Forecasting Electricity Demand In Indonesia: Recommendation for Prediction Models to Support PLN's RUPTL

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Abstract*— The Electricity Supply Business Plan (RUPTL) prepared annually by PLN still shows a high error rate in predicting electricity consumption, exceeding 10% in various provinces, such as North Sumatra (36.92%), DKI Jakarta (24.87%), West Kalimantan (40.24%), and South Sulawesi (31.56%), due to the limitations of the linear regression method used in the RUPTL. This study aims to evaluate and recommend the best electricity consumption forecasting model based on artificial intelligence using a Feed Forward Backpropagation Neural Network (FFBP-NN) combined with six training algorithms: Bayesian Regularization (BR), Conjugate Gradient (CG), Levenberg-Marquardt (L-M), Gradient Descent (GD), Quasi-Newton (Q-N), and Resilient Backpropagation (RB), resulting in a total of 13 algorithmic combinations. The data used consists of RUPTL indicators for DKI Jakarta from 2018 to 2023. Testing results of the 13 training functions on the FFBP-NN demonstrate that the TRAINOSS (Quasi-Newton) algorithm achieves the best performance with the lowest Mean Square Error (MSE) of 0.0000065546 and Mean Absolute Percentage Error (MAPE) of 0.06696%. This algorithm outperforms the linear regression method currently used in PLN's RUPTL, which has a MAPE of approximately 21.14%. The second and third best algorithms are TRAINSCG and TRAINLM, with MAPE values of 0.09455% and 0.10020%, and MSE values of 0.0012160450 and 0.0012229340, respectively. The FFBP-NN model trained with TRAINOSS is highly recommended as the primary alternative to support long-term electricity load planning such as in PLN's RUPTL.

Keywords*— Forecasting, National Recommendation, Neural Network, PLN, RUPTL.

I. INTRODUCTION

Indonesia continues to strive to meet current electricity demand while also preparing for future supply [1]. In 2023, Indonesia's total electricity production and rental reached 183,980.89 GWh, while PLN's production, including third-party purchases, totaled 323,320.62 GWh. Installed capacity grew by 0.34% from 2022, and customers increased by 4.11% to 89,153,278, indicating rising electricity demand [2]. To anticipate future electricity demand, PLN developed the Electricity Supply Business Plan (RUPTL), a ten-year planning document that guides power system development [3]. Besides serving internal needs, RUPTL also complies with Law No. 30/2009 and Government Regulation No. 14/2012, amended by No. 23/2014 [4], and refers to the National Electricity Plan (RUKN) and the National Energy Policy (KEN) under Government Regulation No. 79/2014 [5].

Although PLN's RUPTL serves as the main reference for electricity system planning, there are notable issues in the form of significant errors in electricity consumption forecasts. In North Sumatra Province, forecast errors for electricity consumption from 2018 to 2023 consistently exceeded 10%. In 2018, actual consumption was recorded at 10,445.02 GWh compared to a forecast of 11,500 GWh, resulting in a 10.10% error [3][6]. In 2019, the error increased to 11.95%, with actual consumption at 10,943.86 GWh versus a forecast of 12,252 GWh [3][7]. In 2020, the error rose to 21.45%, with actual consumption at 11,192.85 GWh and a forecast of 13,594 GWh [3][8]. This trend continued in 2021 with a 25.38% error [3][9], 31.59% in 2022 [3][10], and peaked in 2023 at 36.92%, where actual consumption was 12,472.84 GWh against a forecast of 17,078 GWh [3][11].

To ensure that the sample data reflects broader conditions, analysis was also conducted in Java, specifically in the Province of DKI Jakarta. The results show that forecast errors in this region also consistently exceeded 10% from 2018 to 2023. In 2018, actual consumption was 32,779.20 GWh compared to a forecast of 36,444 GWh, with an error rate of 11.18% [3][6]. In 2019, the error increased to 11.74%, with actual consumption of 34,107.98 GWh and a forecast of 38,111 GWh [3][7]. In 2020, forecast error significantly jumped to 23.80% [3][8], and continued to rise in 2021 to 28.01% [3][9]. Although in 2022 the error slightly declined to 27.25% [3][10], it still reflected poor prediction accuracy. In 2023, the error was recorded at 24.87%, with actual consumption of 36,992.35 GWh compared to a forecast of 46,194 GWh [3][11].

