APPLICATION OF DEEP LEARNING MODELS FOR FORECASTING HYDROPOWER PLANT POWER GENERATION

Mohd Qaedi Faiz Abdul Aziz [1] and Sofianita Mutalib [1]

[1] College of Computing Informatics and Mathematics, Universiti Teknologi MARA, Cawangan Selangor, Shah Alam, Malaysia.
lncs@springer.com

Abstract. Converting into Renewable Energy (RE) is one of the solutions for the "Climate Action" goal in the 13th Sustainable Development Goal (SDG). Renewable energy must meet the current energy demand if it wants to fully be converted from conventional energy sources like fossil fuels. Weathers play important parameters that can alter renewable energy power generation. With the application of Artificial Intelligent (AI) into our daily work increased in demand, incorporate this technology can be beneficial to optimized RE power production. This research investigates the relationship between weather conditions and power generation, aiming to identify the most significant variables and compare the accuracy of various Deep Learning models in hydropower forecasting. Using Mutual Information (MI) test for feature selection, the research identifies seven key variables. Subsequently, four Deep Learning models—Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), CNN-LSTM and CNN-LSTM models were trained to forecast hydropower generation with different time steps of 7, 30 and 90 days. LSTM performed the best either using filtered or unfiltered dataset, and at the least time steps. Resulting the performance metrics of MAE: 0.580, MSE: 0.531 and RMSE: 0.723. The findings contribute to a deeper understanding of how weather affects hydropower generation and provide insights into the optimal Deep Learning techniques for accurate forecasting.

Keywords: Renewable Energy, Hydropower, Hybrid Deep Learning Models, CNN, LSTM, Feature Selection, Weather Variability, Climate Action.

1 Introduction

Greenhouse gases (GHGs) in our atmosphere, such as water vapor, nitrous oxides, carbon dioxide, and methane, have the capacity to trap infrared radiation, thereby preventing heat from escaping. According to Our World in Data, energy use is responsible for up to 70% of greenhouse gas emissions. These emissions are produced from various activities, including residential energy use, transportation, and industrial processes [1]. By far the most major contributions to global climate change are fossil fuels, which are largely used for energy generation [2]. Many researcher studies in Renewable Energy (RE) domain to address this issue help to increase the conversion of traditional energy sources into safer and more ecologically friendly energy sources. According to the

International Renewable Energy Agency (IRENA), renewable energy can and should provide 90 per cent of the world's electricity by 2050 [3].

This study contributes on the application of deep learning model to forecast hydropower generation at specific area in Malaysia. Temenggor Dam in Perak, Malaysia, has unique tropical conditions with high humidity, heavy rainfall, and seasonal monsoons. The need for studies that use localized data can better reflect the region's environmental variables, providing more reliable forecasts. In addition, together with the emergence of Artificial Intelligence (AI), this technology potentially can play a vital role in designing more sophisticated energy power generation systems, allowing for better integration with the grid and reducing reliance on backup fossil fuels. Through advanced data analytics and machine learning, AI can forecast energy generation patterns, enabling better planning and management of renewable resources. This can lead to a more consistent energy supply, minimizing the need for backup power from fossil fuels [4], [5].

However, renewable energy must meet the current energy demand if it wants to fully be converted. One of the major challenges with renewable energy sources is their intermittent nature, which poses a significant problem in meeting overall energy demand. Climate patterns that are not constant may have an impact on hydropower's operational patterns, which might lead to intermittent energy supply and reliability [6]. According to Li Wei's [7] evaluation, power output at the hydropower plant is expected to rise throughout specific seasons of the year in response to fluctuations in precipitation. In Malaysia, the rainy season can drastically affect the water levels of dams and runoff, which in turn may impacts the rate of power generation. For that reason, some researchers suggested a runoff prediction model. Study conducted by Khor [8] and Mohammad [9] that focused on Malaysia weather. Both highlight the need for accurate runoff prediction and flood control infrastructure design, with Khor emphasizing the role of land use changes. Thus, understanding the relation between weather conditions and power output is essential for optimizing the prediction model.

One of the ways to increase accuracy is through feature selection. Feature selection is essential in this approach since it may considerably affect the predicted accuracy of the models [10]. Several studies have demonstrated that selecting relevant features can enhance model performance. For solar power generation, studies have demonstrated that feature selection may greatly improve the overall performance of probabilistic modelling [11]. It also concludes that the low importance of feature act as noise and reduce the accuracy of models. Additionally, weather variables including temperature and precipitation, are particularly important for predicting hydropower and solar power generation [12], [13]. This study aims to understand the weather patterns for Malaysia’s climates which give an insight on the possibility of weather effecting hydropower generation. Data from Temenggor Power Station was selected in this study and the production pattern was analyzed. Feature selection technique was also applied to the dataset to identify the most relevant variables to deep learning models. Finally, the performance of developed deep learning models was compared by analyzing the impact of feature selection and varying training time steps. Accuracy and the ability to future forecast on different period is important to measure the reliability of the model.

2 Literature Review

Hydropower is forms of Renewable Energy (RE), often known as hydroelectric power produces electricity by utilizing the natural flow of flowing water. With the abundant water sources and topographical diversity in Malaysia, the country holds great potential for further hydropower development. The Malaysian Investment Development Authority reports that renewable energy constituted 23% of Malaysia's energy mix as of 2021, with hydropower playing a dominant role at approximately 17% [14]. Temenggor Power Station is a hydroelectric power plant with a 348 MW installed capacity. It is situated on the Sungai Perak River/basin in Perak, Malaysia. The type of turbine used is the Vertical Francis turbine with the maximum capacity of 87 megawatts (MW) per unit. Francis turbines are suitable for usage with heads ranging from 30 to 300 meters, and equivalent items are available for a wide range of head sizes [15], [16].

2.1 Hydropower Generation Concept

Hydropower is an energy that is produced from conversion kinetic energy into electricity. It follows the law of conservation energy which says that energy is neither created nor destroyed [17]. The rate at which energy is produced is called power. Kilowatts (kW) or Watts (W) are used to measure power. Kilowatt-hours (kWh) or megawatt-hours (MWh) are units of energy that are utilized to perform work. The equation below represents the formula to calculate estimated power output of a hydropower system.

$$\boldsymbol{P = m \times g \times H_{net} \times \eta} \quad \textbf{(1)}$$

where the given parameters are $\boldsymbol{P}$, $\boldsymbol{m}$, $\boldsymbol{g}$, $\boldsymbol{H_{net}}$ and $\boldsymbol{\eta}$, which represent power (Watts, W), mass flow rate (kg/s), gravitational acceleration constant (9.81 m/s^2), net head (m) and general efficiency. The net head, which is measured in meters, is the height difference between the points where water enters and leaves a hydroelectric system. Typically, this would be the distance between the hydro intake screen and where the water exits the turbine and returns to the watercourse, or the height of a weir at the turbine entry if the site is underdeveloped [18]. Based on the water head mentioned, gaining as much head as possible is essential when using hydropower since more head results in more power (and energy) for not much more money, which boosts return on investment. Depending on how much flow you have, a hydro system's absolute minimum head requirement varies. Installing a hydro system will not be very economical if the heads and flow are low.

