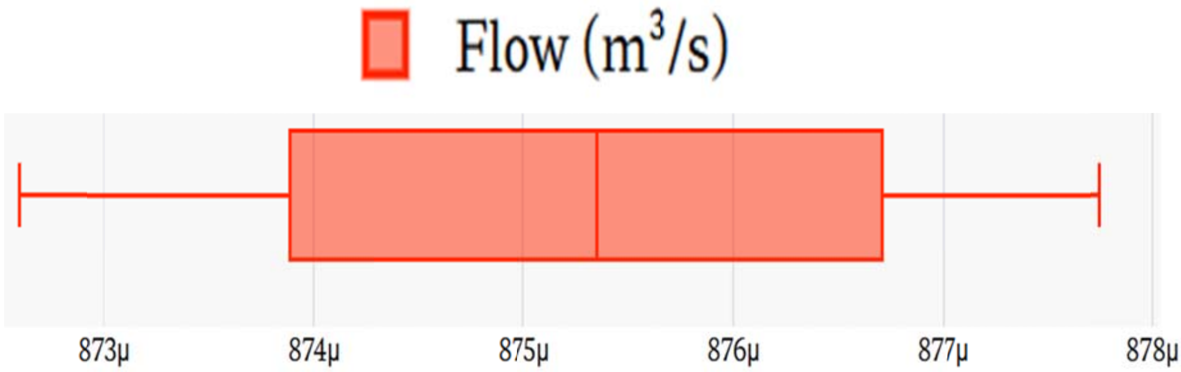

Figure 3 The Boxplot for the dataset on flow rate

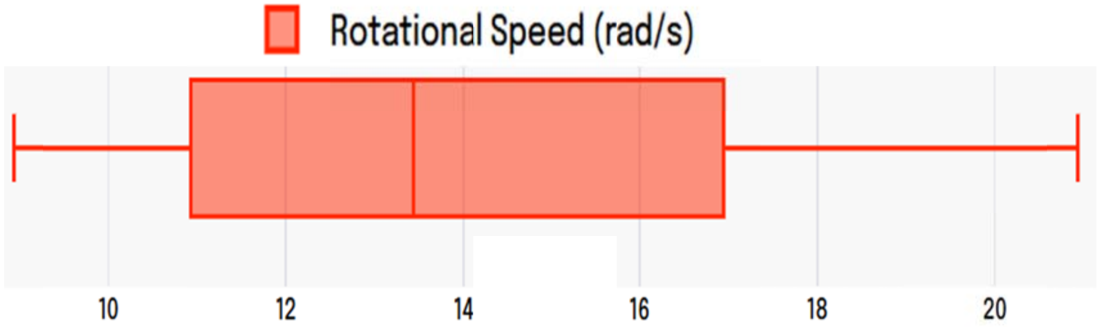

Figure 4 The Boxplot for the dataset on rotational speed of the hydro turbine

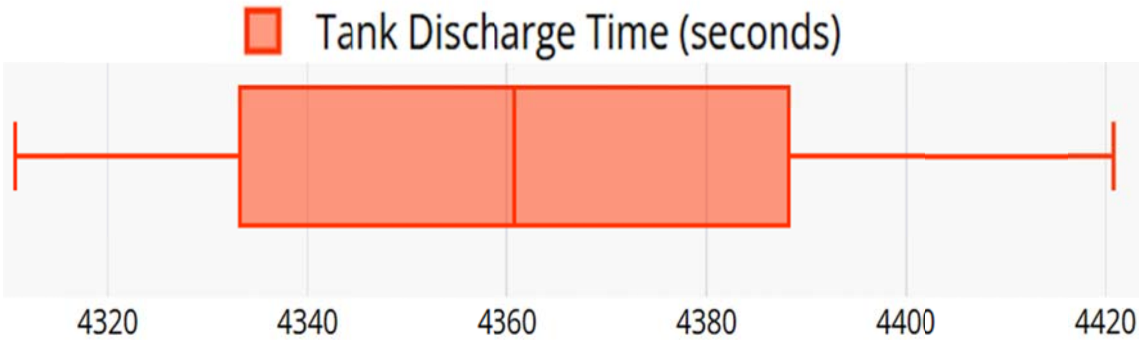

Figure 5 The Boxplot for the dataset tank discharge time

Figure 6 The Boxplot for the dataset on power output of the system

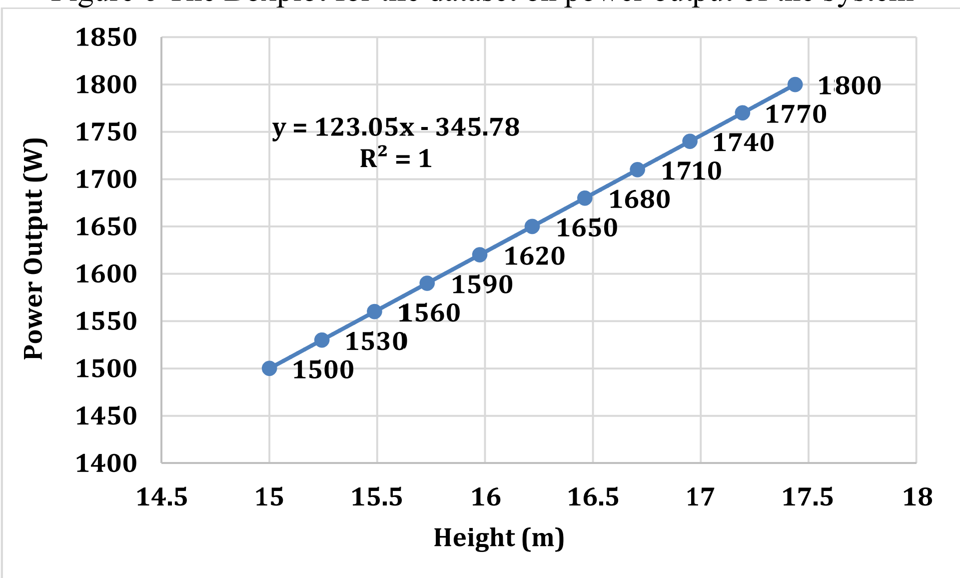

Figure 7 The graph of power output versus height

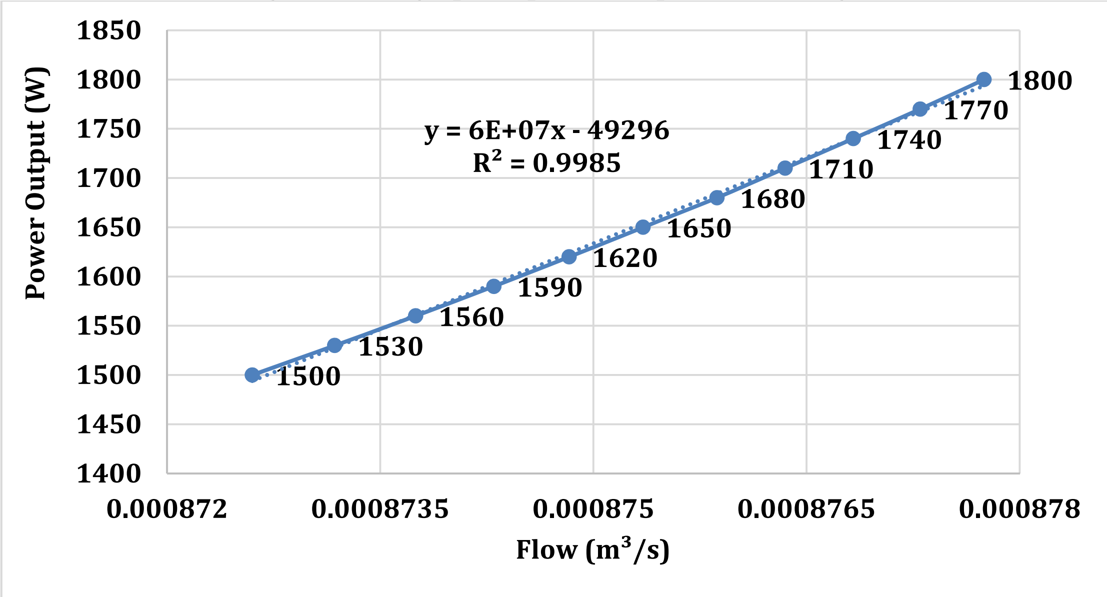

Figure 8 The graph of power output versus flow rate

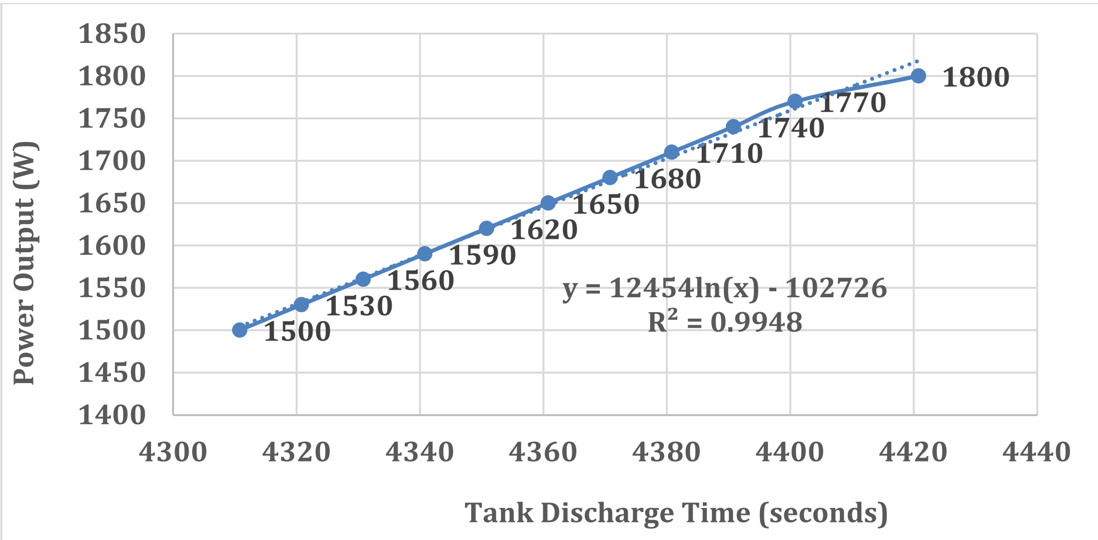

Figure 9 The graph of power output versus tank discharge time

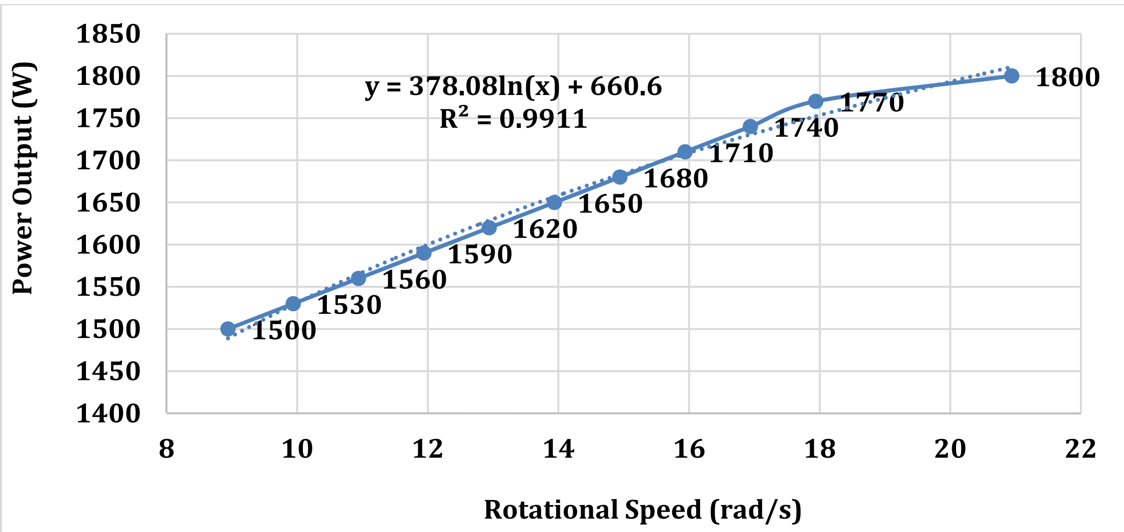

