Modeling and Control of a Based Extreme Learning Machine as Distributed Setpoint for the HEPP Cascade System in a Nickel Processing Plant

Yayan Iscahyadi Sarira[1,*], Syafaruddin[2], Indar Chaerah Gunadin[3], Dianti Utamidewi[4]

[1,2,3,4]Department of Electrical Engineering, Hasanuddin University, Gowa, 92127, South Sulawesi, Indonesia

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Abstract

The aim of this research is to model the cascade system of hydropower plants in order to predict the set point power value of each generator. The model simulates several input data variables to obtain an accurate prediction of the set point value. Various historical data are used in this study to evaluate the relationship between input and output variables. This paper presents an Extreme Learning Machine (ELM) method for modeling system models and generating set point values for each generator in a hydroelectric power plant (HEPP) cascade system in a nickel processing plant (NPP). The issue of coordination time between the production and utility departments is addressed. The research aims to use the ELM method to auto-generate setpoint values. The MATLAB application serves as a simulator for generating the expected ELM model. As a result, this allows for automatic changes to the set point of each generator in the cascade system. The ELM method yields a MAPE value of 13.94%, indicating accurate predictions.

Keywords: ELM, HEPP, MATLAB, Cascade, NPP

1. Introduction

The operation method of the NPP's hydropower cascade system is a crucial focus due to the high level of coordination required between various parties within the company [1], [2]. Communication between the production department and the utility regarding production power needs is a key parameter for making decisions on generation input values. Numerous parameters are analyzed to obtain information as a hydropower input parameter. The power output of each generating unit is significantly impacted by production power requirements. Additionally, the changing climate poses a particular concern as it can greatly affect the volume of reservoirs or dams in each hydropower area. The complexity of the system often leads to human error in decision-making. Currently, all parameters are manually set by the operator for each generating unit.

Artificial intelligence-based modeling is often preferred over conventional modeling that uses physical-based models due to its superior performance [14]. The literature describes a diverse range of applications for artificial neural network methods in power plant modeling, including river flow modeling, daily discharge, short-term and long-term water levels, and automatic generation control of electric power systems [2], [3].

According to other research, cascade hydropower modeling is used to simulate an increase in power generation capacity using the ANN method. This provides a benefit-cost analysis for the unit with a stable water level record in the three ponds [4]. Additionally, hydropower modeling is used to predict power generation by comparing three machine learning methods: ANN, ARIMA, and SVM [13], [17], [19], [20]. The ANN and SVM methods yield the best results. However, the input parameters do not consider the degree of inflow, temperature, drought variability, and climate change [5].

Artificial intelligence methods offer a control solution for various applications or plants [2]. The methods presented do not necessitate intricate mathematical computations [2]. However, the implementation of artificial intelligence demands a significant amount of historical data. The accuracy of the expected results increases with the amount of data

*Corresponding author: Yayan Iscahyadi Sarira (yayansarira@gmail.com)
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used. This paper proposes an artificial intelligence method with a rapid learning system to expedite the calculation process and obtain precise results.

2. Cascade System

2.1. Operation of Cascade Hydropower System

Efficient management is essential for operating a cascade hydropower system with distributed water usage to effectively handle any emerging issues [6]. Figure 1 depicts the process flow of the cascade hydropower system that will be analyzed in this study. The cascade topology illustrates the sequence of levels, commencing with the main reservoir, Larona Hydropower, Balambano Reservoir, Balambano Hydropower, Karebbe Reservoir, and Karebbe Hydropower.

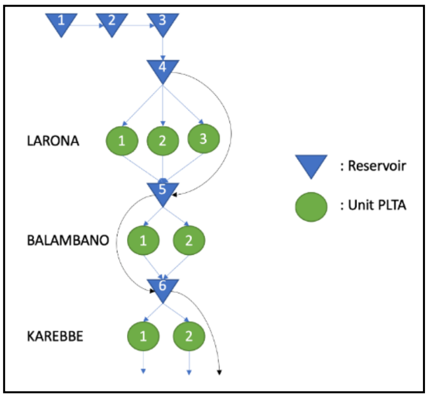

Figure 1. The Topology of Cascade Hydropower

2.2. Characteristic of Cascade Hydropower Plants

The characteristics of cascade hydropower plants demonstrate the relationship between three variables in multi-unit operations [3]. Each unit utilizes a different water discharge to generate electricity, resulting in varying reductions in water levels in each reservoir during operational time. Other factors that can cause differences include reservoir tampering capacity, maximum reservoir height, head, and climate change factors.