In the real situation of hydropower plants, engineers do not calculate manually the generated power based on the formula mentioned. Usually, in the plant there is a monitoring system that will calculate the estimated value of the power generated with various sensors installed. A case study conducted by Achitaev et al.[19] demonstrated the use of sensors that are embedded with mathematical formulation. This study involves the development of a nonlinear dynamic model of a hydraulic unit, given start-up and emergency processes, and the consideration of the effect of water hammer during transients. Additionally, this study also used the Francis turbine as experimental equipment.

2.2 Factor Effecting Hydropower Generation

Malaysia's climate is characterized by uniform temperatures, high humidity, and abundant rainfall. It experiences four distinct monsoon seasons due to wind flow patterns: the northeast monsoon (November to March), the southwest monsoon (May to September), and two inter-monsoon periods. These wind patterns, along with local topography, influence rainfall distribution, which varies seasonally across different regions [20]. Researchers have conducted numerous studies to identify the independent variables that influence precipitation patterns.

After carefully reviewing the research papers, it is evident that several independent variables have been identified as significant influences of precipitation patterns. The main findings revealed that factors such as temperature, wind patterns, humidity, and elevation have substantial impacts on precipitation. Additionally, land cover and vegetation types were also found to play a crucial role in determining precipitation patterns. These findings underline the complex interplay of various factors in shaping precipitation, highlighting the multifaceted nature of this meteorological phenomenon [21], [22].

Besides, a study made by Liyew that uses Machine Learning (ML) techniques to predict daily rainfall [23]. To find the best machine learning algorithms for precise rainfall prediction, this research analyzed many machine learning techniques. Rainfall's presence and intensity are influenced by several environmental conditions. Rainfall and its intensity are influenced by several elements such as temperature, relative humidity, sunlight, pressure, evaporation, and more, either directly or indirectly.

2.3 Related Work

The evolution of time series forecasting techniques in renewable energy has mirrored advancements in data science and computational power, transforming how energy systems are analyzed and optimized. According to review by Mystakidis et al. [24], that overview the forecasting techniques from statistical to deep learning and assemble methods. The improvement of approaches and technology have had a major impact on the evolution of the time series forecasting for renewable energy. Statistical time series analysis has been a key method in data analysis for a long time. It helps researchers understand changes over time for a single observation. This method, rooted in econometrics and business forecasting, is very useful in many fields, including epidemiology, environmental sciences, neuroscience, and medicine [25], [26].

Deep learning models composed of Neural Network structure are characterized by their multi-layered architecture, capable of learning hierarchical representations from data. They are also categorized into supervised and unsupervised learning approaches [27]. In the context of time series forecasting, this literature review focuses on two specific deep learning models: Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN). Based on the taxonomy of Machine Learning models, these networks fall under the supervised learning of deep learning models [28]. Table 1 show studies use CNN and LSTM models including optimization using feature selection techniques in renewable energy domain. From the overall observation of this literature review on CNN, it is a highly accurate model for predicting renewable energy power generation. The long Short-Term Memory (LSTM) model remains the most popular time series method in forecasting power generation.

Besides, a hybrid model is also applicable which combines CNN and LSTM. Hybrid models are useful when there are other complex parameters to be included. Also, it can predict difficult aspects of adapting and controlling uncertain conditions. Some studies have incorporated climate or weather data as independent variables, with power generation as the dependent variable. This approach involves analysing the correlation between these variables. For example, Numerical Weather Prediction (NWP) is also used in a prediction model, which will be an input for the model of energy power generation [29]. Predicting rainwater precipitation based on the Quantitative Precipitation Estimation (QPE) radar, then the data is connected to another model to predict power generation, also showing the need for a hybrid model. It demonstrates that the overall accuracy of hybrid models is much higher than other independent models [30].

Forecasting power generation, especially for hydropower plants, relies on understanding complex environmental factors and using advanced predictive models. Despite progress in using deep learning models like CNN, LSTM, and CNN-LSTM, key research gaps remain. Two important gaps are the need for regional data specificity and the impact of weather. These factors are crucial for improving the accuracy of hydropower generation forecasts. Temenggor Dam in Perak, Malaysia, has unique tropical conditions with high humidity, heavy rainfall, and seasonal monsoons. Upon searching for related papers from 2019 until 2024, most of the research is technically studied on the specific hydropower plants other than Malaysia climate. For instance, study made by Yang S [30] use the daily power generation and precipitation data of small hydropower stations in Hechi City and Guilin City in southern China. This observation showed more opportunities for research available for Malaysia's climate. The need for studies that use localized data can better reflect the region's environmental variables, providing more reliable forecasts. Besides that, climate has the possibility to alters precipitation patterns, increases extreme weather events, and shifts water availability, which may be impacting hydropower predictability especially at Temenggor Hydropower Plant. Research is needed to develop models that incorporate climate scenarios, ensuring more resilient and adaptable forecasting tools for sustainable hydropower management.

Table 1: Related work for CNN, LSTM and hybrid models.

References	Main Findings	Algorithms
[31]	The LSTM model outperformed the WNN model, achieving higher accuracy in predicting average monthly basin rainfall.	LSTM and WNN
[32]	The LSTM network can accurately forecast future power system load.	RNN and LSTM
[33]	Using a neural network approach like LSTM can significantly reduce the error in power demand forecasting compared to traditional statistical models.	LSTM, AR, MA, ARMA and ARIMA
[34]	100-layer LSTM model, using 120 months of hydroelectric generation time data, achieved the highest estimation accuracy	LSTM
[35]	The proposed hybrid model outperformed ARIMA and LSTM	LSTM-CNN, ARIMA,
[36]	CNN and LSTM models provide good prediction performance.	CNN and LSTM
[37]	The forecasting algorithms overall performed satisfactorily.	CNN, CNN-LSTM, ARMA and MLR
[38]	The CNN-BiLSTM model improves upon the prediction accuracy of the individual CNN and BiLSTM models, demonstrating its potential for forecasting energy consumption in the residential and commercial sectors.	BiLSTM, CNN, LSTM, SVR, RF, LSSVR, etc.
[39]	The proposed DSCLANet framework outperforms recent methods in solar power prediction.	CNN-LSTM, DSCLANet
[40]	Integrating sophisticated machine learning models with effective feature selection can significantly improve the precision of regional wind power predictions.	LSTM, ANN, SVM, CNN, ELM

Note. WNN = Wavelet neural network, AR = Autoregressive, MA = Moving Average, ARMA = Autoregressive Moving Average, ARIMA = Autoregressive Integrated Moving Average, MLR = Multiple Linear Regression, BiLSTM = Bidirectional Long Short-Term Memory, SVR = Support Vector Regression, RF = Radom Forest, LSSVR = Least Squares Support Vector Regression, DSCLANet = Self-Attention Mechanism Network, ANN = Artificial Neural Network, SVM = Support Vector Machines, ELM = Extreme-Learning Machines.