Figure 10 The graph of power output versus rotational speed of turbine

The ANN was trained over 500 epochs using four key input parameters derived from the system's experimental dataset. Particularly, the results showed that the output power value ranges from 1500 W at the height of 15 m to 1800 W at the height of 17.438 m. The results also showed that the output power value ranges from 1500 W at the flow rate of 0.00087260 m³/s to 1800 W at the flow rate of 0.00087775 m³/s. The output power increased linearly with power output from the Tank Discharge Time until the 4400.8 seconds at which point the power output begins to drop.

It was observed that all three error metrics declined significantly as training progressed, reflecting effective model convergence. The low MAPE value indicated high reliability in predicting power output, while the MSE and MAE suggested minimal deviation between actual and predicted values. This level of accuracy confirms that ANN tools can be deployed to manage real-time optimization and automated control of PHES systems, especially under fluctuating renewable energy inputs or changing hydraulic head conditions. The error metrics (MAPE, MSE, and MAE) obtained from the ANN model training and validation process are presented in Figure 11 to Figure 13. Also, the results for the training and validation MSE at epoch 1 and at epoch 500 are presented in Table 1. The results for the training and validation MAE at epoch 1 and at epoch 500 are presented in Table 2 while results for the training and validation MAPE at epoch 1 and at epoch 500 are presented in Table 3. The results showed that after 500 epochs, the MSE dropped by about 35.2 % for the training and 36.44% for the validation set (as shown in Table 1). Also, after 500 epochs the MAE dropped by about 20.3 % for the training and 20.62% for the validation set (as shown in Table 2) and similar results is obtained for the MAPE, (as shown in Table 3).

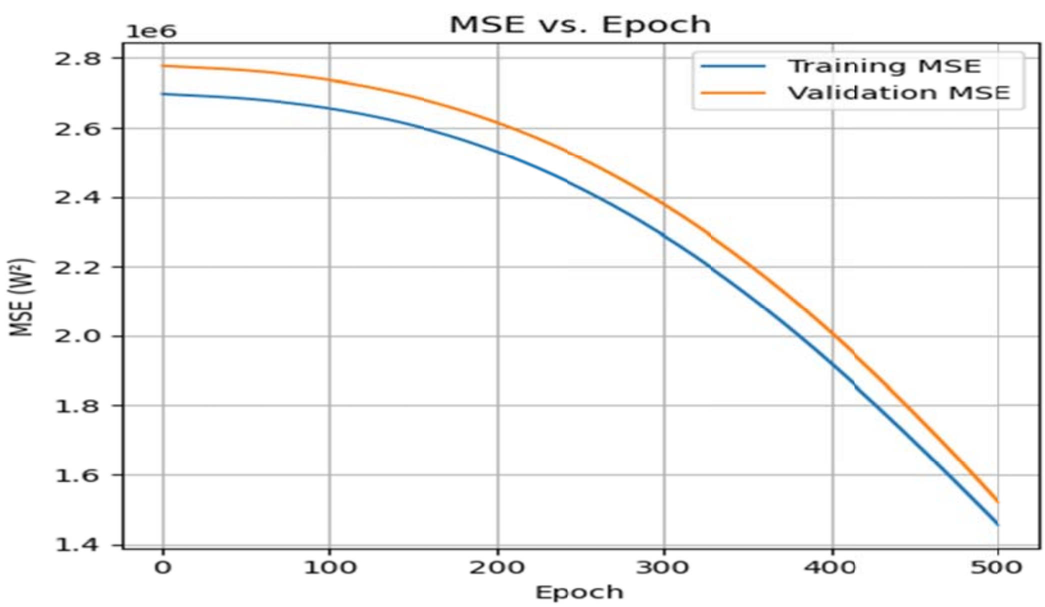

Figure 11 MSE Generated from ANN

Table 2 The training and validation MSE at epoch 1 and at epoch 500.