In addition to North Sumatra and DKI Jakarta, sample data analysis was also carried out in Kalimantan, specifically in West Kalimantan Province. The results indicated even higher levels of forecast errors, with percentages consistently above 30% from 2018 to 2023. In 2018, actual consumption was 2,372.67 GWh, while the forecast reached 3,103 GWh, resulting in a 30.78% error [3][6]. In 2019, the error rose to 31.19%, with actual consumption of 2,572.69 GWh and a forecast of 3,375 GWh [3][7]. In 2020, the error increased to 34.00% [3][8], and continued rising to peak at 41.16% in 2022 [3][10]. Although the error slightly decreased to 40.24% in

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2023, this still reflected a significant discrepancy between forecasted and actual consumption [3][11].

To further support the argument for improving forecast accuracy in RUPTL, data was also sampled from Sulawesi, particularly South Sulawesi Province. The analysis revealed forecast errors consistently above 16% throughout 2018-2023. In 2018, actual electricity consumption was 5,472.48 GWh compared to a forecast of 6,397 GWh, resulting in a 16.89% error [3][6]. Prediction errors continued to rise in the following years, peaking in 2020 at 31.56%, where actual consumption was 5,977.49 GWh, far below the forecast of 7,864 GWh [3][8]. Although the error rate slightly declined in 2022 and 2023 to 20.69% and 20.99%, respectively, these figures still indicate a considerable mismatch [3][10][11].

Electricity consumption forecasts in Indonesia show error rates exceeding 10%, highlighting the limitations of RUPTL's regression-based models that rely on linear relationships among indicators such as sales, capacity, customers, economic growth, population, and tariffs, which often exhibit non-linear patterns [3]-[12]. Neural networks, particularly the Feed Forward Backpropagation Neural Network (FFBP-NN), overcome these limitations through layered structures, non-linear activation functions, and backpropagation-based weight optimization, making them effective for capturing complex patterns in forecasting [13]-[27].

Studies show that FFBP-NN consistently delivers high forecasting accuracy, with [28] achieving RMSE 0.5344, MAE 3.3845, MAPE 0.1773, and SI 0.0003, and [29] predicting Lhokseumawe's 2023-2025 loads at 158.1 MV with MAPE 0.004%. In other cases, the model reached MAPE 5.4% using LEARNGDM-traingdx-30 neurons [30], 0.39% error vs. PLN's RUPTL [31], and for Bandung's system 4,169.22 MWh (2022) and 4,246.97 MWh (2023) with MAPE 0.3976, RMSE 0.0120 [32]. Additional results include Banjarbaru (MAPE 6.60% train, 7.92% test) [33], West Java (MAPE 2.96%) [34], Cascade Forward NN best on April 8 2007 with MAPE 7.6% [35], and Bali's traingdx model yielding MAPE 6.24% and 93.75% accuracy [36].

It should be noted that the MAPE values reported in prior studies are not directly comparable due to differences in temporal resolution, dataset size, and validation protocols; they are cited to demonstrate methodological relevance rather than quantitative superiority.

Accurate electricity demand forecasting is crucial for PLN to avoid resource waste [37], requiring time-based data [38], customer and location factors [39], meteorological integration [40], and feature engineering [41]. This study trains an FFBP-NN using Bayesian Regularization, Conjugate Gradient, Levenberg-Marquardt, Gradient Descent, Quasi-Newton, and Resilient Backpropagation to forecast DKI Jakarta's 2018-2023 demand [3]-[11], compares its MAPE and MSE with RUPTL, and applies the best algorithm to Bali's 2018-2023 data [2][3][6]-[11] to assess forecasting accuracy for issues like the recent blackout.

Unlike previous studies that primarily focus on ranking neural network algorithms based on accuracy metrics, this study contributes by positioning forecasting accuracy within the national electricity planning. The main contribution lies not merely in identifying the best-performing algorithm, but in demonstrating how methodological choices in forecasting models can significantly affect long-term planning outputs such as PLN's RUPTL. By highlighting the magnitude of deviation produced by conventional regression-based planning compared to AI-based alternatives, this study provides methodological insight and policy-relevant evidence for improving demand forecasting practices in Indonesia's power sector.

