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Hydropower Plant Generation Forecasting using Long Short-Term Memory (LSTM) for Optimizing Water Utilization*

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Abstrak
Pembangkit listrik tenaga air menghadapi tantangan signifikan terkait ketersediaan air karena perubahan iklim yang meningkatkan ketidakpastian cuaca, sehingga memengaruhi efisiensi penggunaan air. Untuk meningkatkan efisiensi penggunaan air, pengambilan keputusan perlu didasarkan pada data jangka panjang dan metode prediksi yang melampaui sekadar tinggi muka air dan prakiraan cuaca. Oleh karena itu, diperlukan perbaikan dalam pengambilan keputusan terkait pola operasi guna meningkatkan efisiensi pembangkit listrik tenaga air. Metode *Long Short-Term Memory* (LSTM) dalam prediksi penggunaan air menawarkan pendekatan inovatif untuk meningkatkan efisiensi dan mengurangi pemborosan sumber daya air. LSTM, yang merupakan varian dari Recurrent Neural Network (RNN), mampu mengenali pola jangka panjang dan ketergantungan dalam data runtun waktu (*time series*), sehingga sangat ideal untuk memprediksi kapasitas produksi energi yang berfluktuasi. Dengan menerapkan LSTM untuk memprediksi produksi energi, model prediksi yang lebih akurat dan andal dapat diperoleh. Model ini dirancang untuk meningkatkan prediksi penggunaan air, mengoptimalkan operasi pembangkit listrik tenaga air dalam pengelolaan sumber daya yang efisien, serta mendukung pengambilan keputusan berbasis ilmiah yang didasarkan pada data dalam pengelolaan air. Hasil eksperimen menunjukkan kesalahan prediksi yang rendah dengan nilai normalized RMSE sebesar 0,06170 dan nilai R^2 sebesar 0,96391. Hasil ini kemudian dapat digunakan dalam skenario operasi nyata. Disimpulkan bahwa model LSTM merupakan strategi yang baik untuk memprediksi aliran air dalam studi efisiensi turbin hidroelektrik. Makalah ini membahas strategi peramalan kapasitas produksi di PM Noor yang menggunakan metode LSTM untuk membantu skenario operasi.

Kata kunci: LSTM, Pembangkit Listrik Tenaga Air, Operasi

Abstract
Hydropower plants face significant challenges with water availability as climate change increases weather uncertainty, affecting water usage efficiency. To improve the efficiency of water usage, decision-making should be based on long-term data and prediction methods beyond just water levels and weather forecasts. Therefore, improvements are needed in decision-making regarding operating patterns to increase hydropower efficiency. Long Short-Term Memory (LSTM) methods in water use prediction offer an innovative approach to increase efficiency and reduce waste of water resources. LSTM, a variant of Recurrent Neural Network (RNN), can recognize long-term patterns and dependencies in time series data, making it ideal for predicting fluctuating energy production capacity. By applying LSTM to predict production energy, a more accurate and reliable prediction model could be obtained. The model is designed to enhance water use predictions, optimize hydropower operations for efficient resource management, and support scientific basis decision-making based on data in water management. Experimental results show a lower error according to its predictive capacity with the normalized RMSE of 0.06170 and 0.96391 R2 value. The results can then be used in real operation scenarios. It is concluded that the LSTM model is a good strategy for the forecast of water flow for the study of hydroelectric turbine efficiency. This paper discusses the forecasting strategy of production capacity at PM Noor, which uses the LSTM method to assist operation scenarios.

Keywords: *LSTM, Hydro Power Plant, Operation*

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1. INTRODUCTION

Hydropower plants face significant challenges in maintaining water availability, especially with climate change affecting weather uncertainty. Changes in precipitation patterns and river flow variability affect inefficiencies in hydropower plant operations (Falchetta *et al.,* 2019; Jabbari *et al.,* 2019). Prolonged drought and changing hydrological conditions further complicate the efficiency and operation of hydropower turbines, where when less water is available, hydropower turbines are less efficient (Yildiz *et al.,* 2024). Due to the fluctuating nature of renewable energy sources, power generation from these resources is highly unpredictable, making accurate supply calculations and estimations for the electricity grid essential.