	Training MSE	Validation MSE	Difference between training and validation MSE	Percentage difference in MSE
At Epoch 1	2631240.00	2980730.50	349490.50	13.28
At Epoch 500	1703873.38	1894661.38	190788.00	11.20
Percentage difference in MSE (%)	35.24	36.44		2.09

Table 1 The training and validation MAE at epoch 1 and at epoch 500.

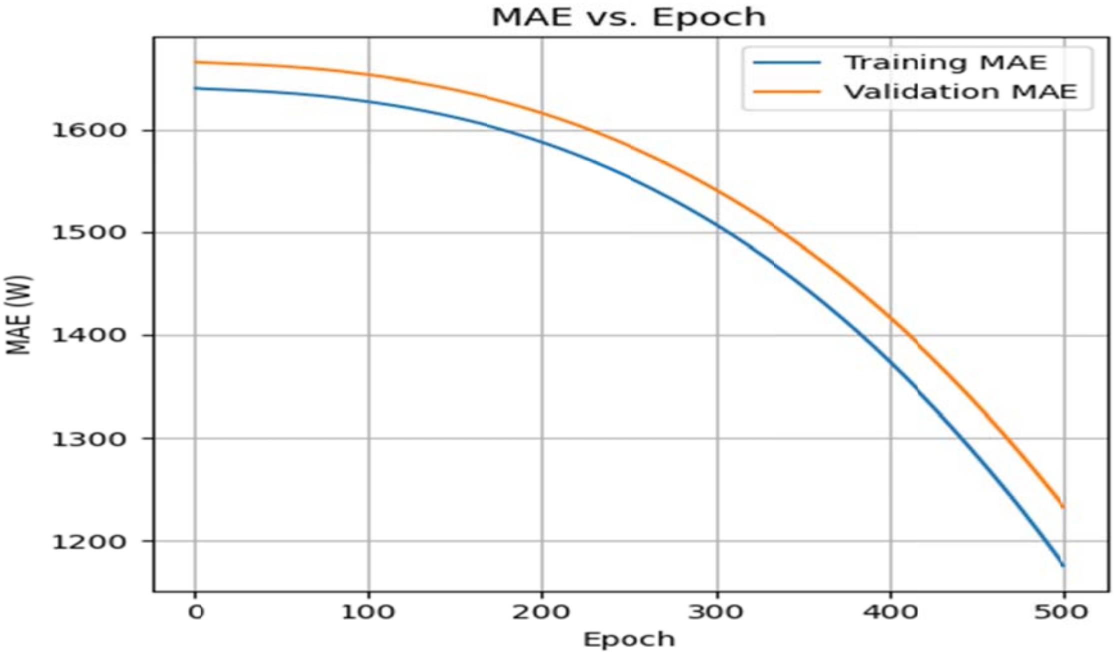

Figure 12: MAE Generated from ANN

Table 2 The training and validation MAE at epoch 1 and at epoch 500.

	Training MAE	Validation MAE	Difference between training and validation MAE	Percentage difference in MAE
At Epoch 1	1619.98	1724.85	104.87	6.47
At Epoch 500	1291.02	1369.24	78.21	6.06
Percentage difference in MAE (%)	20.31	20.62		0.42