3 Methodology

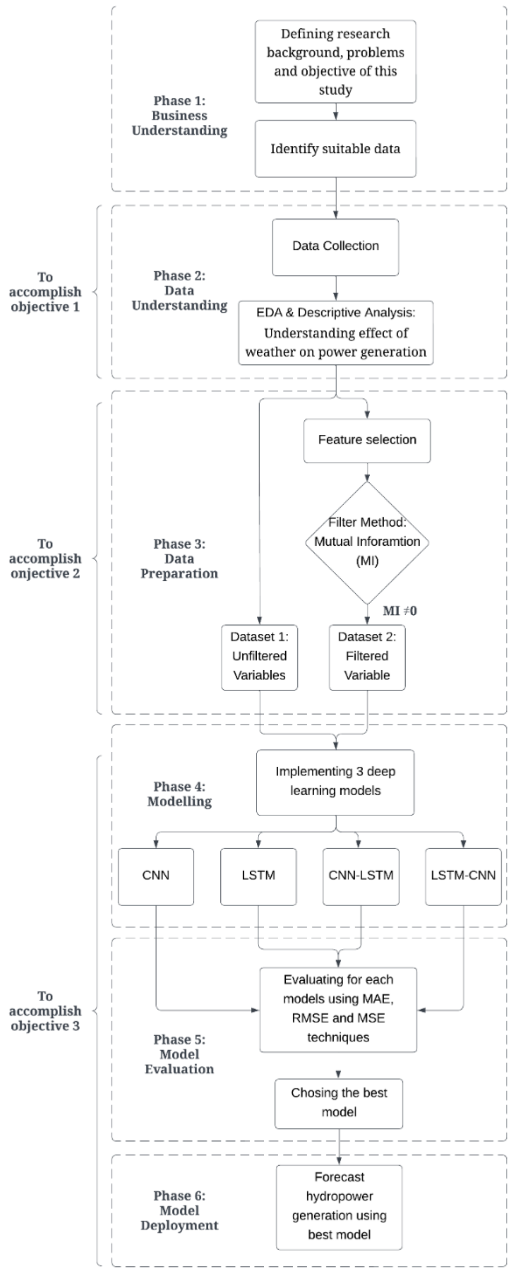

Figure 1: Research framework for Temenggor's hydropower generation forecasting models.

CRISP-DM (Cross-Industry Standard Process for Data Mining) framework was utilized in this research on forecasting hydropower generation using deep learning to ensure a systematic approach. The process begins with understanding the business objectives and defining the problem, then ends with the deployment phase that integrates the model into a future prediction. Figure 1 shows the research framework of this research. The goal of this study is to conduct Exploratory Data Analysis (EDA) and gain relevant insights of the dataset. Then, feature selection procedures will be utilized to identify the most significant variables that can help improve time-series forecasting accuracy by reducing numbers of variables. Finally, the study intends to develop and test deep learning models, then comparing their performance to understand the effects of feature selection and various training time steps on anticipated outcomes.

3.1 Datasets

Two different kinds of data were used. The ERA5 dataset from ClimateEngine.org is a worldwide climate reanalysis that provides a variety of climatic variables and is produced by the ECMWF's Copernicus Climate Change Service (C3S). Climate & hydrology, remote sensing, Hazards and forecast are the four kinds of information that can be extracted. However, only climate & hydrology variables were used in this study. Temenggor's Plant hydropower generating was used for the second dataset. In normal everyday operations, the power was measured every 30 minutes, with Megawatts (MW) serving as the unit of measurement. The hydropower dataset then transformed into daily basis for easier analysis. Overall, both ERA5 and power generation datasets are collected for five years period from 2019 until 2023. All variables are described in Table 2. Subsequently, preparing for feature selection and modelling, the dataset will be split into two samples with 70% and 30% ratio respectively: the training (in-sample) data and the testing (out-of-sample) data.

Table 2: Description of the ERA5 and Temenggor's hydropower generation dataset.

Variable	Datatype	Description
Date	Ordinal	The date of the daily observation.
Power Generation (MW)	Numerical	Temenggor Power Plan hydropower generation
Precipitation (mm)	Numerical	Total precipitation amount (mm or kg/m²).
Minimum Temperature (℃)	Numerical	Lowest temperature recorded during the day in degrees Celsius.
Maximum Temperature (℃)	Numerical	Highest temperature recorded during the day in degrees Celsius.
Mean Temperature (℃)	Numerical	Average temperature during the day in degrees Celsius.
Mean Dew Point Temperature (℃)	Numerical	Average temperature at which dew forms in degrees Celsius.
Hargreaves Potential Evaporation (mm)	Numerical	Estimated potential evaporation based on the Hargreaves method in millimeters.
Potential Water Deficit (PPT - Hargreaves PET) (mm)	Numerical	Difference between precipitation and potential evaporation in millimeters.

Wind Speed (m/s)	Numerical	Average wind speed in meters per second.
Eastward Wind Component (m/s)	Numerical	Wind velocity component in the eastward direction in meters per second.
Northward Wind Component (m/s)	Numerical	Wind velocity component in the northward direction in meters per second.
Sea Level Pressure (kPa)	Numerical	Atmospheric pressure adjusted to sea level in kilopascals.
Surface Pressure (kPa)	Numerical	Atmospheric pressure at the surface level in kilopascals.

3.2 Models

During the modelling phase, four different neural network configurations (CNN, LSTM, CNN-LSTM, and LSTM-CNN) were compared for forecasting performance. The models used the Rectified Linear Unit (ReLU) with Keras library in Python. This CNN model processes 1D sequential data with a batch size of 32. It starts with a Conv1D layer to extract local patterns, followed by BatchNormalization to stabilize and accelerate training. A MaxPooling1D layer reduces the spatial dimensions, emphasizing key features. The data is then flattened via a Flatten layer to transition from spatial representation to dense layers. A Dense layer with 25 units further processes the data, followed by another BatchNormalization layer for better generalization. Finally, a single-unit Dense layer produces the output, suitable for binary classification or regression tasks.

On the other hand, the LSTM model is designed to process sequential data and generate predictions, making it well-suited for time-series analysis or other sequence-based tasks. The architecture begins with an LSTM layer featuring 50 units to capture temporal dependencies in the input data, followed by a BatchNormalization layer that stabilizes learning by normalizing activations, improving convergence. The final Dense layer of LSTM model with a single unit serves as the output layer, suitable for binary classification or regression. The model has a total of 11,851 parameters, with 11,751 trainable parameters and 100 non-trainable parameters.