3. Method

The ELM represents an innovative approach within the realm of artificial neural networks [7], [15], [16], [18]. ELM stands as a feedforward artificial neural network featuring a solitary hidden layer, also recognized as a single hidden layer feedforward neural network. Its learning technique, developed to counter the deficiencies of conventional feedforward artificial neural networks, notably focuses on enhancing learning speed. According to [5], conventional feedforward NN exhibit sluggish learning speeds, primarily attributed to two factors:

1) Using a gradient-based learning algorithm for training at a slow pace.

2) All network parameters are established through iterative application of the learning method.

In conventional gradient-based learning methods like backpropagation (BP), the feedforward NN requires manual configuration of parameters during learning, such as input weights and hidden biases. These parameters, linked across layers, often lead to extended learning periods and frequent entrapment in local minima. Conversely, ELM parameters, like weights and biases, are generated randomly, enabling fast learning rates and the capacity to achieve strong generalization performance.

The ELM approach employs a distinct mathematical model compared to feedforward artificial neural networks, one that is simpler yet more efficient in its application. For N different input and target output pairs (x_i, t_i), where $x_i = [x_{i1}, x_{i2}, \dots, x_{in}]^T \in R^n$ and $t_i = [t_{i1}, t_{i2}, \dots, t_{in}]^T \in R^n$, standard SLFNs with $\widetilde{N}$ and $g(x)$ activation function can be mathematically modeled as follows:

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$$\sum_{i=1}^{\tilde{N}} \beta_i g_i(x_j) = \sum_{i=1}^{\tilde{N}} \beta_i g(w_j . x_j + b_i) = o_j \qquad (1)$$
$$j = 1,2, \dots, N$$

Where:

The weight vector connecting the i-th hidden node to the input nodes is denoted by $w_i = [w_{i1}, w_{i2}, \dots, w_{in}]^T$.

Likewise, the weight vector linking the i-th hidden node to the output nodes is denoted by $\beta_i = [\beta_{i1}, \beta_{i2}, \dots, \beta_{in}]^T$.

The threshold for the i-th hidden node is denoted as b_i .

The inner product w_i and x_j is represented by $w_i . x_j$.

Assuming $\tilde{N}$ hidden nodes and activation function $g(x)$, standard SLFNs are used to estimate any N samples with an error rate of 0. This implies that $\sum_j^N \|o_j - t_j\| = 0$, and as a result, there β_i, w_i and b_i:

$$\sum_{i=1}^{\tilde{N}} \beta_i g(w_j . x_j + b_i) = t_j, \qquad j = 1,2, \dots, N \qquad (2)$$

The above equation can simply be expressed as:

$$H\beta = T, \qquad (3)$$

Where:

$$H = \begin{bmatrix} g(w_1 . x_1 + b_1) & \cdots & g(w_{\tilde{N}} . x_1 + b_{\tilde{N}}) \\ \vdots & \ddots & \vdots \\ g(w_1 . x_N + b_1) & \cdots & g(w_{\tilde{N}} . x_N + b_{\tilde{N}}) \end{bmatrix} \qquad (4)$$
$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}}^T \end{bmatrix} \text{ and } T = \begin{bmatrix} t_1^T \\ \vdots \\ t_{\tilde{N}}^T \end{bmatrix}$$

In the provided equation, H symbolizes the output of the NN's hidden layer. The output of the hidden neuron corresponding to input x_j is denoted by $g(w_j . x_j + b_i)$. β and T denote the matrices of output weights and targets, respectively. Within ELM, the weight and bias are randomly generated, enabling the computation of the output weight linked with the hidden layer using the provided equation.