II. METHODS

A. Data Collection

This study uses DKI Jakarta's 2018-2023 data on electricity sales (GWh), connected capacity (MVA), customer numbers, tariffs (Rp/kWh), GRDP (billion rupiah, constant prices), and population, as in PLN's RUPTL [3], compiled as FFBP-NN inputs in Table I and targets in Table II [2],[6]-[11],[42][43], with Table III showing RUPTL data [3]. To strengthen the analysis, Bali's 2018-2023 blackout-related load issue is examined using the best algorithm from the main case study, with FFBP-NN inputs in Table IV, targets in Table V [2],[6]-[11],[44][45], and RUPTL data in Table VI [3]. Electricity consumption is included among the input variables to reflect the autoregressive nature of demand evolution commonly used in planning-based forecasting. This approach aligns with PLN's RUPTL methodology, which also relies on historical consumption trends. While this may introduce correlation among variables, the objective of this study is not causal inference, but pattern recognition within a planning-oriented forecasting framework. It should be explicitly acknowledged that this study is conducted under a limited data setting, with only six annual observations (2018-2023). Given this limitation, the objective of the study is not to claim universal forecasting superiority, but to evaluate the relative performance of different neural network training algorithms under identical data conditions. While simpler time-series approaches such as ARIMA or exponential smoothing could be considered, they typically rely on longer historical sequences to achieve stable parameter estimation. Therefore, this study focuses on comparing neural-network-based optimization strategies using the same small-sample input structure currently adopted in PLN's planning framework.

TABLE I. FFBP-NN INPUT DATA DKI JAKARTA [2],[6]-[11],[42][43]

Variable	2018	2019	2020	2021	2022	2023
Electricity Consumption (GWh)	32,779.20	34,107.98	32,166.71	32,709.30	34,578.29	36,992.35
Connected Capacity (MVA)	18,563.30	19,175.15	19,674.66	20,250.52	20,889.58	21,634.72
Number of Customers	4,395,066	4,583,706	4,755,494	4,915,913	5,064,418	5,225,077
Electricity Tariff (Rp/kWh)	1,057.01	1,264.24	1,261.34	1,252.77	1,292.69	1,320.85
GRDP (billion Rp)	1,735,208	1,836,240	1,792,291	1,856,000	1,953,488	2,050,465
Population (persons)	10,467,629	10,557,810	10,562,088	10,605,437	10,640,007	10,672,100

TABLE II. FFBP-NN TARGET DATA DKI JAKARTA [2],[6]-[11],[42][43]

Year	2018	2019	2020	2021	2022	2023
Target Data (GWh)	32,779.20	34,107.98	32,166.71	32,709.30	34,578.29	36,992.35

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TABLE III. RUPTL DATA FOR DKI JAKARTA FROM 2018 TO 2023 [3]

Year	Actual Consumption Data (GWh)	RUPTL Data (GWh)
2018	32,779.20	36,444
2019	34,107.98	38,111
2020	32,166.71	39,821
2021	32,709.30	41,870
2022	34,578.29	44,000
2023	36,992.35	46,194

TABLE IV. FFBP-NN INPUT DATA FOR BALI PROVINCE 2018-2023[2],[6]-[11],[44][45]

Variable	2018	2019	2020	2021	2022	2023
Electricity Energy (GWh)	5,302.67	5,706.72	4,946.86	4,708.02	5,470.51	6,354.53
Connected Capacity (MVA)	3,492.70	3,741.72	3,845.81	3,997.57	4,213.32	4,536.74
Number of Customers	1,392,939	1,466,750	1,528,854	1,579,283	1,630,528	1,701,512
Electricity Tariff (Rp/kWh)	877.83	1,281.12	1,256.16	1,252.38	1,306.49	1,333.12
GRDP (billion Rp)	233,636.77	251,934.10	224,225.72	220,466.43	245,367.89	274,358.18
Population (persons)	4,309,200	4,362,100	4,317,400	4,343,450	4,374,310	4,404,260

