SEMARAK ILMU PUBLISHING

Semarak International Journal of Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.my/index.php/sijaset/index
ISSN: 3030-5314

Long-Term Forecasting of Hydropower Generation and Electricity Demand using Artificial Neural Networks: Energy Gap Analysis between the Wlingi Hydropower Plant and Electricity Demand in Blitar Regency, Indonesia

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ARTICLE INFO

Article history:
Received 27 November 2025
Received in revised form 20 February 2026
Accepted 15 April 2026
Available online 14 May 2026

Keywords:
Hydropower; climate change; energy forecasting; artificial neural network; renewable energy resilience

ABSTRACT

This study investigates the long-term structural electricity production–consumption gap under climate-induced hydrological variability, focusing on the Wlingi Hydroelectric Power Plant and Blitar Regency, Indonesia. Using historical operational and hydro-meteorological data from 2020–2025 as baseline input, three Artificial Neural Network (ANN) architectures Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU) are comparatively evaluated to forecast electricity production, demand growth, and the resulting energy deficit over the 2026–2045 horizon. The predictive simulation reveals a progressively widening structural gap, expanding from approximately −427 GWh in 2026 to nearly −1,668 GWh in 2045, driven by exponential regional demand escalation and gradual hydropower performance degradation linked to global warming induced river discharge instability. While historically contributing 25%–37% of regional electricity demand, the hydropower fulfillment ratio is projected to decline to below 8% by 2045, indicating a substantial erosion of local renewable energy autonomy. Computational evaluation confirms that LSTM and GRU exhibit superior robustness and long-term dependency modeling compared to conventional RNN, particularly under stochastic hydro-climatic conditions. The novelty of this research lies in integrating climate-driven hydrological uncertainty into ANN based energy gap forecasting for operational hydropower systems. The findings underscore the vulnerability of climate-dependent renewable infrastructure and highlight the urgency of climate-adaptive energy diversification and storage integration strategies to sustain regional grid resilience under accelerating global warming pressures.

1. Introduction

The escalating demand for electrical energy in Indonesia, particularly within rapidly developing regions such as Blitar Regency, necessitates a more resilient and sustainable energy diversification

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strategy in tandem with the global transition towards renewable energy [1]. Historically, local energy planning has remained vulnerable to environmental shifts, rendering renewable sources like hydropower susceptible to extreme climate anomalies [2]. The Wlingi Hydroelectric Power Plant, a crucial energy asset, faces multidimensional risks driven by global warming and climate change, which significantly reduce river water discharge and disrupt power production capacity [3]. These conditions necessitate the accelerated optimization and adaptive management of renewable energy sources to cultivate a resilient green energy ecosystem [4,5]. Strategic implementation in the form of precise predictive modeling is expected to significantly mitigate the risk of energy deficits [6]. This integrative approach aims not only to enhance operational efficiency but also to strengthen national energy resilience in the face of future climate challenges and consumption trends [7].

The optimization of hydropower systems in vital regions possesses high strategic urgency, considering the continuous growth in local electricity demand [8]. Although renewable energy systems like the Wlingi Hydroelectric Power Plant offer sustainability potential, their effectiveness is highly contingent upon the ability to predict hydrological intermittency caused by climate change and stochastic load demand fluctuations [9,10]. In the context of time-series data modeling, Recurrent Neural Network (RNN) methods are frequently utilized as a baseline; however, this architecture suffers from a fundamental weakness known as the vanishing gradient problem, which impedes prediction accuracy over long data periods. To address these limitations, this study focuses on energy gap analysis by comparing the performance of RNN against advanced Artificial Neural Network (ANN) architectures, namely Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). This research aims to validate whether the gating mechanisms in these state-of-the-art models can significantly improve power balance precision between the declining production capabilities of the Wlingi Hydroelectric Power Plant and Blitar Regency's electricity demand compared to basic methods. A comprehensive evaluation is conducted on vital indicators such as prediction accuracy, loss function, and energy gap mapping to serve as a basis for optimal technical decision-making [11].

Table 1
Comparative literature review

Reference	Methods	System	Results
[12]	Coupled Hydrologic–Operations Modeling (WATFLOOD–MODSIM, HEC-HMS–MODSIM)	Cascade Hydropower System – Lower Nelson River Basin	Climate change projections indicate seasonal shifts in inflow patterns, with increased spring generation potential but significant winter reductions (up to 37%). The study highlights high climate sensitivity and operational uncertainty in large-scale cascade hydropower systems.
[13]	SWAT Hydrological Modeling + Climate Scenario Analysis	Rio Jubones Basin Hydropower Plant	Climate change scenarios (↑2.9°C, ↓15% rainfall) may reduce dry-season hydropower generation by 13.14%. The SWAT model successfully simulated seasonal flow variability (NSE ≈ 0.61–0.66).
[14]	Artificial Neural Network (Feed-Forward Backpropagation)	Small Hydropower Plant – Himreen Lake Dam	ANN achieved high predictive accuracy ($R > 0.96$) in modeling nonlinear relationships between net head, discharge, and power generation. Demonstrated strong capability for short-term hydropower forecasting.
[15]	ANN, SVM, ARIMA (Machine Learning Comparison)	Three Gorges Dam Hydropower System	Machine learning models effectively predicted daily, monthly, and seasonal hydropower generation. ANN and SVM outperformed ARIMA under nonlinear and stochastic conditions, with uncertainty analysis showing 95PPU within 80–100%.

[16]	AHP–COPRAS–Integer Programming (MSO Optimization)	Large-Scale Hydroelectric Power Plant (571 Equipment Units)	Integrated MCDM–IP framework optimized maintenance strategies, minimizing generation downtime and improving operational reliability at system level. Demonstrated feasibility for complex multi-equipment hydropower systems.

This study introduces Novelty in different technical frameworks for predicting energy gaps in operational hydropower systems by rigorously evaluating RNN, LSTM, and GRU algorithms. Unlike existing literature that predominantly focuses on standard load forecasting, this research addresses the critical power imbalance caused by climate-induced water discharge reduction and escalating electricity demands in Blitar Regency. The core novelty lies in the comparative analysis of LSTM and GRU gating mechanisms against standard RNN architectures to determine their predictive resilience under extreme, dual-sided stochastic variations. Specifically, this framework pioneers the application of these ANN models to project multi-decadal structural energy deficits from 2026 to 2045 rather than conventional short-term daily load fluctuations. We explicitly investigate whether the computational complexity of these advanced deep learning models is technically justifiable by a significant reduction in Root Mean Square Error (RMSE) and improved convergence speed under these prolonged climate-stress conditions. Furthermore, by utilizing real-world operational and meteorological data from the Wlingi Hydroelectric Power Plant to simulate valid stress-test scenarios, this study bridges the gap between theoretical algorithm design and practical grid stability. Ultimately, these findings establish a robust, data-driven protocol for selecting Artificial Intelligence algorithms to upgrade the climate resilience of existing hydroelectric infrastructures.