Sequential hybrid model was created by using same layer as in the individual models. CNN-LSTM and LSTM-CNN hybrid sequential architectures combine the temporal data processing capabilities of CNNs and LSTMs. The CNN-LSTM architecture starts by feeding data into the Conv1D layer, which extracts spatial patterns from the input data. Overall architecture of these models shown in Figure 2 and Figure 3 also with their parameters in Table 3 until Table 6. In the deployment phase, the model, originally trained on historical data from 2019 to 2023, was set up to handle future forecasting for new data from early 2024 and 90 days onwards.

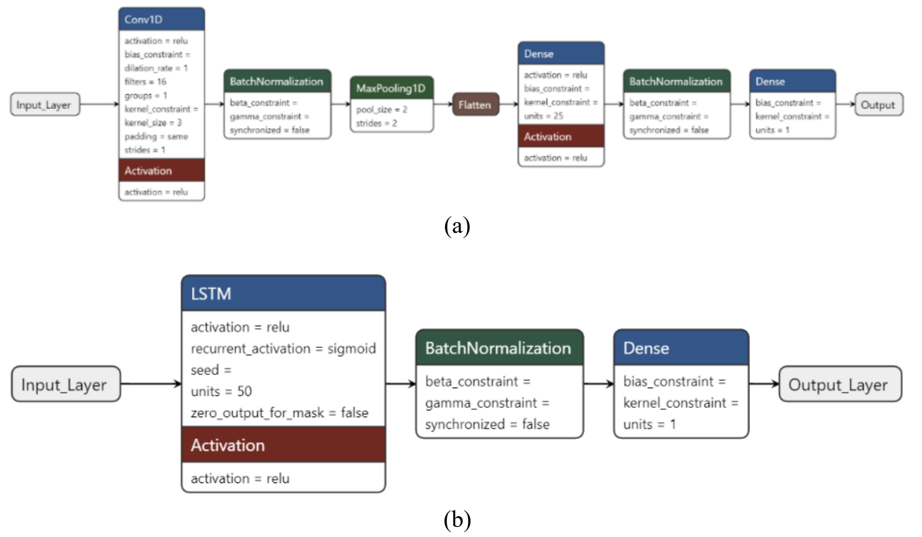

Figure 2: Individual CNN (a) and LSTM (b) models

Table 3: CNN model parameters

Layer (Type)	Output Shape	Parameters
Convolutional Layer (Conv1D)	(32, 7, 16)	352
Batch_Normalization (BatchNormalization)	(32, 7, 16)	64
Max Pooling Layer (MaxPooling1D)	(32, 3, 16)	0
Flatten Layer (Flatten)	(32, 48)	0
Fully Connected Layer (Dense)	(32, 25)	1,225
Batch Normalization (BatchNormalization)	(32, 25)	100
Output (Dense)	(32, 1)	26

Table 4: LSTM model architecture

Layer (Type)	Output Shape	Parameters
LSTM Layer (LSTM)	(32, 50)	11,600
Batch Normalization (BatchNormalization)	(32, 50)	200
Output Layer (Dense)	(32, 1)	51

In the hybrid sequential model architecture, BatchNormalization was applied to stabilise the learning process by normalising the intermediate results. After that, MaxPooling1D is used to reduce the dimension of feature maps by retaining only the most striking features while reducing computational overhead. The output from the convolution module is fed into a Dense layer for further refinement of the extracted feature and more, which is succeeded by another BatchNormalization layer to stabilize its training. Finally, the processed features are fed into the LSTM layer.

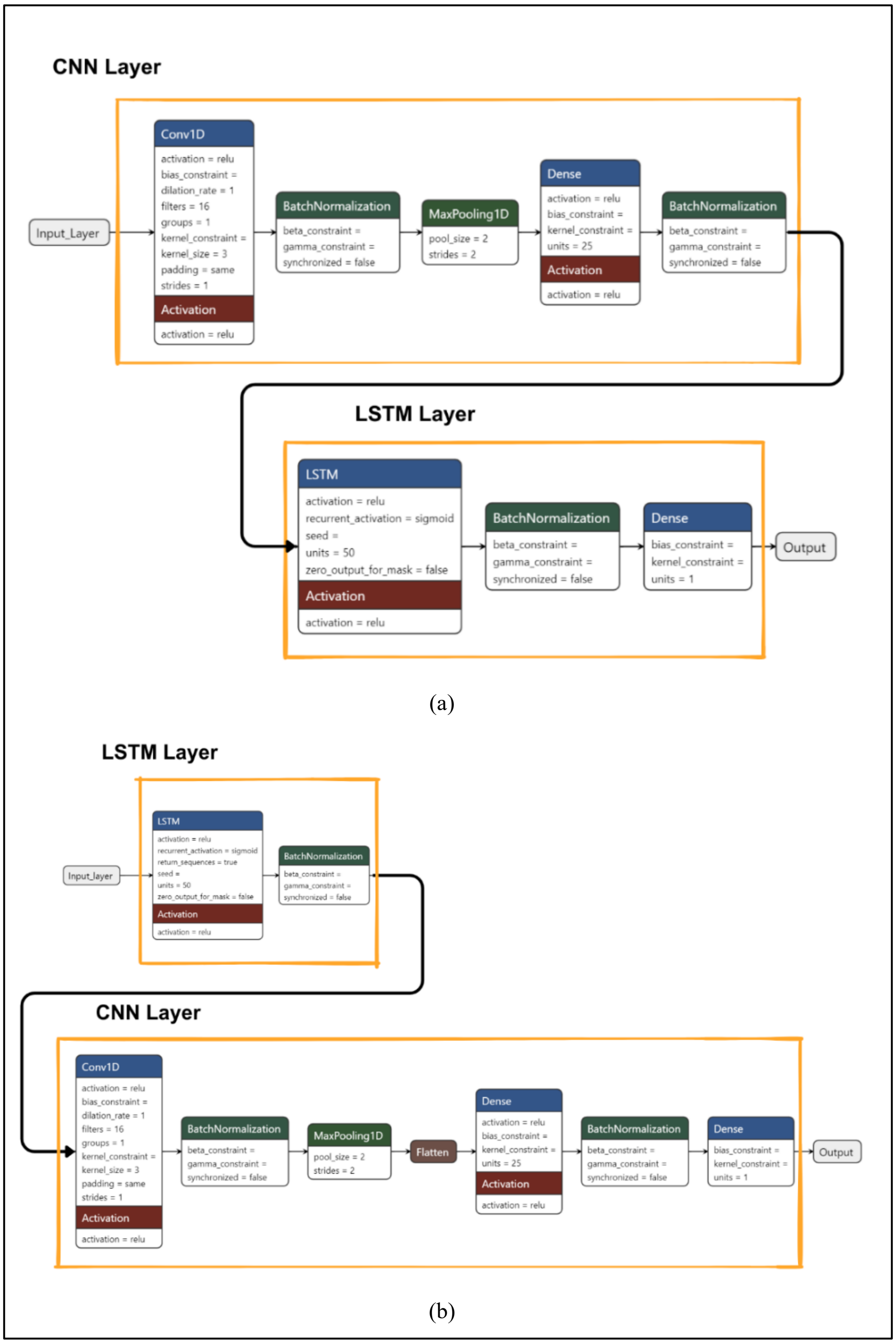

Figure 3: Hybrid sequential models: CNN-LSTM (a), LSTM-CNN (b)

Unlike the CNN-LSTM model, the LSTM-CNN architecture starts with an LSTM layer that directly processes the input series to capture temporal relationships. To achieve robust training, the output of the LSTM layer was normalised using BatchNormalization. A Conv1D layer collects spatial features from temporal outputs, which are then downsampled and improved with another BatchNormalization layer and MaxPooling1D. The data was flattened before being sent to a Dense layer to process the extracted features, which are then routed to a final Dense output layer for prediction. The LSTM-CNN model consists of 15,631 parameters, of which 15,449 are trainable.