TABLE V. FFBP-NN TARGET DATA FOR BALI PROVINCE 2018-2023 [2], [6]-[11],[44][45]

Year	2018	2019	2020	2021	2022	2023
Target Data (GWh)	5,302.67	5,706.72	4,946.86	4,708.02	5,470.51	6,354.53

TABLE VI. RUPTL DATA FOR BALI PROVINCE 2018-2023 [3]

Year	Actual Consumption Data (GWh)	RUPTL Data (GWh)
2018	5,302.67	5,866
2019	5,706.72	6,221
2020	4,946.86	6,630
2021	4,708.02	7,105
2022	5,470.51	7,595
2023	6,354.53	8,101

B. Electricity Load Forecasting

This study used MATLAB to simulate load forecasting with six training algorithms. The primary model, FFBP-NN, follows an 11-stage process including weight initialization, feed-forward processing, error calculation, and weight-bias adjustment [34]. This was combined with the Gradient Descent (GD) algorithm, with the *traingdm* variant using Additive Momentum as shown in (1) [46]:

$$\Delta X\,(t+1) = mc.\Delta X(t) + lr.\frac{\delta E}{\delta X} \tag{1}$$

where ΔX is the correction function at the next iteration (t + 1), t is the training duration in seconds, mc is the momentum factor with a typical value of 0.95, and lr is the learning rate within the range of $0 < \text{lr} \leq 1.0$. The term $\frac{\delta E}{\delta X}$ represents the gradient of the error function with respect to the weight X.

Another GD variant is the Self-Adaptive Learning Rate method (*traingd, traingda, traingdx*), where the learning rate adapts dynamically to error function changes, as shown in (2) [47]:

$$lr\,(t+1) = \begin{Bmatrix} 1.05lr(t) \\ 0.7lr(t) \\ lr(t) \end{Bmatrix} \begin{matrix} \text{if MSE}\,(t+1) < \text{MSE}\,(t) \\ \text{if MSE}\,(t+1) > 1.04\,.\,\text{MSE}\,(t) \\ \text{etc} \end{matrix} \tag{2}$$

where $lr(t)$ is the learning rate at epoch t, and MSE refers to the Mean Squared Error at epoch t. The constants 1.05 and 0.7 are adjustment factors used to increase or decrease the learning rate based on the change in MSE between epochs.

Then, Resilient Backpropagation (RB) algorithm introduces a weight and bias update mechanism that relies only on the sign of the partial derivatives $\frac{\delta E}{\delta X}$, not its magnitude. As a result, RB achieves more stable convergence without complex parameter tuning. The update equations used in the *trainrp* function are shown in (3) [47]:

$$\Delta X_{ij^{(t)}=} f(x) = \begin{Bmatrix} -\Delta_{ij}{}^{(t)}, \text{ if } \frac{\delta E}{\delta X} > 0 \\ \Delta_{ij}{}^{(t)}, \text{ if } \frac{\delta E}{\delta X} < 0 \\ 0, \text{ etc} \end{Bmatrix} \tag{3}$$

where $\Delta X_{ij^{(t)}}$ represents the weight change between neuron i and j at iteration t. The value depends on the direction of the error gradient $\frac{\delta E}{\delta X}$. If the gradient is positive, the weight is decreased by $\Delta_{ij}{}^{(t)}$; if the gradient is negative, the weight is increased by $-\Delta_{ij}{}^{(t)}$; and if the gradient is zero, no change is made.

The Conjugate Gradient backpropagation algorithm adjusts step size without Hessian matrix calculations, lowering computational costs, and is implemented in variants like *traincgb, traincgp, traincgf,* and *trainscg* (4)(5) [48]:

$$y^{(i+1)} = v^{(i+1)} + y^{(i)} + c^{(i)} \quad (4)$$

$$w^{(i+1)} = w^{(i)} + y^{(i)}\eta^{(i)} \quad (5)$$

where the training direction at iteration $(i+1)$, denoted as $y^{(i+1)}$, is computed by summing the current gradient $v^{(i+1)}$, the previous direction $y^{(i)}$, and the conjugate parameter $c^{(i)}$. $y^{(i)}$, represents the direction from the previous iteration, while $c^{(i)}$ adjusts the influence of the past step based on the conjugate gradient method. The parameter update where $w^{(i)}$ and $w^{(i+1)}$are the weights at iteration *i* and $(i+1)$, respectively, and $\eta^{(i)}$ is the learning rate at iteration i.