$$\beta = H^{\dagger} T, \qquad (5)$$

The following is the algorithm for the ELM [20]:

Input: Given the pattern x_j and its corresponding target output pattern t_j, where $j = 1, 2, \dots, N$

Output: This yields the input weight w_i, output weight β_i, and bias bi, i = 1, 2, …, $\tilde{N}$

Phase 1: Define the activation function (g(x)) and specify the number of hidden nodes $\tilde{N}$

Phase 2: Randomly assign values of the input weights wi and bias bi, i = 1, 2, …, $\tilde{N}$

Phase 3: Compute the output matrix H in the hidden layer

Phase 4: Compute the output weight β by using $\beta = H^{\dagger} T$

3.1. ELM Network Architecture

The ELM comprises a hierarchical arrangement featuring three distinct layers, as detailed in reference [8]. A weight vector, labeled as 'w', serves to establish connections from the input to the hidden layer, with its values initialized randomly. Moreover, the biases associated with nodes within the hidden layer are also randomly generate. The quantity hidden layer situated in the initial layer corresponds to the number of statistical attributes provided as input. The architecture of the ELM network utilized in this study is depicted in figure 2, as outlined in references [9], [10].

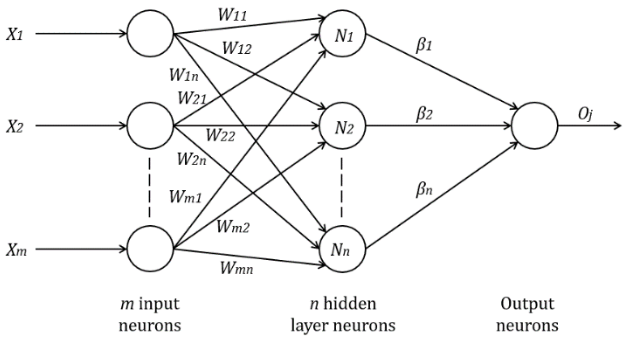

Figure 2. The Architecture of ELM model

3.2. Modeling and Control Cascade System with Extreme Learning Machine

The study utilized historical and hydrological data from the Utilities department of PT Vale Indonesia, collected between July and December 2022.

The model system developed for this study employed 23 input variables and as for data output using 7 variable data outputs. The figure 3 depicts an overview of the ELM model.

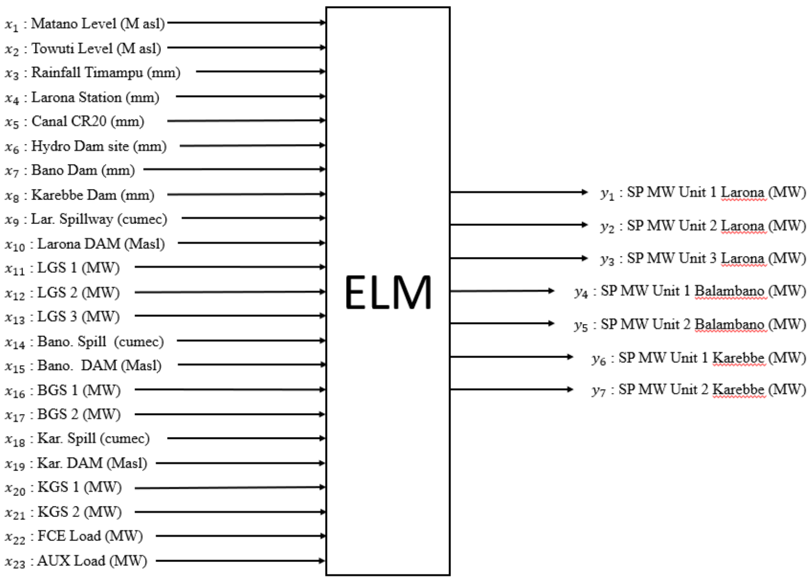

Figure 3. The ELM model

The ELM model employs 23 input layers, 100 hidden layers, and 7 output layers with a sigmoid activation function.