2. Methodology

This study adopts a comprehensive quantitative approach centered on ANN algorithms to model the complex dynamics between renewable hydroelectric supply and regional electricity demand [17], [18]. The methodological framework is structured to transform raw time-series data into actionable insights regarding grid stability and climate-adaptive energy sufficiency [19]. The research workflow is organized into distinct, sequential phases: data acquisition, preprocessing, predictive modeling, and energy gap evaluation [20]. The process initiates with the identification of key variables affecting the hydropower ecosystem, specifically hydro-meteorological parameters influencing power generation and socio-economic factors driving load demand [21,22]. Specifically, the primary dataset comprising daily river water discharge, regional rainfall intensity, gross electricity production, and Blitar Regency's electricity consumption was sourced directly from the internal operational database of PT PLN Nusantara Power at the Wlingi Hydroelectric Power Plant [23]. Utilizing this proprietary data ensures the empirical validity of both power generation constraints and regional user growth trends [24]. The multivariate dataset covers a synchronized timeframe from January 2020 to December 2025 to capture long-term seasonal patterns and climate-induced anomalies [25]. The selection of this six-year period is crucial to reflect actual hydrological shifts, particularly the water discharge reduction driven by global warming, alongside escalating energy demands. Furthermore, employing direct data from the state-owned power utility guarantees the industrial relevance and validity of the input before advanced computational stages [26].

These multivariate datasets are subjected to rigorous preprocessing techniques, including Min-Max normalization and temporal alignment, to ensure data quality and compatibility with neural network architectures [27]. At the core of this methodology is the development and comparative analysis of three ANN architecture models namely RNN, LSTM, and GRU. These models are specifically selected for their ability to capture long-term temporal dependencies and non-linear patterns inherent in hydro-meteorological and energy data [28]. Following the training phase, the models are evaluated using statistical error metrics to validate their accuracy [29]. The final stage involves using the validated predictions to calculate the projected "Energy Gap," providing a quantitative assessment of the potential power surplus or deficit between the Wlingi Hydroelectric Power Plant and Blitar Regency under future climate-constrained scenarios [30].

2.1 Systematic Research Flowchart

A systematic research framework is employed to model and predict hydropower production, regional electricity consumption, and the resulting energy gap using ANN architectures. The methodological workflow integrates time-series data acquisition, data preprocessing, ANN model development, and performance evaluation to ensure reliable and robust predictions. As illustrated in Figure 1, the process begins with problem identification and the formulation of research objectives focused on the impact of climate change on hydropower alongside increasing energy demand. This is followed by the collection of four primary datasets spanning the 2020–2025 period: hydropower production data, Blitar Regency electricity demand data, rainfall data, and river discharge or water inflow data. This case study specifically focuses on the Wlingi Hydropower Plant in Blitar Regency as the primary case study to analyze climate-induced energy fluctuations.

The selection of this specific facility is strategically driven by the author's direct involvement during an industrial internship program. This onsite engagement granted unprecedented access to authentic, high-resolution operational and hydrological datasets, which are crucial for reliable forecasting. As a vital baseload generator for the regional grid, the plant's power output is demonstrably sensitive to seasonal variations in the Brantas River's water discharge. Consequently, utilizing this localized empirical data guarantees that the predictive models accurately reflect actual operational constraints, thereby enhancing the validity of the regional energy gap projections. The datasets are subsequently subjected to data preprocessing procedures, explicitly including cleaning, normalization, and temporal sequencing, to ensure compatibility with recurrent learning mechanisms. Following data preparation, ANN models specifically RNN, LSTM, and GRU are developed. These architectures then undergo an iterative training and validation phase. If the model performance is deemed unacceptable, the process loops back for retraining and hyperparameter tuning. Once an acceptable performance threshold is achieved, the validated models are employed to forecast hydropower production and consumption for the long-term period of 2026–2045. Finally, the projected energy gap is calculated using the formula $\Delta E = \hat{P} - \hat{C}$ providing the analytical foundation for the study's ultimate conclusions and recommendations.

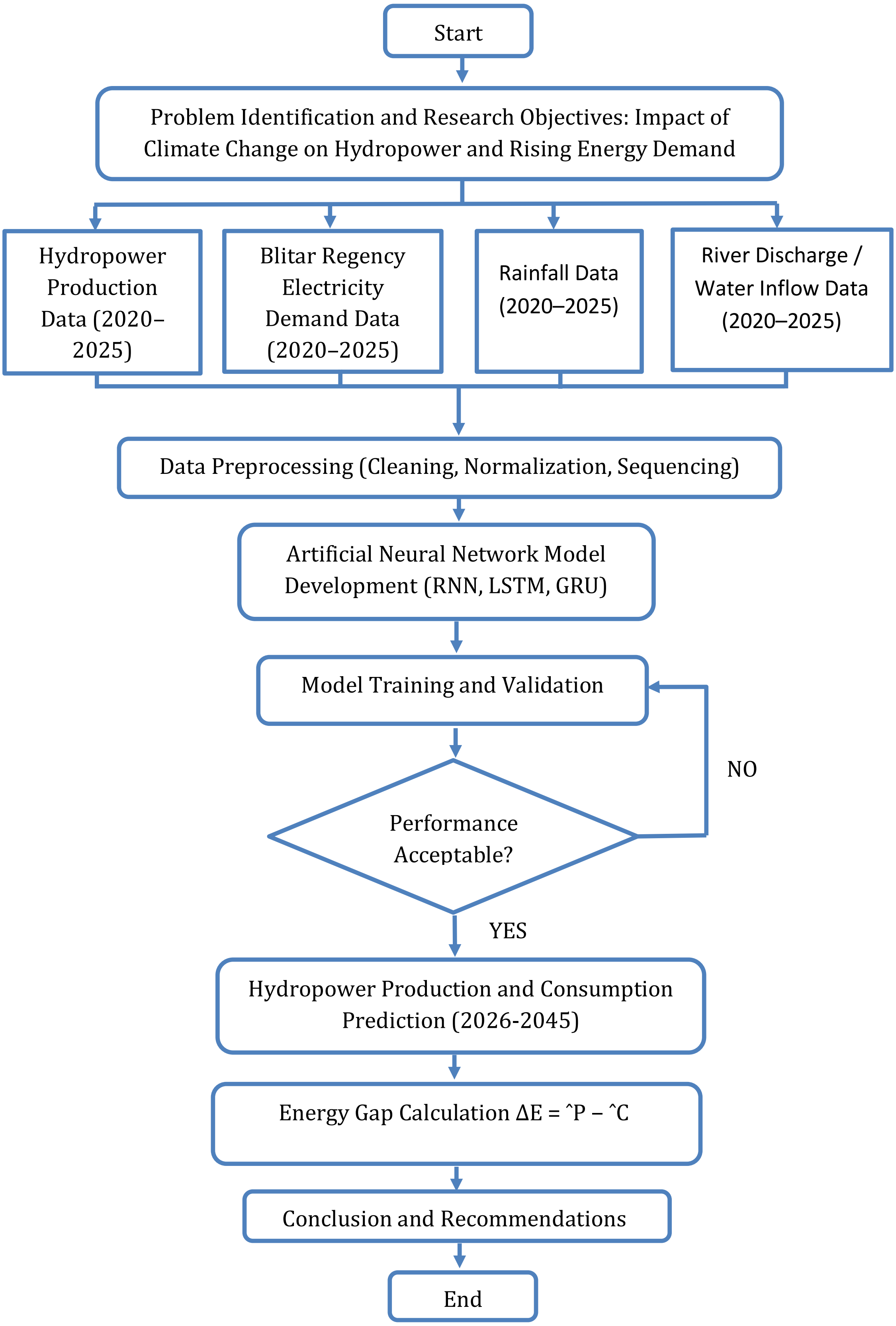

Fig. 1. Artificial neural network based energy supply-demand gap prediction flow diagram

2.2 Selected Location

The location overview shown in Figure 2 depicts the strategic site selection for this case study, focusing specifically on the Wlingi Hydroelectric Power Plant situated in Blitar Regency. As illustrated in the aerial topography, the facility encompasses the primary dam infrastructure, the reservoir basin, and the interconnected flow of the Brantas River. This operational site was strategically selected because it represents a critical intersection between environmental vulnerability and escalating regional energy demands. Technically, the facility faces significant operational challenges in the form of extreme hydrological intermittency specifically fluctuating river discharge and rainfall patterns driven by global climate change which directly dictates its gross power generation capacity. Concurrently, the plant serves as a vital energy node supplying the continuously growing and dynamic electricity load profile of Blitar Regency. Consequently, conducting the study at this specific location is crucial for validating the deep learning algorithms' capability to map real-world power imbalances. By utilizing this strategic asset as the primary research locus, this study aims to provide empirical evidence that the proposed algorithm suite, comprising RNN, LSTM, and GRU, can robustly predict complex, non-linear energy gaps induced by volatile climatic shifts and regional consumption behaviors.