Next, the BR method, also known as trainbr, is used to improve the generalization capability of the neural network. The equations for this training function are shown in (6) and (7) [49]:

$$F = \alpha E_w + \beta E_d \quad (6)$$

$$E_D = \frac{1}{m}\sum_{i=1}^{m} w_{i^2} \quad (7)$$

F is the combined penalty function being optimized, α is the control parameter for the contribution of the penalty E_w, β is the control parameter for the contribution of the penalty E_d, E_w is the training error function, E_d is the average sum of the squared connection weights, m is the total number of connection weights, and w_i is the i-th connection weight.

Then, the Q-N approach offers computational efficiency as it requires fewer operations to evaluate the Hessian matrix and compute its inverse, as shown in (8) [47]:

$$w^{(i+1)} = w^{(i)} - (G^{(i)}g^{(i)})\,\eta^{(i)} \quad (8)$$

$w^{(i)}$ is the weight at the i-th iteration, $G^{(i)}$ is the estimated inverse Hessian matrix at the i-th iteration, $g^{(i)}$ is the gradient of the loss function at the i-th iteration, and $\eta^{(i)}$ is the learning rate at the i-th iteration.

Next, the Levenberg-Marquardt (L-M) algorithm utilizes the gradient vector and the Jacobian matrix, allowing it to avoid the computation of the Hessian matrix, which is typically time-consuming and resource-intensive. The loss function in this method is expressed as the sum of squared errors as (9) and (10) present its formulation [50]:

$$w_{jk}(t+1) = w_{jk}(t) + \Delta w_{jk}(t \quad (9)$$

$$\Delta w_{jk}(t) = \frac{1}{[J^T(W)J(W)+\alpha I]} J^T(w)E(w) \quad (10)$$

$w_{jk}(t)$ is the network weight value at the t-th iteration, $\Delta w_{jk}(t)$ is the weight change at the t-th iteration, $j(W)$ is the first derivative Jacobian matrix, $J^T(w)$ is the transpose of the Jacobian matrix, α is the scalar constant that adjusts the descent, I is the identity matrix, and $E(w)$ is the error vector at the t-th iteration.

The equation will use the *tansig* function with data range (-1, 1), as shown in (11) [51]:

$$Xn = 2 . \frac{Xp - \min(Xp)}{\max(Xp) - \min(Xp)} - 1 \quad (11)$$

where, the real data value before normalization is represented as Xp, $max\{Xp\}$ denotes the maximum real data value, and $min\{Xp\}$ signifies the minimum real data value. The forecasting simulation output will be evaluated using MSE, as expressed in (12) [52]:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(Y_i - \hat{y_t})^2 \quad (12)$$

MSE is the Mean Square Error, n is the number of data points, Y_i is the actual data, and $\hat{y_t}$ is the forecasted data. Next, the data is denormalized to return it to the actual values using (13) [51]:

$$X = 0.5(Xn+1).(\max(Xp)) - \min(Xp)) + \min(Xp) \quad (13)$$

X represents the real data that has been denormalized, and X*n* is the normalized data. The maximum value of the original real data is denoted as max{Xp}, while the minimum value is represented by min{Xp}.

Then, the MAPE between the FFBP-NN algorithm and the RUPTL is calculated for comparison using Equation (14) [34]:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Yt - \dot{Y}t}{Yt}\right| . 100\% \quad (14)$$

where n represents the total number of data points, Yt denotes the actual data values, and $\dot{Y}t$ signifies the forecasted values.

Due to the limited number of annual observations, the evaluation in this study is performed using in-sample fitting rather than rolling-origin or out-of-sample validation. Consequently, the reported MSE and MAPE values should be interpreted as goodness-of-fit indicators instead of pure forecasting accuracy. The primary purpose of this evaluation is to compare the relative behavior of different training algorithms under the same data constraints, not to estimate long-horizon predictive uncertainty.