Table 5: CNN-LSTM Model Architecture

Layer (Type)	Output Shape	Parameters
Convolutional Layer (Conv1D)	(32, 7, 16)	352
Batch Normalization (BatchNormalization)	(32, 7, 16)	64
Max Pooling Layer 1 (MaxPooling1D)	(32, 3, 16)	0
CNN Fully Connected Layer (Dense)	(32, 3, 25)	425
Batch Normalization (BatchNormalization)	(32, 3, 25)	100
LSTM Layer (LSTM)	(32, 50)	15,200
Batch Normalization (BatchNormalization)	(32, 50)	200
Output (Dense)	(32, 1)	51

Table 6: LSTM-CNN Model Architecture

Layer (Type)	Output Shape	Parameters
LSTM Layer (LSTM)	(32, 7, 50)	11,600
Batch Normalization (BatchNormalization)	(32, 7, 50)	200
Convolutional Layer (Conv1D)	(32, 7, 16)	2,416
Batch Normalization (BatchNormalization)	(32, 7, 16)	64
Max Pooling Layer (MaxPooling1D)	(32, 3, 16)	0
Flatten Layer (Flatten)	(32, 48)	0
CNN Fully Connected Layer (Dense)	(32, 25)	1,225
Batch Normalization (BatchNormalization)	(32, 25)	100
Output (Dense)	(32, 1)	26

3.3 Evaluation

Model accuracy was assessed using three common metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). By employing these metrics, the performance of the CNN, LSTM, CNN-LSTM and LSTM-CNN models in forecasting will be comprehensively evaluated, enabling insights into their relative strengths and weaknesses in capturing and predicting patterns in the data. There are four steps that need to be taken:

1) **Data Splitting**
   - Training Data (In-Sample): 70% of the dataset will used to train the models.
   - Testing Data (Out-of-Sample): The remaining 30% of the dataset, used to evaluate the models.

2) **Model Training**
    - Train the CNN, LSTM, CNN-LSTM and LSTM-CNN models using the training data.
    - Three different time steps were taken as a data window for the model to take the sample and forecast the next values. The time steps are 7 days (1 week), 30 days (1 month) and 90 days (1 quarter).

3) **Model Evaluation**
    - Evaluate the models using MAE, MSE, and RMSE to measure accuracy and reliability.
    - The ability of the model to different time steps also was evaluated.

4) **Comparative Analysis**
    - Compare the MAE, MSE, and RMSE values for the CNN, LSTM, CNN-LSTM models and LSTM-CNN.

4 Results and Discussion

Analysis, model development and experimentation discussed in this section, explained based on the sequence in research framework and to meet research objectives. Starting from the first objective which to conduct an Exploratory Data Analysis (EDA) to gain insights and a comprehensive understanding of the dataset. Then, feature selection is the second part of this section from second objective, performing feature selection methods to identify key variables. Lastly, the third objective is to develop and compare the accuracy of the model between the Deep Learning techniques, that are explained in model development, model accuracy and model training runtime parts.

4.1 Exploratory Data Analysis (EDA)

Based on the power generation of Temenggor Plant from 2019 until 2023 as shown in Figure 4, the temporal series for power generation demonstrates high variability and significant noise, indicating irregular patterns and fluctuations in the data. This aligns with previous observations that outliers are present, confirming the noisy nature of the dataset. However, the trend of the hydropower generation series increases at around 600 days, estimated in the year 2020. The second line graph was plotted in Figure 5 to zoom in the series for the year 2020 only.

The Hydropower generation for 2020 plot shown in Figure 5 clearly shows the sudden increase in power generation. It was observed on the 213th day of 2020, which specifically starts to increase on 31st July 2020. Then, the power generation series continues to maintain its production rate until 2022, then decreases slightly at the end of 2023. The trend from this noisy hydropower generation can be clearly seen in the time series decomposition section which will be explained later. These changes of trend of the target variables for this project may affect the predictability of the forecasting model.

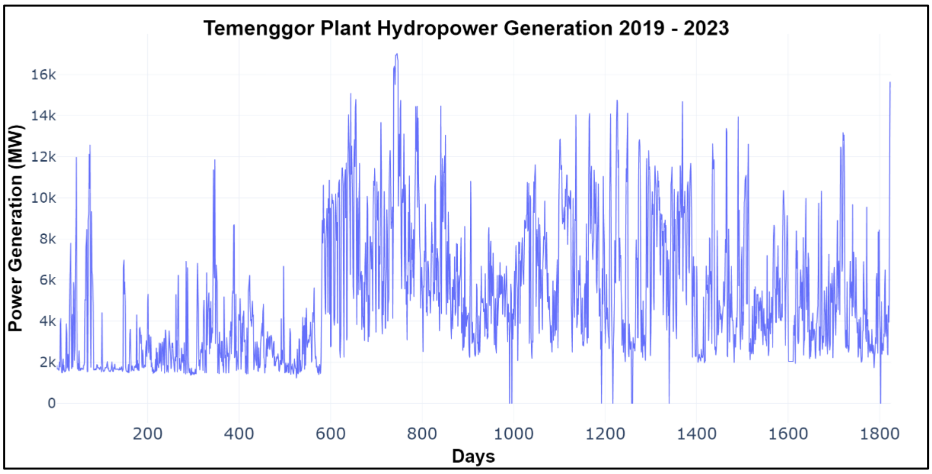

Figure 4: Line chart for Temenggor Plant hydropower generation from 2019 until 2023