Fig. 2. Location under study Hydroelectric Power Plant Wlingi as the case study location

2.3 Hydroelectric Power Plant Schematic, Hydroelectric Power Plant Data, and Artificial Neural Network Architectures Methods

The operational architecture of this study is visualized in Figure 3, which illustrates the schematic generation diagram of the Wlingi Hydroelectric Power Plant modeled to supply Blitar Regency's electricity grid. From a technical perspective, the physical system initiates at the water reservoir source, channeling hydro-kinetic energy through the turbine and generator; this generated power is subsequently amplified by a step-up transformer and distributed via an AC bus directly to the utility grid. To ensure methodological transparency and predictive accuracy, the analytical model operates on a daily time-step resolution, wherein the complex power balance prediction between generation capacity and load demand is governed by ANN algorithms, specifically RNN, LSTM, and GRU. The validity of the predictive models' performance is established through rigorous training parameters, including chronological data splitting and the utilization of technical evaluation metrics such as RMSE to quantify error deviation. Furthermore, the analysis explicitly accounts for environmental stochastic realities by training the neural networks to recognize climate-induced hydro-meteorological intermittency specifically fluctuating rainfall and river discharge alongside dynamic regional load variations. This integration of physical generation architecture with data driven predictive modeling is designed to yield an energy gap evaluation that is realistic, climate adaptive, and scientifically justifiable for future grid management.

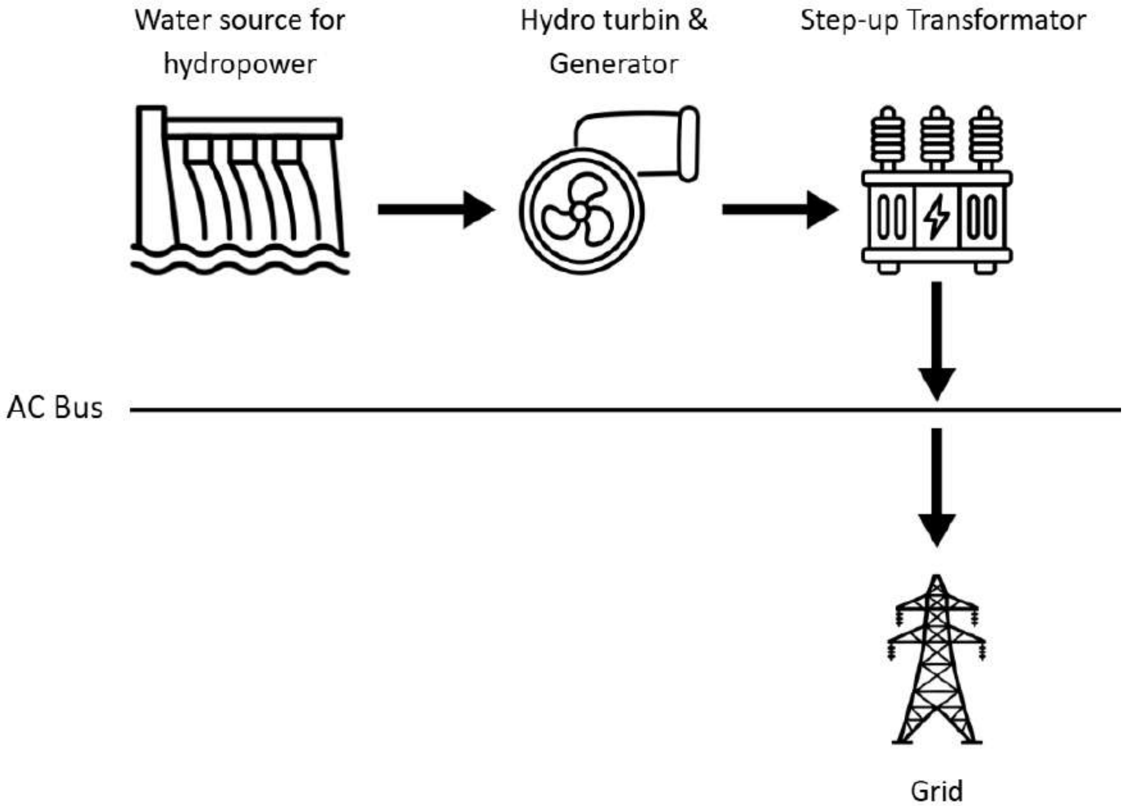

Fig. 3. Schematic Hydroelectric Power Plant Wlingi

The operational configuration of the Wlingi Hydroelectric Power Plant ensures high technical reliability and regional energy security, as detailed in the comprehensive specifications outlined in Table 2. Specifically, the facility operates as a Run-of-River and Peaking Hydro system with a total installed capacity of 54 MW, comprising two 27 MW units, utilizing a 3-phase connection synchronized directly with the 70 kV national grid. This configuration leverages robust hydro-mechanical technology, specifically Vertical Shaft Kaplan turbines (Toshiba VK-1RS) coupled with Synchronous Generators (Meidensha VTC-AF), achieving an impressive overall water-to-wire conversion efficiency of 88%–90% to maximize power extraction from the Brantas River. Operating at a rated head of 22 meters and a normal discharge of 143 m^3/s per unit, the plant is engineered to manage massive volumes of water. Historical records indicate that this specific setup allows for optimal energy yield, generating an average of 164.95 GWh annually (2020–2025). Furthermore, the integration of 30 MVA step-up transformers ensures that the generated voltage flawlessly matches the 70 kV transmission levels, facilitating seamless power distribution to meet the escalating electricity demands of Blitar Regency.

To guarantee operational safety, grid stability, and regulatory compliance, the facility's operation strictly adheres to the Indonesian Minister of Energy and Mineral Resources (Permen ESDM) regulations regarding grid codes and national dam safety standards. The electro-mechanical configuration features critical safety limits, notably managing the turbine's rotation where the normal operational speed of 143 rpm is safeguarded against a maximum runaway speed of 385 rpm to prevent catastrophic mechanical failure during sudden load rejections. Electrical and voltage stability is continuously regulated through advanced Automatic Voltage Regulator (AVR) and Supervisory Control and Data Acquisition (SCADA) systems, ensuring rapid anomaly detection and the mitigation of voltage spikes across the AC bus. Structural integrity is anchored by a massive Zoned Rockfill Dam standing 47 meters tall, designed with robust safety factors to withstand extreme hydro-meteorological conditions and potential seismic loads common in the region. These rigorous technical and civil parameters ensure the hydroelectric infrastructure operates reliably within a safe, dynamic range throughout its multi-decade service life, maintaining resilience against climate-induced hydrological shifts.