C. Architecture Network

The study uses a 6-12-6-1 architecture with two hidden layers and one output neuron for electricity consumption prediction, trained for up to 2000 epochs with a target error of 0, a learning rate of 0.001, and an early stop if no improvement occurs after 1000 validation checks. Fig. 1 shows the architecture and simulation application used in this study. The selection of the 6-12-6-1 architecture is based on empirical heuristics commonly applied in small-sample neural network modeling, where the number of hidden neurons is set as a moderate multiple of the input dimension to balance representation capacity and numerical stability.

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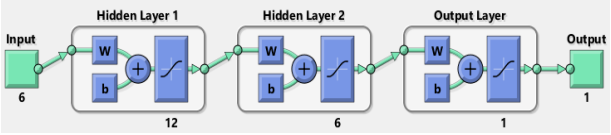


Fig. 1. Architecture 6-12-6-1 FFBP-NN

III. Results aAnd Discussion

Comparison of MAPE among 13 FFBP-NN algorithms, linear regression of PLN's RUPTL, and actual data of DKI Jakarta shows in Fig. 2. In Fig. 2, the training algorithms in the Feed Forward Backpropagation Neural Network (FFBP-NN) have proven capable of producing electricity consumption predictions with significantly higher accuracy compared to the linear regression method currently used in PLN's RUPTL. The best-performing method is TRAINOSS (Q-N) FFBP-NN, achieving the lowest MAPE of 0.06696%, followed by TRAINSCG (CG) FFBP-NN in second place with a MAPE of 0.09455%, and TRAINLM (L-M) FFBP-NN in third place with a MAPE of 0.10020%, all of which are better than linear regression that has MAPE around 21.14%. The MAPE range of FFBP-NN algorithms, from 0.06696% to 0.69131%.