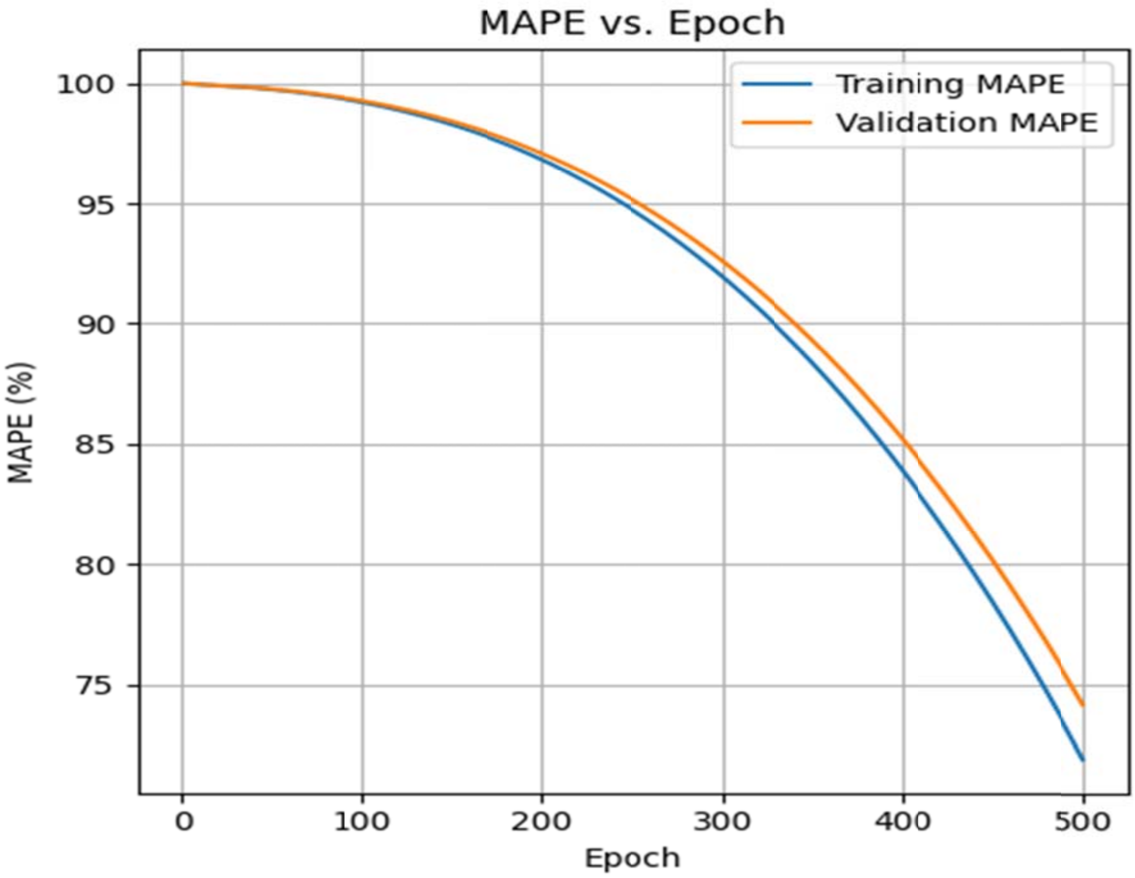

Figure 13: MAPE Generated from ANN

Table 3 The training and validation MAPE at epoch 1 and at epoch 500.

	Training MAPE	Validation MAPE	Difference between training and validation MAPE	Percentage difference in MAPE
At Epoch 1	0.9999	0.9999	0.0000	0.0000
At Epoch 500	0.7942	0.7988	0.0046	0.5792
Percentage difference in MSE (%)	20.57	20.11		0.58

4. Conclusion

The prediction of the output power generated by a solar-powered, waterwheel-based pumped hydroelectric storage system is studied. The artificial neural network (ANN) model is used for the prediction. The study considered the height (m), flow rate (m^3/s), tank discharge time (seconds) and rotational speed (rad/s) and examined regression trend line expression for relating each of the four parameters to the output power. The results showed that the height and flow rate are linearly related to the output power whereas the tank discharge time (seconds) and rotational speed (rad/s) have logarithmic relationship with the output power. The prediction performance of the ANN model is evaluated using the Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE) and Mean Absolute Error (MAE). In all, the model gave good performance for both the training and validation cases. With the ANN model, the designer of the solar-powered, waterwheel-based pumped hydroelectric storage system can effectively predict the expected power output for any combination of the four input parameters.

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