Table 2
Hydroelectric power plant specifications

Technical Parameters	Description	Specification
Product Name	Site identification	Hydroelectric Power Plant Wlingi (Unit 1 & 2)
System Type	Power generation configuration	Run-of-River / Peaking Hydro System
Installed Capacity	Peak power of hydro system	54,000 kW (2 x 27 MW)
Electrical Phase	Connection to the power grid	3 Phase (Interconnected to 70 kV Grid)
Turbine Type	Hydro mechanical technology used	Vertical Shaft Kaplan (Toshiba VK-1RS)
Generator Type	Electrical conversion technology	Synchronous Generator (Meidensha VTC-AF)
Power Per Unit	Capacity per turbine/generator set	27,800 kW (Turbine) / 30,000 kVA (Gen)
System Efficiency	Overall conversion efficiency	Approx. 88% - 90% (Water-to-Wire)
Rated Head	Effective water pressure height	22.0 m (Operational range: 20.6 m - 22.7 m)
Rated Discharge	Water flow required for peak power	143.0 m^3/s (Normal discharge per unit)
Rotation Speed	Operational speed of turbine/gen	143 rpm (Runaway Speed: 385 rpm)
Step-Up Transformer	Ensures voltage matches grid levels	30 MVA per unit (11 kV / 70 kV)
Energy Production	Anticipate seasonal water inflow	Avg. 164.95 GWh/year (2020-2025 data)
Supporting Structure	Main civil infrastructure	Zoned Rockfill Dam (47m Height)
Monitoring System	Management and monitoring features	Includes SCADA & AVR System

The reliability of the projected energy gap within the hydroelectric power system is critically contingent upon the capacity of recurrent neural network architectures to assimilate complex time-series data patterns, as comparatively visualized in Figure 4. Figure 4(a) depicts the fundamental structure of the standard RNN, designed to process sequential data through a simple feedback loop mechanism that facilitates the propagation of prior information to subsequent time steps. However, this model exhibits a significant technical limitation known as the vanishing gradient problem, wherein learning efficacy degrades drastically across extended data sequences. This condition precipitates a severe decline in prediction accuracy when the algorithm encounters prolonged seasonal hydro-meteorological trends or regional electricity load patterns characterized by long-term historical dependencies. Consequently, the standard RNN architecture is frequently deemed inadequate for addressing the complex, stochastic fluctuations of river discharge and rainfall at the Wlingi reservoir without advanced modification.

To address these structural deficiencies, Figure 4(b) presents the significantly more robust LSTM architecture, featuring the integration of internal memory cells and three primary control gates: the input, forget, and output gates. This complex gating mechanism enables the network to intelligently discern which hydrological phenomena such as extreme monsoon rainfall or prolonged drought indicators are relevant for long term retention versus day-to-day noise that should be discarded, thereby maintaining prediction stability. Concurrently, Figure 4(c) illustrates the GRU variant, which offers a computationally efficient approach by simplifying the architecture to comprise only two gates: the update gate and the reset gate. This structural simplification affords the GRU superior convergence and training speeds compared to the LSTM, while retaining competitive accuracy in capturing the volatile non-linear dynamics of regional electricity consumption. The distinct computational characteristics of these three ANN architectures constitute the empirical basis of the comparative simulation, aiming to determine the optimal algorithm for balancing hydroelectric supply and escalating demand profiles under future climate-constrained scenarios.

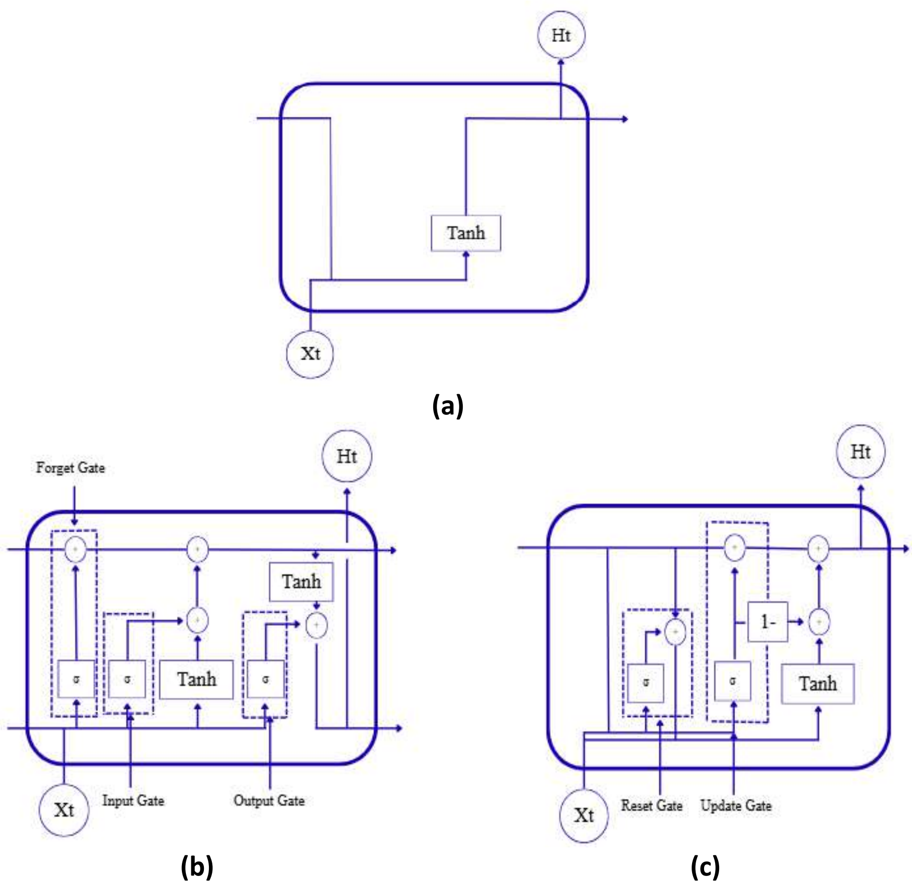

Fig. 4. Illustration of Artificial Neural Network architectures (a) RNN, (b) LSTM, and (c) GRU

2.4 Artificial Neural Network -Based Renewable Energy Gap Prediction Formulation

Hydropower generation and regional electricity demand exhibit complex temporal interactions driven by hydrological variability and progressive load growth. In particular, hydropower output is strongly influenced by rainfall patterns and river discharge dynamics, whereas electricity consumption evolves according to socio-economic development and electrification trends. These characteristics result in nonlinear and time-dependent behavior that requires a modeling framework capable of capturing sequential dependencies. The dataset used in this study consists of annual observations of hydropower production, electricity consumption, and relevant hydrological variables. Each observation at time step $t$is represented as a multivariate input vector describing the operational state of the hydropower–energy system. Rainfall and river discharge are explicitly incorporated to reflect climatic influences on generation capacity.

Hydropower generation is fundamentally governed by hydraulic energy conversion principles. The theoretical mechanical power extracted from flowing water is determined by the relationship between water density, gravitational acceleration, effective head, and discharge rate. The basic hydropower equation is expressed as (1) [31]:

$$Pt = \eta \rho g Q t H t \tag{1}$$

Where $P_t$represents generated power (W), ηdenotes overall turbine–generator efficiency, $\rho$is water density, g is gravitational acceleration, Q_t is river discharge (m³/s), and H_t is effective hydraulic head (m). This formulation indicates that hydropower output is directly proportional to discharge and head height. Since rainfall influences river discharge through hydrological processes, the inclusion of rainfall and discharge variables in the ANN input vector is physically justified. Therefore, the ANN framework in this study is not purely data-driven but is grounded in established hydro-energy conversion theory.