The performance of the model and its predictions undergo analysis utilizing the mean absolute percentage error method [11], [12]. The formula is outlined as follows:

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{6}$$

Where:

At is actual value at time factor t

Ft is the Forecast Value at time factor t

n is the size of the sample

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The presentation of a smaller MAPE value indicates a higher level of prediction accuracy. Table 1 displays the MAPE values for the model's prediction results, categorized as high accuracy, good, reasonable, and inaccurate.

Table 1. Explanation of common MAPE values

MAPE Value	Interpretation Forecasting Result
<10%	High Accuracy
10 – 20 %	Good
20 – 50 %	Reasonable
>50%	Inaccurate

Source: [11]

Table 2 displays an example of the data used in this study. The table shows 23 input data variables and 7 output data variables.

Table 2. Example of Input and Output Data Variables

x_1	x_2	.	.	.	x_{22}	x_{23}	y_1	y_2	y_3	y_4	y_5	y_6	y_7
392.39	319.38	.	.	.	204.76	42.47	21,00	64,00	64,00	56,24	58,00	45,00	33,79
392.37	319.37	.	.	.	236.06	43.90	36,00	63,00	63,00	59,89	60,00	58,00	19,72
392.41	319.37	.	.	.	219.59	43.88	20,00	60,00	60,00	55,00	59,00	55,75	35,57
392.37	319.36	.	.	.	221.21	44.62	21,00	62,00	62,00	57,36	62,00	43,14	35,89
392.37	319.34	.	.	.	205.36	46.17	44,00	61,00	58,00	53,89	62,00	45,00	23,32
392.34	319.32	.	.	.	162.60	44.24	46,00	62,00	62,00	38,00	42,00	48,00	28,00
392.35	319.28	.	.	.	171.50	47.11	44,00	60,00	60,00	42,54	45,97	48,00	22,24
392.34	319.29	.	.	.	198.52	47.18	20,00	62,00	62,00	40,00	48,43	57,00	42,00
392.34	319.32	.	.	.	216.76	46.48	20,00	60,00	60,00	60,00	63,00	58,00	45,97
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4. Result and Discussion

The simulation results indicate a MAPE value of 13.94, which was obtained by comparing the training and testing data.

This places the prediction in the 'good' category. Despite the non-linearity factor in the data, the prediction results remain at a satisfactory level. Table 3 displays the MAPE results for each prediction.

Table 3. The MAPE Results for Active Power Set Point Prediction

	MAPE Value (%)
Active Power SP of #1 Larona	10.69
Active Power SP of #2 Larona	13.70
Active Power SP of #3 Larona	34.93
Active Power SP of #1 Balambano	9.59
Active Power SP of #2 Balambano	6.46

Active Power SP of #1 Karebbe	6.65
Active Power SP of #2 Karebbe	15.58
Average	**13.94**

The data was sampled daily at 00:00. The training data consists of 23 variables and is sourced from July 16, 2022 to December 31, 2022, totaling 3178 data points.

This study aims to predict the daily values of set point power, output power, and spillway flow rate for each power plant. The ELM method was used for data training, and the results are shown in figure 4. The optimal number of hidden layers from this training process is 100. Additionally, the input weights and biases are randomly generated. The activation used is sigmoid. These parameters are crucial for achieving optimal results during the training process.