Therefore, improvements in decision-making related to operating patterns are needed to increase hydropower efficiency. So far, decision-making on operating patterns has been based on water level conditions, weather, changes in water levels from the previous few days, and BMKG predictions. Furthermore, the operation of the hydroelectric power plant can be improved by applying a water addition prediction method using data collected over the last decade.

The use of stochastic dynamic programming and machine learning can improve the operational efficiency of hydropower plants through better water resource management with better predictions through existing data, thus ensuring environmental sustainability and optimal performance (Zhang *et al.,* 2022; Bernardes *et al.,* 2022). Forecasting optimal energy production from hydropower plants is essential to manage operations efficiently and ensure environmental sustainability (Khaniya *et al.,* 2020).

In this context, the advancement of deep learning technology has yielded significant achievements in various domains, particularly in computer vision and predictive modeling. Long Short-Term Memory (LSTM) method in generation prediction offers an innovative approach to improve efficiency and reduce waste of water resources (Kratzert *et al.,* 2018). Artificial intelligence technology, especially LSTM as a Recurrent Neural Network (RNN) variant, can recognize long-term patterns and dependencies in time series data, making it ideal for predicting fluctuating energy production capacity (Hochreiter *et al.,* 1997). The forecasting of monthly hydroelectric power demand based on annual capacity and monthly production data can be done with deep learning LSTM (M. Bulut, 2021). The results show that a 100-layer LSTM model with 10 years of data gives the best MAPE, while 12 years of data yields the lowest RMSE, confirming that more data improves prediction accuracy. LSTM modeling has been applied to several sites such as a hybrid CNN-LSTM model for medium- and long- term power load forecasting, enhancing feature extraction and accuracy through seasonal inflection point corrections, as demonstrated with 20 years of Shaoxing City's load data (Cheng *et al.,* 2023). LSTM-based neural network for forecasting water flow at the Madeira River, showing high accuracy and potential for improving efficiency and management at the Jirau Hydroelectric Power Plant (Filho *et al.,* 2020). Also, a joint scheduling model incorporating power load prediction using a CNN- GRU algorithm was implemented at Shatuo Hydropower Station, achieving high accuracy and improved scheduling efficiency, with potential applicability to other stations (Huang *et al.,* 2024).

This study aims to develop an accurate power generation prediction model for the Ir. PM Noor Hydropower Plant or PM Noor HPP using the Long-Short-Term Memory (LSTM) method. The model is designed to enhance water use predictions, optimize hydropower operations for efficient resource management, and support scientific basis decision- making based on data in water management. By applying the LSTM approach, the model is expected to deliver reliable predictions, serving as a foundation for optimizing the plant's operating strategy and improving overall energy production efficiency.

2. METHODOLOGY

2.1. Long Short Term Memory

Long-short-term memory (LSTM) is a type of recurrent neural network (RNN) architecture used in deep learning (Hochreiter *et al.,* 1997). LSTM is particularly well-suited for tasks involving sequential data streams, such as recognizing non-segmented handwriting or interpreting speech. Unlike traditional RNNs, LSTM can retain information over long periods, making it ideal for predicting time series with varying and unknown time intervals.

The structure of an LSTM network as shown Figure. 1 includes memory cells that contain self-loops and three regulators controlling information flow within the cell. The self-loops are key for storing temporal information encoded in the cell state. The three regulators, known as the input gate (ig), forget gate (fg), and output gate (og), manage the processes of writing, erasing, and reading data from the memory state (Filho *et al.,* 2020).