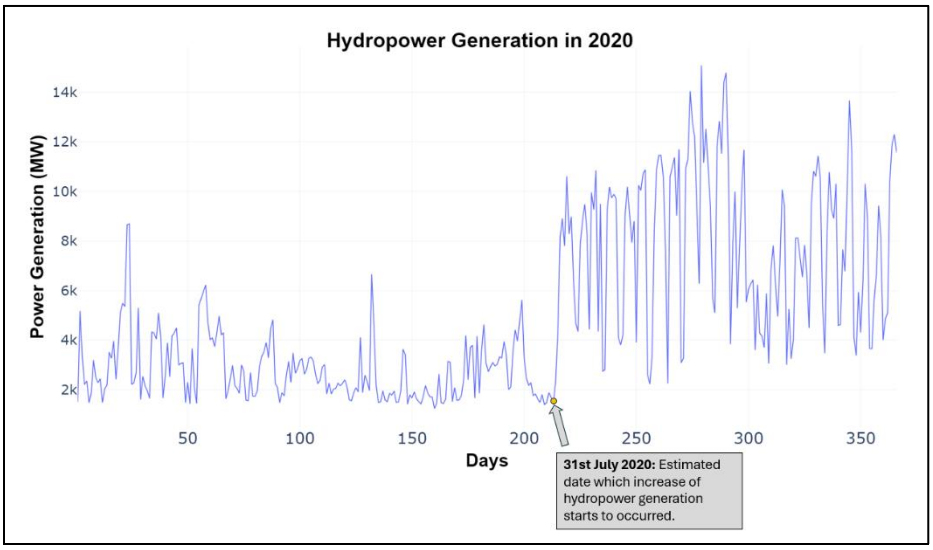

Figure 5: Line chart for Temenggor Plant hydropower generation for year 2020.

Nevertheless, it was assumed that the unexpected increase was not entirely due to climate change or a rise in the consumption for energy during the Malaysia Movement Control (MCO) order for the COVID-19 epidemic. Some of the researchers study the patterns of electricity demand in Malaysia and around the world, concluded that the electricity demand pattern was greatly altered by the COVID-19 epidemic. During lockdowns, overall electricity demand decreased due to the closure of economic sectors [41]. Similar patterns were seen around the world, as household consumption rose by up to 30% while overall electricity demand decreased [42], [43]. Future energy management plans and regulations may will be impacted by these shifts in energy usage trends.

The increase in the hydropower generation may because of the operational shift in Temenggor Power Plant. As mentioned in the literature review Temenggor Power Station section, current target from TNB is to increase the production of Sungai Perak power plants (SSJ Sungai Perak) to 650.75 megawatts (MW) to meet Malaysia's goals for renewable energy (RE) and to ensure its sustainable economic growth [44]. To meet this target, the power plant needs to generate more energy than previous year. Despite the Temenggor power plant, there are also other power plants built in cascade scheme to meet the renewable energy goal for instance Bersia, Kenering and Chenderoh power plant [45].

4.2 Feature Selection

The bar chart in Figure 6 displays the mutual information (MI) scores of several attributes, highlighting their relationship to the target variable which is Power Generation (MW). This approach assists in identifying the most important features for modelling while deprioritizing fewer impacting ones.

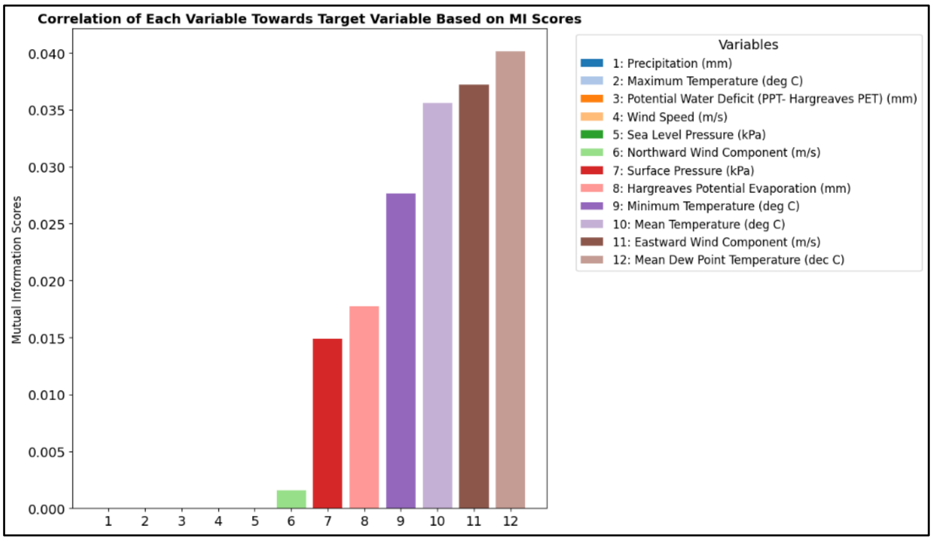

Figure 6: Correlation of Each Variable Towards Target Variable Based on MI Scores (Higher MI score means higher dependency to target variables).

The features having the highest MI scores are Mean Dew Point Temperature (°C), Eastward Wind Component (m/s), Mean Temperature (°C), and Minimum Temperature (°C), indicating a significant relevance to the objective. Hargreaves Potential Evaporation (mm), Surface Pressure (kPa), and Northward Wind Component (m/s) all make moderate contributions, but Wind Speed (m/s), Potential Water Deficit (mm), and Sea Level Pressure (kPa) have weaker connections. Precipitation (mm) has the lowest MI score, indicating that it is of minor value in predicting the desired outcome. Therefore, the filtered dataset will have eight variables including the target variable.

4.3 Model development

Sequential hybrid technique was used to investigate the potential performance advantages and complementing capabilities of CNN and LSTM when combined in different sequential orders. This technique enabled an examination of how model structure influences overall model efficiency and adaptability to the forecasting tasks. However, to make this model successfully able to do forecasting of hydropower generation, trial and error with slight modification will be discussed in this section. The final model was stated and explained in methodology section.

During the model development, underfitting happens when a machine learning model contains a small number of predictors, resulting in a very simplistic model that does not accurately represent the prevalent data pattern. This problem also occurs when the training data set is insufficient or not representative of the population data [46]. Figure 7 shows the forecasted values using an underfitted model and take CNN-LSTM as an example.

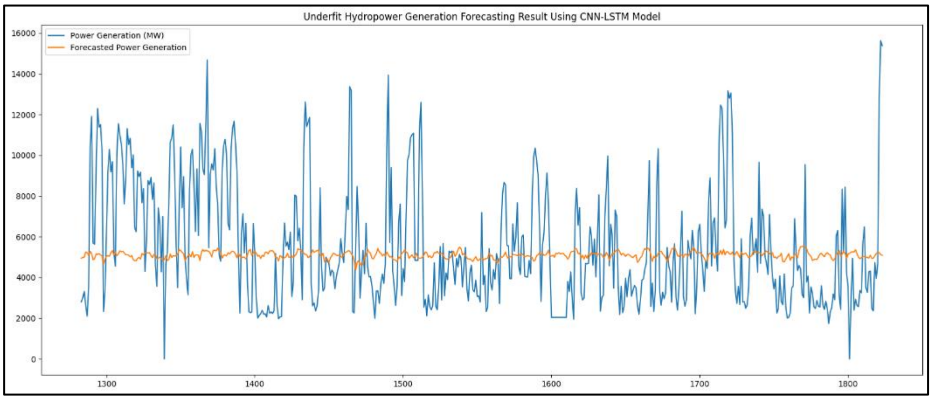

Figure 7: Underfit CNN-LSTM model: Actual vs forecasted hydropower generation for 7 days timesteps process.