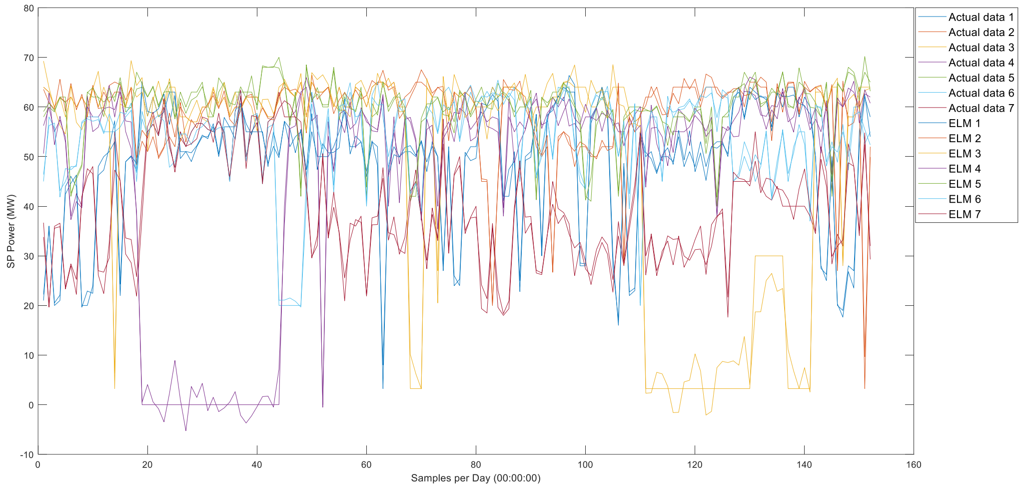

Figure 4. Training of ELM model

The remaining data was then tested and validated. The results of the ELM method during the testing process are shown in figure 5. The performance of the test results was validated using the MAPE method, which yielded a result of 13.94. This prediction demonstrates good accuracy. Additionally, the simulation results indicate an average prediction error of 7.28.

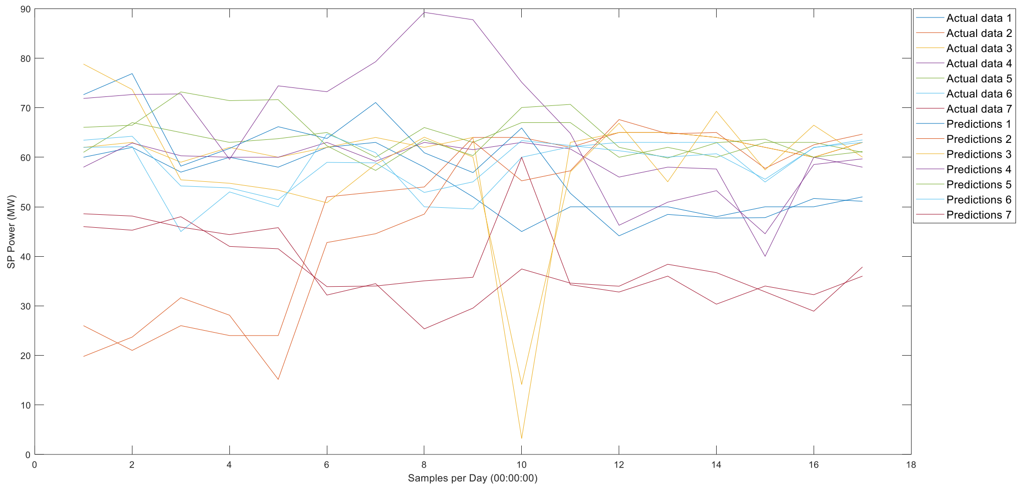

Figure 5. Testing of ELM model

5. Conclusion

The cascade hydroelectric power plant system can be modeled using the ELM method. The ELM modeling process flow involves training data, testing training data, and data validation tests.

The proposed modeling method provides a precise and efficient approach to decision-making for balancing power against furnace and auxiliary loads in plant operations. The technique yields accurate results in determining the expected set point value, as evidenced by the training and testing results that closely follow the actual values. The model is supported by software simulation using MATLAB software.

This model predicts the set point value of active power for each generating unit, reducing the time required to determine the set point value. This study predicts set point values using 23 input variables and 7 output variables. The proposed method, ELM, provides accurate predictions with a MAPE value of 13.94 percents and average forecasting error of 7.28.

6. Declarations

6.1. Author Contributions

Conceptualization: Y.I.S. and I.C.G.; Methodology: I.C.G.; Software: Y.I.S.; Validation: Y.I.S., I.C.G.; Formal Analysis: Y.I.S., I.C.G.; Investigation: Y.I.S.; Resources: I.C.G.; Data Curation: I.C.G.; Writing Original Draft Preparation: Y.I.S. and I.C.G.; Writing Review and Editing: I.C.G. and Y.I.S.; Visualization: Y.I.S.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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