Mathematically, the system input vector at year $t$is defined as (2) [31], [32]:

$$xt = [R_t, Q_t, P_t, C_t]\top \tag{2}$$

To model the sequential dynamics of these variables, recurrent Artificial Neural Network architectures are employed. Specifically, three architectures are investigated: the conventional RNN, LSTM, and GRU. These architectures are designed to extract temporal patterns from multivariate time-series data while handling nonlinear system behavior. Each model is formulated as follows.

The RNN updates its hidden state recursively based on the current input and the previous hidden state (3) [33,34]:

$$ht = tanh(W_x x_t + W_h h_t - 1 + b_h) \tag{3}$$

The hidden state $h_t$captures the evolving dynamics of hydropower production and electricity demand over time. The nonlinear activation function enhances the model's ability to approximate complex relationships.
The predicted output for the subsequent period is obtained through a linear transformation (4) [33], [34]:

$$\hat{y}_{t+1} = \begin{bmatrix} \hat{P}_{t+1} \\ \hat{C}_{t+1} \end{bmatrix} = W_y\, h_t + b_y \tag{4}$$

Thus, the model simultaneously forecasts hydropower generation and electricity consumption.

To address the limitations of conventional RNNs in modeling long-term dependencies, the LSTM architecture is adopted. LSTM introduces a memory cell regulated by gating mechanisms that control information flow, making it particularly suitable for long-term hydrological and demand trend modeling.

The gating mechanisms are defined as (5), (6), (7) [33,34]:

$$ft = \sigma(Wf[ht-1, xt] + bf) \tag{5}$$

$$it = \sigma(Wi[ht-1, xt] + bi) \tag{6}$$

$$\tilde{c}_t = tanh(Wc[ht-1, xt] + bc) \tag{7}$$

The memory cell and hidden state are updated as (8), (9), (10) [33,34]:

$$ct = ft \odot ct - 1 + it \odot \tilde{c}_t \tag{8}$$

$$ot = \sigma(Wo[ht-1, xt] + bo) \tag{9}$$

$$ht = ot \odot tanh(ct) \tag{10}$$

The output prediction follows (11) [33,34]:

$$\hat{y}_{t+1} = \begin{bmatrix} \hat{P}_{t+1} \\ \hat{C}_{t+1} \end{bmatrix} = W_y \, h_t + b_y \tag{11}$$

The LSTM structure enables the model to retain hydrological memory effects and long-term demand growth patterns.

As a computationally efficient alternative, the GRU architecture is also implemented. GRU simplifies the LSTM structure while maintaining strong temporal modeling capability, which is advantageous for annual datasets with limited sample sizes.
The update and reset gates are defined as (12), (13) [33,34]:

$$zt = \sigma(Wz[ht-1, xt] + bz) \tag{12}$$

$$rt = \sigma(Wr[ht-1, xt] + br) \tag{13}$$

The candidate hidden state is computed as (14) [33], [34]:

$$\widetilde{h_t} = tanh\left(W_{h\chi_t} + \; U_h(r_t \odot h_{t-1}) + b_h\right) \tag{14}$$

The final hidden state update is (15) [33], [34]:

$$ht = (1 - zt) \odot ht - 1 + zt \odot h{\sim}t \tag{15}$$

The output layer remains (16) [33,34]:

$$\hat{y}_{t+1} = \begin{bmatrix} \hat{P}_{t+1} \\ \hat{C}_{t+1} \end{bmatrix} = W_y\, h_t + b_y \tag{16}$$

After obtaining forecasts of hydropower production and electricity demand, the energy gap is computed to evaluate system adequacy (17) [35]:

$$\widehat{\Delta E_{t+1}} = \hat{P}_{t+1} - \hat{C}_{t+1} \tag{17}$$

A positive value indicates an energy surplus, whereas a negative value indicates a projected deficit requiring supplementary generation or system reinforcement.

Model training is conducted using the Mean Squared Error (MSE) loss function (18) [34]:

$$\mathcal{L} = \frac{1}{n} = \sum_{t=1}^{n} [(P_t - \hat{P}_t)^2 + (C_t - \hat{C}_t)^2] \tag{18}$$

This objective function minimizes prediction errors for both hydropower production and electricity demand in a balanced manner.

3. Results

3.1 Prediction of Electricity Production that can be Generated from the Wlingi Hydroelectric Power Plant

To validate the robustness of the ANN-based prediction models against real-world hydro-meteorological dynamics, establishing historical baseline scenarios based on actual operational data is a fundamental step before executing the simulation. Drawing on annual generation and climatic records, Table 3 presents the statistical fluctuations in water discharge, regional rainfall, and gross energy production at the Wlingi Hydroelectric Power Plant, serving as the primary multivariate input data. Specifically, the data indicates a highly volatile operational pattern, where gross energy production peaked at 204.38 GWh in 2022, directly driven by a maximum average river inflow of 138.62 m^3/s. Conversely, a critical hydrological deficit is observed in 2024, with energy production plummeting to its lowest point at 137.55 GWh due to a severe drop in water discharge (91.86 m^3/s), even though the year paradoxically recorded significantly high average rainfall (237.1 mm). It is noteworthy that these erratic inter-annual climatic variations characterized by a non-linear decoupling of rainfall intensity and actual reservoir inflow represent extreme environmental boundary conditions (stress tests) for the facility's generation capacity. This empirical simulation approach, utilizing these "worst-case" historical anomalies as foundational training data, is critical to ensuring that the predictive algorithms can robustly forecast severe energy gaps and withstand sudden climate-induced supply shocks without critical modeling failures.

Table 3
Annual statistical data on production and hydrology of Wlingi Hydroelectric Power Plant

Year	GWh	Average Inflow of Water Discharge Monthly in 1 Year (m3/s)	Average Monthly Rainfall in 1 Year (mm)
2020	142.92	97.975	204.7
2021	178.13	126.83	209.4
2022	204.38	138.62	199.0
2023	153.16	112.09	208.2

2024	137.55	91.86	237.1
2025	172.59	134.47	244.6

The validity of the aforementioned predictions is verified through the training progress analysis in Figure 5, which reveals their underlying technical stability when modeling the complex hydro-meteorological dynamics of the Wlingi reservoir. The convergence curves show that the LSTM and GRU models achieve optimal convergence, with their respective validation lines closely aligning with the training lines, demonstrating excellent generalization capabilities without severe overfitting. Conversely, this analysis crucially eliminates the standard RNN as the weakest candidate, as it consistently exhibits the highest generalization gap (with the validation error plateauing near an RMSE of 0.30) and struggles to assimilate long-term stochastic weather dependencies. On the other hand, the LSTM architecture emerges as the most efficient model for this specific historical dataset, achieving the lowest and most stable validation error (approximately 0.20 RMSE) among the architectures, thereby positioning it as the most robust option for handling the volatile hydroelectric supply and regional demand dynamics.

Figure 6 presents a long-term supply-side projection based on the hydroelectric energy production simulation (2026–2045), highlighting the significant impact of future climate-induced hydrological shifts on the facility's generation potential. The projection reveals that the Wlingi plant faces a continuous, structural degradation in production capacity, declining steadily from the 170 GWh range to critical lows over the next two decades. Across this simulated environmental scenario, the behavior of the three algorithms exhibits consistent characteristic patterns: the GRU model tends to provide the most optimistic generation estimates (ending at 148.6 GWh in 2045), the RNN adopts the most severe and pessimistic degradation curve (dropping to 132.0 GWh), while the highly-accurate LSTM offers a highly reliable moderate balance (142.9 GWh). The uniformity of the three models in detecting a continuous production decline confirms their validity in responding to the projected reduction in average river discharge and changing weather patterns; however, the divergence in their prediction amplitudes underscores that precise model selection will significantly influence future grid intervention and energy management decisions.