Based on the observation of Figure 7, the forecasted values do not match the actual data pattern. Sudden increase of hydropower generation in 2020 as mentioned in discussion of EDA part may be related to underfit model. The model does not have sufficient information after the sudden increase occurred. In addition, it also does not represent overall population data because human intervention caused the hydropower generation pattern to be changed.

The solution to adapt with noisy and fluctuated datasets is to apply preprocessing techniques in the deep learning layers. Alternatively, regularization techniques can be employed to overcome an underfit model with noisy and fluctuated data. This method is applied between the neural network layers, normalizing the layer's inputs in small batches by subtracting the Mean and dividing by the Standard Deviation. Despite batch normalization to resolve the underfit, weight initialization was experimented to solve the underfit model problem. The He weight initializer was recommended to work better for layers with activations of ReLU and LeakyReLU as it solving dying neuron problems [47], [48]. Also, He weight initializer improves the performance of the LSTM model for respiratory signal prediction compared to other initializers [49].

On the epoch number for model training, it was decided to use 100 epochs for training all the models after trial and error. Because all the model's learning curves can converge in less than 100 epochs. Moreover, ReLU was initially planned to be used for CNN and Tanh for LSTM model. Sigmoid recurrent activation function for LSTM model is by default in Keras library. Since this project utilized a single layer of deep learning, recurrent activation function was excluded. To make a proper comparison between CNN and LSTM, the Tanh activation function in LSTM was replaced by ReLU to complement the application of the He weight initializers for all the models.

4.4 Model Evaluation

This section analyzed the model performance using unfiltered and filtered datasets. Table 7 below shows the performance metrics for models using unfiltered datasets in MAE, MSE, and RMSE. These results were analyzed at three time-intervals: 7, 30, and 90 days.

Table 7: Performance metrics using unfiltered dataset.

Time steps (Days)	Models / Metrices	CNN	LSTM	CNN-LSTM	LSTM-CNN
	MAE	0.610	0.587	0.681	0.663
7	MSE	0.578	0.522	0.737	0.698
	RMSE	0.760	0.723	0.858	0.836
	MAE	0.694	0.620	0.691	0.726
30	MSE	0.730	0.605	0.729	0.828
	RMSE	0.854	0.778	0.854	0.91
	MAE	0.817	0.611	0.674	0.946
90	MSE	1.056	0.570	0.718	1.45
	RMSE	1.028	0.755	0.847	1.204

On the short timesteps of 7 days, as shown in Figure 8, the LSTM model consistently outperforms all others, achieving the lowest error values (MAE: 0.587, MSE: 0.522, RMSE: 0.723). While CNN also performs reasonably well, it lags slightly behind LSTM. The hybrid models, CNN-LSTM and LSTM-CNN, show higher error values, suggesting reduced performance although training with shorter sequences of data. At medium the timesteps (30 days) as shown in Figure 4-11, LSTM continues to demonstrate superior performance (MAE: 0.620, MSE: 0.605, RMSE: 0.778). CNN performs similarly to CNN-LSTM, with a little higher MSE. In terms of MAE (0.694 vs. 0.691) and RMSE (both 0.854) respectively.

Figure 8: Model performance using unfiltered datasets for all timesteps: (a) 7 days, (b) 30 days and (c) 90 days

Filtered dataset resulted from feature selection step using Mutual Information (MI) consist only of key significant variables, which are Minimum Temperature (deg C), Mean Temperature (deg C), Mean Dew Point Temperature (dec C), Hargreaves Potential Evaporation (mm), Eastward Wind Component (m/s), Northward Wind Component (m/s) and Surface Pressure (kPa). Deep learning models in this project were trained again using filtered datasets to compare with models that have been trained using unfiltered datasets. The performance recorded in Table 8. Based on the result, LSTM model continues to demonstrate the best performance across all time steps, achieving the lowest error metrics (MAE, MSE, RMSE). Like its performance with the unfiltered dataset, CNN works well for shorter time steps (7 days) but suffers greatly from longer time steps (90 days). Although it performs consistently, the CNN-LSTM model cannot outperform the LSTM alone. In addition, even after feature selection, the LSTM-CNN model still records the most errors, especially for longer time steps, demonstrating its inefficiency in processing lengthy sequences.

Table 8: Performance metrics using filtered dataset.

Time steps (Days)	Models / Metrices	CNN	LSTM	CNN-LSTM	LSTM-CNN
	MAE	0.612	0.580	0.611	0.629
7	MSE	0.571	0.531	0.586	0.626
	RMSE	0.756	0.729	0.766	0.791
	MAE	0.653	0.626	0.640	0.745
30	MSE	0.676	0.598	0.642	0.871
	RMSE	0.822	0.773	0.801	0.933
	MAE	0.748	0.624	0.629	0.893
90	MSE	0.865	0.589	0.611	1.246
	RMSE	0.930	0.767	0.782	1.116

The filtered dataset exhibits a little better performance for most models when compared to the unfiltered dataset. LSTM is the most advantageous, particularly for longer time steps, indicating that feature selection enhances its effectiveness. Additionally, CNN performs slightly better for shorter time steps but struggles with longer time steps. The hybrid models like CNN-LSTM and LSTM-CNN show slight improvements with the filtered dataset, but LSTM-CNN still performs lowest overall. To see clear impact of the feature selection, the model improvement in terms of percentage can be analyzed that compare the errors between filtered and unfiltered datasets, showing the changes of the model performance after feature selection. Positive values in the table indicate that the improvement has occurred, whereas negative values indicate the reduction in performance. Significant performance differences between CNN, LSTM, CNN-LSTM, and LSTM-CNN models at 7, 30, and 90-day time steps are shown in Table 9 when the feature selection was applied.

Moreover, based on the result in Table 9, CNN and hybrid models (CNN-LSTM, LSTM-CNN) benefit the most from feature selection at shorter and longer time horizons. LSTM alone generally suffers from filtering, suggesting that its performance relies more on the full feature set rather than a subset of selected features. The CNN-LSTM and LSTM-CNN models exhibit significant gains for shorter time steps at 7 days. Feature selection also greatly improves CNN and hybrid models at the longest time step (90 days), with CNN showing the greatest improvement in MAE (8.446%) and MSE (18.087%). Significant improvements are also seen in all metrics using CNN-LSTM and LSTM-CNN, especially MSE (14.903% and 14.069%). But LSTM by itself still has a detrimental effect, especially in MAE (-2.128%) and MSE (-3.333%).

Table 9: Changes of The Models Performance After Feature Selection.