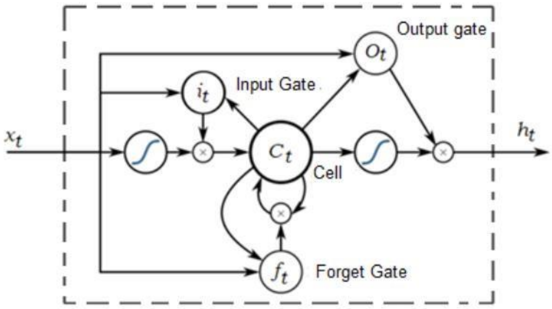

Figure. 1. LSTM Structure Model

2.2. Dataset

In this research, data from PM Noor HPP is used for predictive modeling of HPP operations using LSTM. As the only hydroelectric power plant operating in Kalimantan, PM Noor HPP is vital in continuously and stably supplying electricity to the interconnection network. In addition, PM Noor HPP functions as a black start for the electricity system in Kalimantan, so the availability of water resources and the operational readiness of the Hydro Power must be maintained. PM Noor HPP must also operate continuously, even in the dry season, because of the demand for water from residents downstream for their fish cages. Furthermore, the relatively small size of the Riam Kanan Reservoir as a water storage place for PM Noor HPP limits the amount of water that can be accommodated. During high rainfall, water can overflow into the spillway when the water level rises suddenly, resulting in the wastage of water as fuel. This happened in June 2024 when the water rose relatively high in the 8-15 cm range a day, so the water overflowed. The unusable water overflow show a significant loss for the hydroelectric power plant.

The dataset for the LSTM model consists of the reservoir water level shown in Figure. 2(a) and electricity production in kilowatt-hours (kWh) in Figure. 2(b) of the PM Noor HPP spanning from 2005 to 2023. This extensive dataset provides a detailed view of the power generation patterns over nearly two decades, capturing seasonal variations, annual trends, and any significant changes or anomalies in production. As seen in the graph, the inconsistent trend of hydroelectric power generation shows the challenge of predicting the potential energy production for hydroelectric power plant operation patterns. This is due to hydroelectric power generation's dependence on weather conditions and water levels. Water availability is a crucial factor that is highly influenced by weather. In "wet" years, electricity production tends to be high, while in "dry" years, electricity production from hydroelectric power plants decreases drastically due to limited water resources.

Water level parameters need to be added to the model so that the system can learn that electricity production is influenced by time and weather conditions, which can be represented by water availability. The model can adjust to current climate conditions to predict production for the next time.

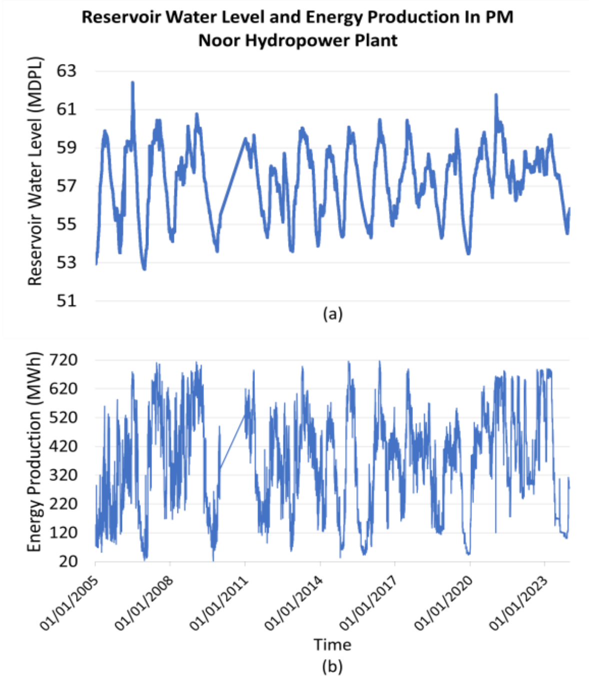

Figure. 2. Reservoir Water Level and Energy Production in Riam Kanan Over Decades as Variable input

The time series data is crucial for training the LSTM model to predict future electricity output. The model leverages the data's sequential nature to understand and forecast production patterns. The LSTM model's analysis of this dataset is vital in optimizing power generation strategies, which in turn significantly improves the plant's overall efficiency.