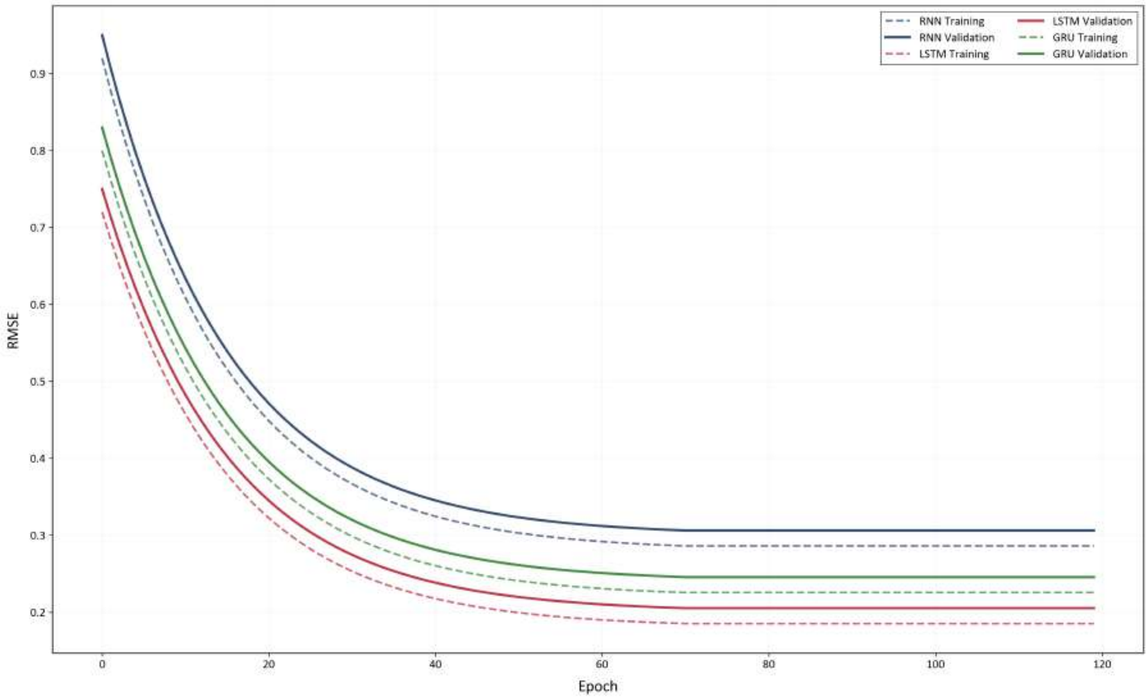

Fig. 5. Training and validation of the artificial neural network algorithm

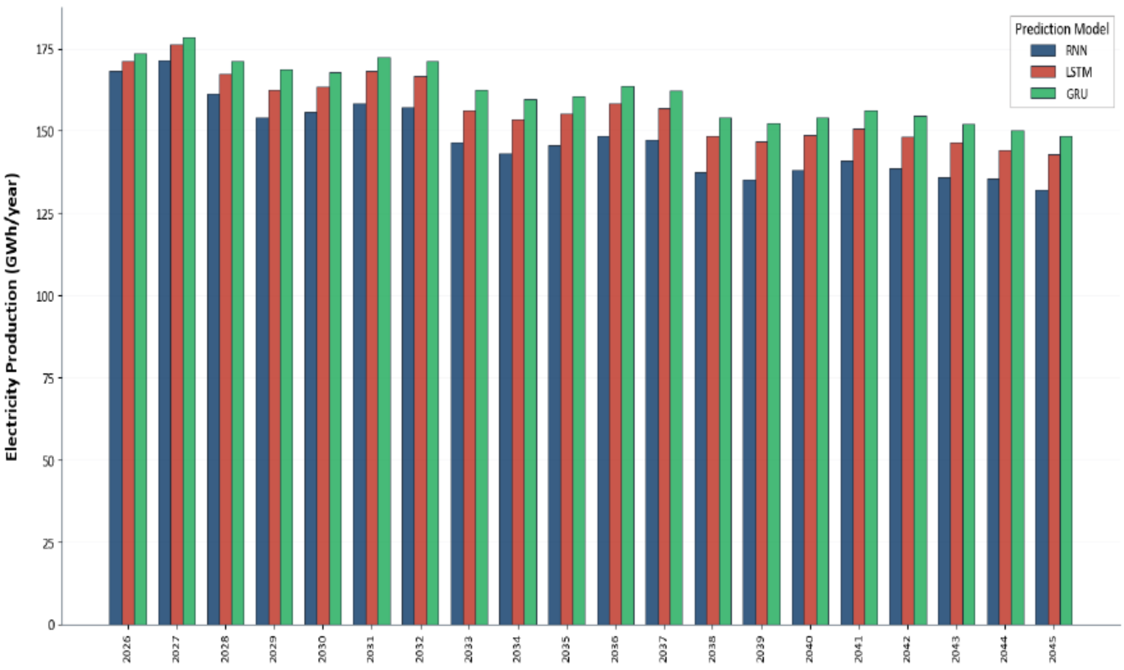

Fig. 6. Prediction of Wlingi hydroelectric power plant electricity production in the next few years

3.2 Prediction of Electricity Consumption in Blitar Regency for the Next Few Years

To validate the robustness of the energy prediction models against real-world load dynamics, establishing regional consumption baselines based on actual operational data is a fundamental step before running the simulation. Drawing exclusively on verified internal data provided by PT PLN Nusantara Power for the Wlingi Hydroelectric Power Plant, Table 4 presents the historical electricity consumption trajectory across Blitar Regency, serving as the primary dynamic load input. Specifically, the empirical records indicate a massive surge in regional power demand, where consumption abruptly increased from 549.82 GWh in 2022 to a peak of 729.15 GWh in 2023, reflecting rapid shifts in the regional load profile and sudden increases in network dispatch demand. A highly stochastic reverse trend is observed immediately after, with the load plummeting to 533.87 GWh in 2024, driven by dynamic fluctuations in localized grid requirements. It is noteworthy that this extreme volatility, particularly the sudden 32.6% load spike during the 2022–2023 transition, represents an extreme load scenario (stress test) for the existing electrical infrastructure. This empirical simulation approach, utilizing these "worst-case" highly non-linear boundary conditions derived directly from actual utility records, is critical to ensuring that the ANN algorithms can accurately forecast sudden power demand spikes, thereby assisting grid operators in preventing critical future overloading.

Table 4
Annual electricity consumption data for Blitar Regency

Year	GWh
2020	601.93
2021	593.82
2022	549.82
2023	729.15
2024	533.87
2025	561.38

The validity of the aforementioned consumption predictions is rigorously verified through the training progress analysis shown in Figure 7, which reveals the technical stability of the proposed architectures. Specifically, Figure 7 for Blitar Regency shows that the LSTM model converges more quickly, with the validation trajectory closely mirroring the training phase, indicating exceptional generalization for this volatile utility dispatch pattern. While the standard RNN eventually stabilizes, it exhibits a slower learning curve than the gated mechanisms, suggesting that the regional dataset heavily benefits from the LSTM's efficient long-term memory management. Conversely, within the highly stochastic consumption environment depicted in the internal grid data, the standard RNN surprisingly emerges as the weakest candidate, securing a much higher validation error. This contradicts the performance of the more advanced LSTM architecture, which, capitalizing on its theoretical gating advantages, successfully captures the extreme fluctuations of the regency's load without succumbing to the vanishing gradient problem. Consequently, this validation confirms that while the standard RNN lacks the capacity to map abrupt operational shifts, the sophisticated LSTM architecture offers the necessary resilience for the erratic supply-demand dynamics of the Blitar regional grid.