Time steps (Days)	**Metrices**	**CNN**	**LSTM**	**CNN-LSTM**	**LSTM-CNN**
		Performance Difference (%)			
7	MAE	-0.328	1.193	10.279	5.128
	MSE	1.211	-1.724	20.488	10.315
	RMSE	0.526	-0.830	10.723	5.383
30	MAE	5.908	-0.968	7.381	-2.617
	MSE	7.397	1.157	11.934	-5.193
	RMSE	3.747	0.643	6.206	-2.527
90	MAE	8.446	-2.128	6.677	5.603
	MSE	18.087	-3.333	14.903	14.069
	RMSE	9.533	-1.589	7.674	7.309

Note: Positive values indicate model improvement, and negative values show a reduction in the performance

Overall, in this analysis, the LSTM and CNN-LSTM models showed the most pronounced improvements in model performance when feature selection is done and trained using the filtered dataset. Nonetheless, the overall ranking of the models stays the same, with LSTM being the most successful and LSTM-CNN the least. CNN is at best performance at lower time steps, but further improvement is needed to overcome the overfit issue at higher time steps.

4.5 Forecasted Result Analysis

After analyzing the performance, LSTM outperformed CNN, CNN-LSTM and LSTM-CNN models in all areas, despite the training time for LSTM is higher compared to other models as the timesteps increase. Also, the LSTM model using filtered dataset for training performs slightly better than using unfiltered dataset. The plot in Figure 9 illustrates the comparison between actual and forecasted power generation over a period, with the results generated using LSTM. The first key observation is the forecasted power generation (orange line) closely follows the actual power generation (blue line), indicating that the LSTM model has captured the general trend and patterns of the data.

The second observation is that the model fails to accurately predict some of the severe spikes and drops that are common in time series forecasting due to the difficulty of capturing quick or irregular oscillations. Deep learning algorithms have shown promising results in predicting renewable energy generation, particularly solar and wind power. RNNs, CNNs, and LSTM networks have all demonstrated more accuracy than traditional methodologies [50]. However, some hybrid models struggle to capture abrupt or chaotic changes [51].

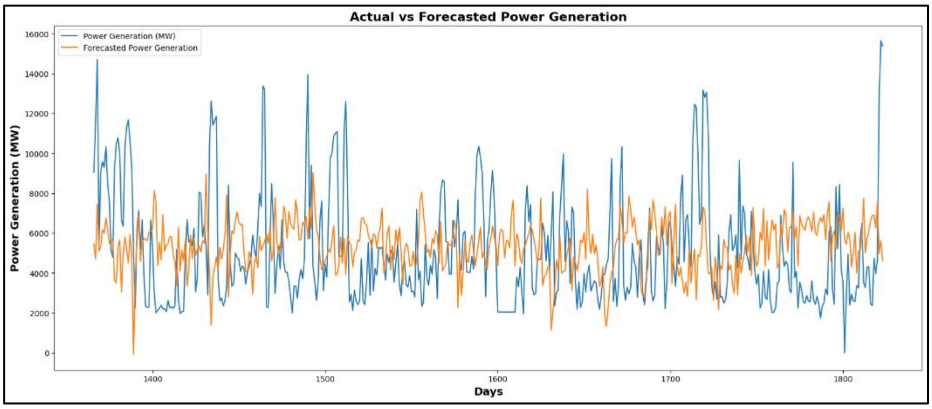

Figure 9: Actual vs Forecasted Power Generation

Overall performance of LSTM model shows there is a good agreement between the two lines, some deviations (gaps between the actual and forecasted values) are noticeable, suggesting room for improvement in the model, such as fine-tuning hyperparameters, increasing the dataset size, or incorporating additional features. Finally, Figure 10 illustrate the future forecast for the Power Generation of Temenggor Power Plant using LSTM model. Actual Power Generation is the Temenggor Power Plant's hydropower generation from 2019 until 2023. The power generation future forecast for 90 days represented the red line in Figure 10.

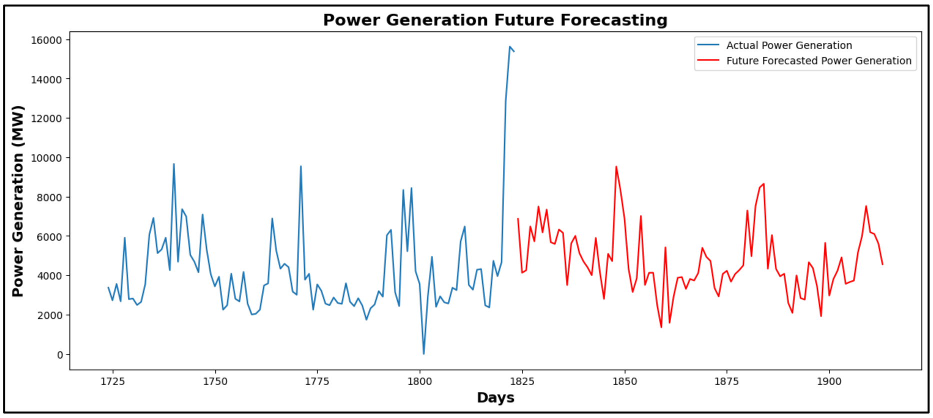

Figure 10: Future Forecast for Power Generation of Temenggor Power Plant using LSTM (Note: The future forecast of power generation represents future values for 90 days after year 2023).

5 Conclusion and Indication for Future Research

This study fills the key research gap by utilizing localized data that more accurately reflects the region's distinct environmental conditions, resulting in more believable energy estimations. Additionally, it creates models that incorporate climate scenarios, resulting in more resilient and flexible forecasting tools for sustainable hydropower management. Exploratory data analysis was conducted to gain insights and a comprehensive understanding of the dataset. Result from this analysis serve as an insight into the behavior of hydropower generation dataset in Temenggor Power Plant that beneficial in developing and selecting proper forecasting model. Furthermore, this research performed feature selection methods to identify key variables in developing forecasting models. Feature selection proved in this project can improve performance which is beneficial in real applications. Lastly, the performance of models was evaluated and LSTM chosen as best models. Model evaluation is critical in choosing the best model before real deployment.

Some tweaks have been made to solve the underfit model by implementing the batch normalization and weight initializer. The model properly fits after that and the result has been discussed, demonstrating the capability of LSTM over other models. CNN is good at lower time steps but the performance declines after increasing time steps. Increasing time steps in CNN model make it capture more data that resulted in the model becoming overfit, and the main reason the error increase at higher time steps. This is another challenge that can be studied further to solve this problem.

Future studies on this subject might investigate more effective ways to raise the precision and robustness of forecasting models for renewable energy. These model performances show a lot of potential for the future of time series forecasting since they give effective solutions for detecting spatial and temporal data relationships. Additionally, the real-world implementation of time series forecasting at Temenggor Plant Hydropower Generation can be examined.

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