The dataset contains 6564 measurements of electric production and the reservoir's water level history from 01/01/2005 to 12/12/2023. Data from 2005 to 2020 will be used as input to train this LSTM model, while data from 2021 to 2023 will be used as a reference to test and compare the LSTM system's forecasting results. The data were preprocessed with transformation to normalization using Eq. (1). This process provides data structure on a scale of typical magnitude and stabilizes variance as data has a high value.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where:

- X is the original value
- X' is the normalized value
- X_{min} is the minimum value in the dataset
- X_{max} is the maximum value in the dataset

Data normalization adjusts the value of all data in the range 0-1. Normalization helps the performance and stability of the forecasting model, especially data that is affected by differences in scale between variables. By ensuring that all variables are in the same range, the relationship between variable models will be more proportional, so the prediction results will be more balanced and accurate.

3. LSTM proposed model

LSTM modeling for this system will predict "Power Produced" at PM Noor HPP within the desired time frame. The two variables inputted into the modeling are actual history data, Energy Produced" and "Reservoir Water Level". Both data are then entered into the LSTM modeling as input variables. The following process sets the number of layers and units so that the data can be trained and the prediction results can match the actual data.

The number of units and layers in an LSTM model significantly affects prediction performance. Layers refer to the number of LSTM layers arranged sequentially. Adding layers can affect the model's capacity to learn deeper feature representations. The number of layers also plays an important role. Adding more layers allows the model to learn deeper and more complex patterns, but it can also increase the risk of overfitting and training time. Conversely, fewer layers make the model train faster, but it may be less able to understand complex temporal patterns. Experimentation and validation are needed to find the optimal combination of the number of units and layers for prediction performance. Since only two variables are used in this system, using fewer layers is more appropriate.

Units (or neurons) are the essential components of an LSTM layer that determine the model's capacity to capture patterns from input data. More units allow the model to capture more complex patterns, but it risks overfitting if the number is too large. Conversely, fewer units speed up training but can reduce accuracy if essential patterns in the data are not captured. The correct number of units should be adjusted to the complexity of the data.

The architecture features a sequence of two and three LSTM layers with units set to 256, 128, 64, and 32, respectively. The design incorporates dropout layers with a rate of 0.3 and batch normalization after each LSTM layer, serving to prevent overfitting and maintain consistent input distribution across layers. This structural setup enhances the training process's stability and generalization capabilities.

4. Prediction Performance Evaluation

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) that have proven effective in handling sequential data, making them popular in time series forecasting, natural language processing, and other applications involving temporal dependencies. Evaluating the performance of an LSTM model is crucial to understanding how well it generalizes to unseen data. This evaluation typically involves several statistical metrics, including Root Mean Square Error (RMSE) and the coefficient of determination (R^2). Each metric provides unique insights into different aspects of the model's accuracy. RMSE is one of the most commonly used metrics to evaluate the accuracy of regression models, including LSTM networks, as expressed in Eq. (2). It measures the square root of the average squared differences between predicted and actual values. RMSE is particularly useful when large errors are undesirable, as it gives higher weight to large discrepancies between predictions and actual outcomes.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (2)$$

The coefficient of determination (R^2) measures the proportion of variance in the dependent variable that is predictable from the independent variables, as expressed in Eq. (3). It is a statistical measure that indicates how well the LSTM model captures the variance in the data.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - y_i)^2} \qquad (3)$$

3. EXPERIMENTAL RESULTS AND ANALYSIS

In performing LSTM modeling, setting the number of layers and units will affect the results of data forecasting. The proposed model is then tested and evaluated using statistical metrics. Based on data collected in the last 20 years, the proposed model LSTM results for power-produced prediction at PM Noor HPP are shown in Table 1. The results evaluation of RMSE and R2 values based on the number of layers and units are also shown to determine the most suitable modeling.