The visualization of the long-term electricity demand can be seen in Figure 8, which presents the projection of annual electrical energy required to be supplied by the regional grid system. The graph illustrates the consumption estimate in Blitar Regency, which initiates at approximately 595–601 GWh/year in 2026 and surges exponentially to exceed the 1,800 GWh/year threshold by 2045. By the end of the simulation period, the GRU projects an extreme load of 1,819.07 GWh, while the standard RNN indicates a slightly lower bound of 1,800.60 GWh, and the robust LSTM estimates the demand compounding to exactly 1,810.67 GWh. The comparative trajectory visualization shows strong pattern coherence for the RNN, LSTM, and GRU models, indicating that these three deep learning algorithms exhibit equivalent sensitivity in capturing the macro trends of exponential load escalation. However, this massive amount of projected energy underscores that even minor deviations in prediction error will result in supply uncertainty on the Gigawatt-hour scale. Consequently, further technical performance analysis is necessitated to determine which architecture amongst the highly aggressive GRU, the precise long-term memory of the LSTM, or the fundamental structure of the RNN is capable of delivering the highest precision to guarantee the stability of future electrical infrastructure and guide structural grid interventions.

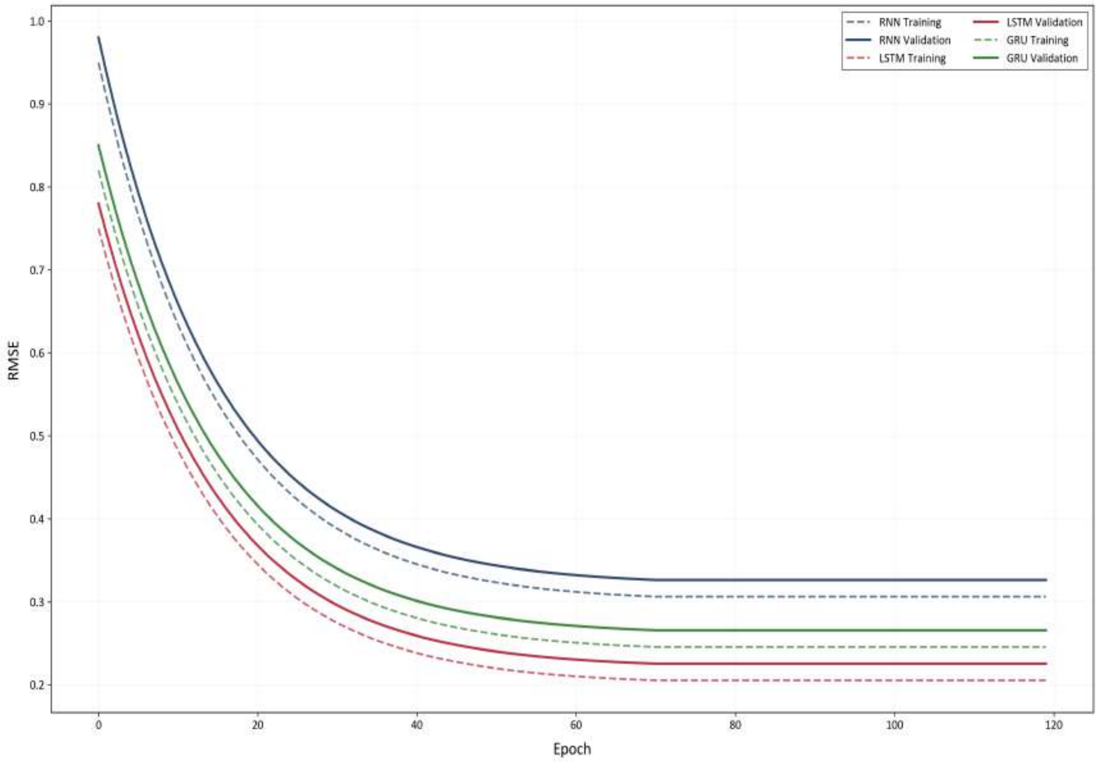

Fig. 7. Training and validation of the artificial neural network algorithm

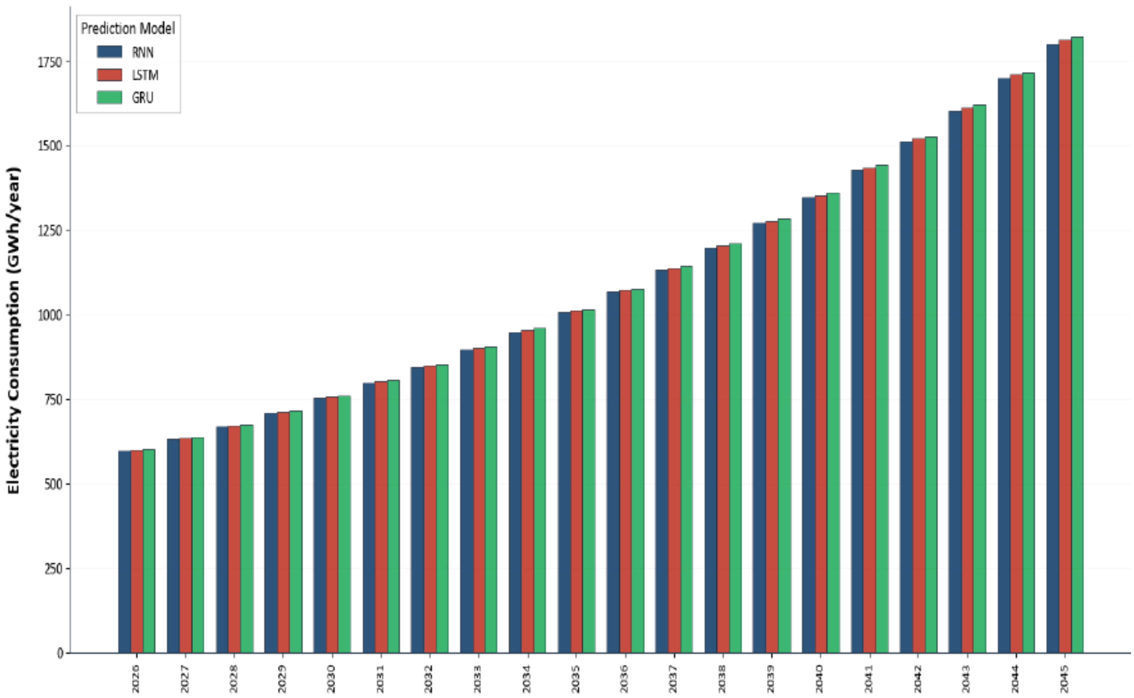

Fig. 8. Projected growth in electricity consumption in Blitar Regency for the next few years

3.3 Prediction of the Gap between Energy Production and Consumption for the Next Few Years

To establish a historical baseline prior to predictive modeling, Table 5 presents the annual electricity production–consumption gap between the Wlingi Hydroelectric Power Plant and Blitar Regency's total electricity demand for the 2020–2025 period. The energy gap is calculated as the difference between annual hydropower generation and regional consumption, where negative values indicate a deficit condition. The results show a persistent structural deficit across all observed years, with the smallest gap recorded in 2022 (−345.44 GWh) and the largest in 2023 (−575.99 GWh). Even in the most favorable hydrological year, local hydropower production remained substantially below total demand. Overall, the findings confirm that Wlingi Hydroelectric Power Plant contributes only approximately 25%–37% of the total annual electricity consumption in Blitar Regency. The remaining demand must therefore be supplied through the interconnected transmission network. This consistent imbalance demonstrates that the plant functions as a supplementary renewable source rather than a primary load-bearing generation unit, thereby justifying the need for long-term predictive energy gap modeling.