Table 1. Training and test results in different layers and units

Layers	Unit	RMSE	R^2
2	**32**	**0.06170**	**0.96391**
2	64	0.06569	0.95909
2	128	0.07892	0.94095
2	256	0.06916	0.95460
3	64	0.09149	0.92056
3	128	0.09518	0.91402
3	256	0.08492	0.93156
5	50	0.08095	0.92265
10	50	0.09033	0.93788

The LSTM model developed for predicting power produced demonstrates a strong predictive capability, as indicated by its performance metrics. The test results show that using a model with the number of layers = 2 and units = 32 shows the values and prediction results that best match the actual data. This is indicated by the Normalised RMSE value, which shows an error value of 0.0617 are relatively small compared to the range of power produced, the most minor compared to other modeling.

Moreover, the model achieves an impressive R^2 value of 0.96391, which means that it explains approximately 96.39% of the variance in the power produced data. This high coefficient of determination underscores the model's effectiveness in capturing the underlying patterns and relationships within the dataset. Whereas the R2 value closest to 1 means that the prediction results are more accurate to the actual data. Therefore, this model can be used predict the potential energy hydropower and producing consistently reliable predictions across the spectrum of data values.

The combined metrics of Normalized RMSE and R^2 reflect a robust model capable of delivering accurate predictions, making it a valuable tool for understanding and anticipating production trends.

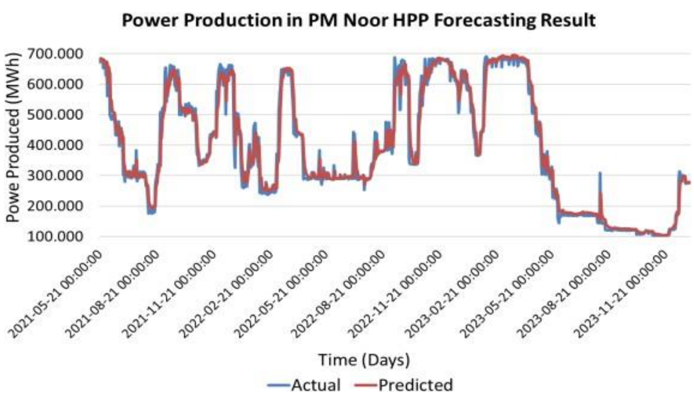

Figure. 3. Comparison Between Prediction Result and Actual Data For The Training and Test Dataset

A comparison of LSTM model forecasting data and actual energy data produced by PM Noor HPP in the 2021- 2023 period using the best model is shown in Figureure 3. The graph shows that the LSTM model can follow the prediction of potential energy production in hydropower plants quite well; in general, the forecasting results can follow the trend of changes in actual data. On average, the error of the prediction results compared to the actual data is 5.89%, whereas the error is still sufficient to be used as a basis for prediction. In the future, the results of this forecasting system modeling can be used to make a prognosis of electricity production from hydropower plants.

4. CONCLUSION

This paper presents an LSTM-based neural network for building a power production forecasting model for a hydroelectric power plant. The model was trained and tested using a dataset obtained from the power production history of the PM Noor Hydro Power Plant. The predictive capacity of the proposed model was evaluated in terms of RMSE and R^2, resulting in low errors for both training and test sets. Various conFigureurations of the number of LSTM layers and units were tested, with the best results achieved using two layers and 32 LSTM units. The average results obtained with this optimal LSTM conFigureuration closely matched the actual power production values of the PM Noor Hydro Power Plant with the normalized RMSE of 0.06170 and 0.96391 of R2 value. Therefore, it can be concluded that the LSTM-based neural network model is a promising approach for power production forecasting at the PM Noor Hydro Power Plant, contributing to efficiency studies, energy production, and hydropower control and management. Future work should explore other neural network conFigureurations, such as using multiple LSTM layers and other deep learning strategies to enhance performance.

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