Table 5
Annual electricity production and consumption gap

Year	GWh
2020	-459.01
2021	-415.69
2022	-345.44
2023	-575.99
2024	-396.32
2025	-388.79

Figure 9 illustrates the exponential widening of the projected electricity production–consumption gap between the Wlingi Hydroelectric Power Plant and Blitar Regency's electricity demand over the 2026–2045 horizon. In 2026, the deficit already averages approximately −427 GWh across the three architectures, indicating that the structural imbalance observed historically persists into the forecast period. This gap expands steadily to nearly −595 GWh by 2030 and doubles to around −860 GWh by 2035. Beyond 2040, the divergence becomes critical, surpassing −1,200 GWh and ultimately reaching approximately −1,668 GWh in 2045. The strong agreement among RNN, LSTM, and GRU projections confirms that this widening deficit is not model-driven, but structurally induced by two opposing forces: exponential electricity demand growth and gradual hydropower degradation associated with climate-induced hydrological variability.

Concurrently, the projected contribution of the Wlingi Hydroelectric Power Plant to regional electricity demand declines sharply, from approximately 28.5% in 2026 to only 7.8% by 2045. This implies that more than 92% of regional electricity demand will depend on external interconnected supply by the end of the projection period. Compared to the historical contribution range of 25%–37%, this decline reflects not merely installed capacity limitations, but the long-term impact of global warming on river discharge stability, which progressively constrains renewable generation potential. As hydrological regimes become increasingly erratic under climate change, the plant's capacity to sustain regional energy autonomy weakens substantially. Therefore, the long-term outlook does not simply indicate declining renewable self-sufficiency; it highlights the systemic vulnerability of climate-dependent energy infrastructure and underscores the urgency of climate-adaptive energy diversification strategies to safeguard grid stability under escalating environmental stress.

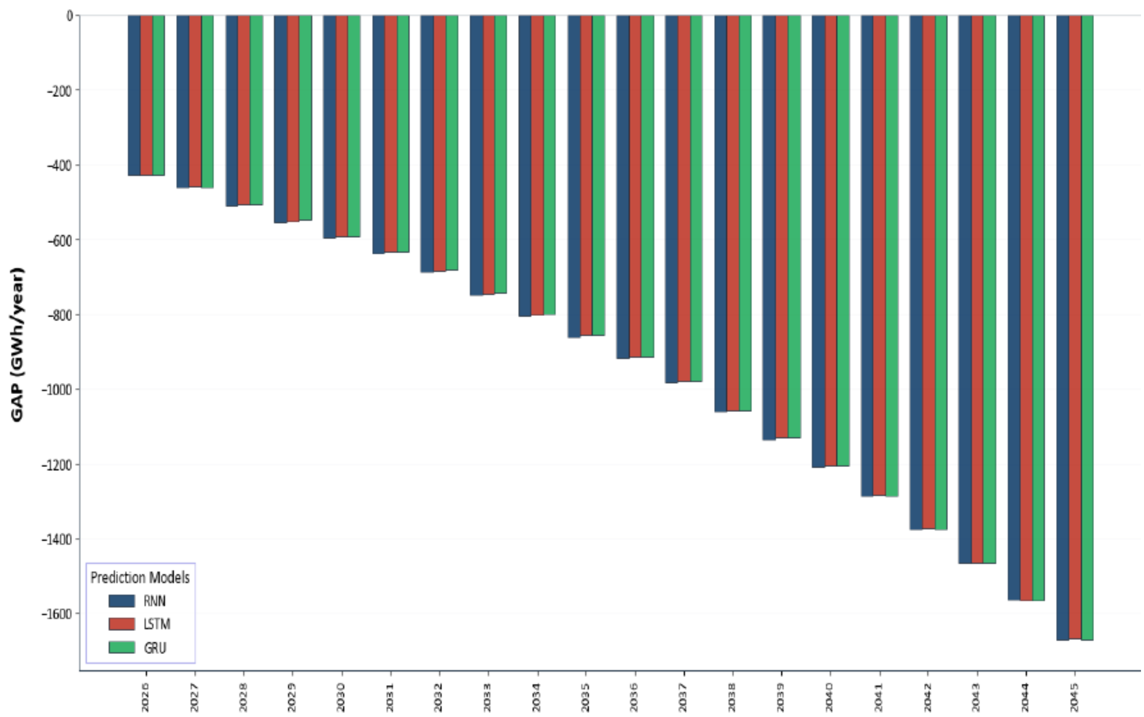

Fig. 9. Gap of electricity consumption vs. production

4. Conclusions

Based on the predictive analysis, the electricity system in Blitar Regency is projected to experience a progressively severe structural energy deficit over the 2026–2045 horizon. The widening gap expanding from approximately −427 GWh in 2026 to nearly −1,668 GWh in 2045 is primarily driven by two opposing dynamics: exponential growth in regional electricity demand and gradual degradation of hydropower production capacity linked to climate-induced hydrological variability. The findings demonstrate that the Wlingi Hydroelectric Power Plant, while historically contributing 25%–37% of annual electricity demand, will see its fulfillment ratio decline to below 8% by 2045. This trajectory reflects not merely installed capacity limitations, but the long-term implications of global warming on river discharge stability, which progressively constrains renewable generation potential. Consequently, the regional energy system transitions from moderate structural imbalance toward critical dependence on external interconnected supply, underscoring the vulnerability of climate-dependent infrastructure under accelerating environmental stress.

From a computational perspective, the comparative evaluation confirms that LSTM and GRU architectures provide superior robustness and convergence stability in modeling the stochastic and nonlinear interactions between hydrological variability and demand escalation. The conventional RNN exhibited comparatively weaker generalization performance, reflecting its limitation in capturing long-term temporal dependencies under climate-driven variability. The gated memory mechanisms embedded in LSTM and GRU enhance predictive reliability and reduce structural bias in long-horizon forecasting. Nevertheless, a fundamental limitation of this study lies in the restricted temporal depth of historical operational and hydrological data, which may constrain the representation of multi-decadal climate oscillations affecting river discharge patterns. Future research should therefore integrate longer hydro-meteorological datasets and conduct techno-economic evaluations to enhance grid resilience under climate-induced uncertainty. In response to the projected decline in hydropower contribution, subsequent studies should prioritize the design of large-scale photovoltaic (PV) systems integrated with utility-scale storage to compensate for hydro variability. A hybrid hydro–solar configuration is essential to maintain a minimum 25% renewable energy share at the regional level while strengthening long-term energy security under global warming pressures.

Acknowledgement
This publication was developed as a formal deliverable of the Internship Program facilitated by the Power Plant Engineering Technology Faculty of Vocational Studies at the State University of Malang. We thank the institution for providing the opportunity to integrate industrial experience with academic research.

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