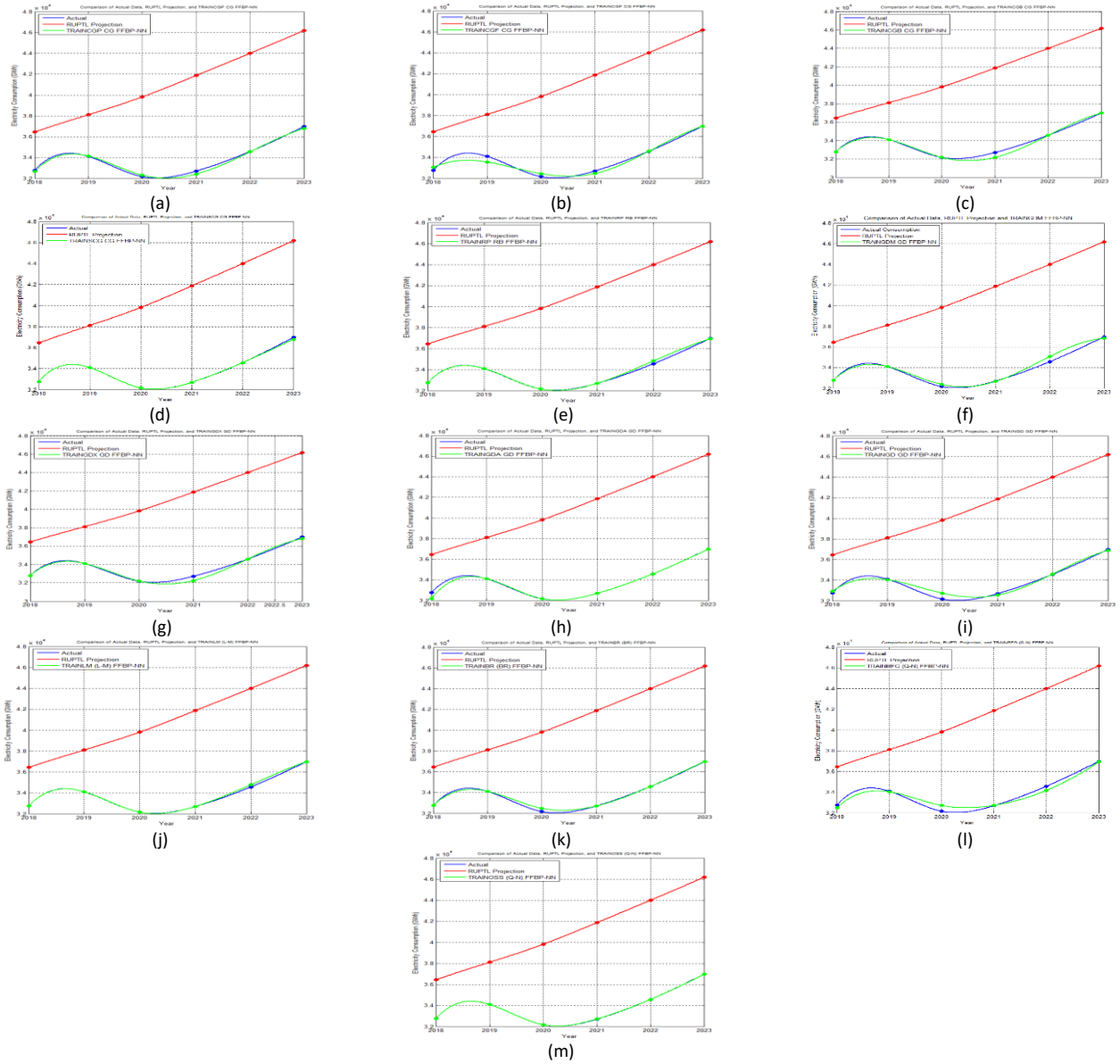


Fig. 2. Comparison of MAPE values between RUPTL, the FFBP-NN algorithm, and the actual data (a) traincgp, (b) traincgf, (c) traincgb, (d) trainscg, (e) trainrp, (f) traingdm, (g) traingdx, (h) traingda, (i) traingd, (j) trainlm, (k) trainbr, (l) trainbfg, and (m) trainoss

Fig. 2 shows that RUPTL's linear regression produces large forecasting errors due to its assumption of linear relationships while actual data is non-linear [12]. FFBP-NN overcomes this through hidden layers that capture non-linear patterns, with Table VII presenting the MAPE and MSE for algorithms (a) traincgp, (b) traincgf, (c) traincgb, (d) trainscg, (e) trainrp, (f) traingdm, (g) traingdx, (h) traingda, (i) traingd, (j) trainlm, (k) trainbr, (l) trainbfg, and (m) trainoss.

Fig. 3 shows that the Quasi-Newton algorithm with TRAINOSS captures complex non-linear electricity consumption patterns with near-zero error, efficiently adjusting weights and biases while avoiding pitfalls common

in regression models [22]. Other models, such as TRAINBFG with an MSE of 0.015794459, TRAINCGF with an MSE of 0.014933142, and TRAINGD with an MSE of 0.011141967, still exhibit relatively high MSE values, reflecting the algorithms' inability to effectively capture the weight-bias relationships within the data. Even widely used training algorithms, such as TRAINLM and TRAINBR, still lag far behind the performance of TRAINOSS. TRAINOSS from the Quasi-Newton family achieves the best MSE and MAPE performance.

TABLE VII. MAPE AND MSE EACH ALGORITHM

Algorithm	MAPE (%)	MSE
(a)	0.39500	0.0044704178
(b)	0.69131	0.0149331420
(c)	0.28750	0.0083091320
(d)	0.09455	0.0012160450
(e)	0.16471	0.0020345730
(f)	0.43886	0.0089342100
(g)	0.11524	0.0073720636
(h)	0.30770	0.0098624690
(i)	0.53870	0.0111419670
(j)	0.10020	0.0012229340
(k)	0.16163	0.0027477770
(l)	0.68676	0.0157944590
(m)	0.06696	0.0000065546

This is because (Q-N) approach is designed to accelerate the convergence process while maintaining high accuracy. This method does not require explicit iterations over the computationally complex Hessian matrix; instead, it approximates it using first-order derivative information obtained from the network. The iterative process of forming an estimated inverse Hessian allows for efficient and accurate weight updates. The combination of the loss function gradient and the estimated inverse Hessian determines the direction and magnitude of each learning step [47]. The accuracy of the FFBP-NN is indeed better to that of the RUPTL, consistent with related research [29][31],[34]-[36].

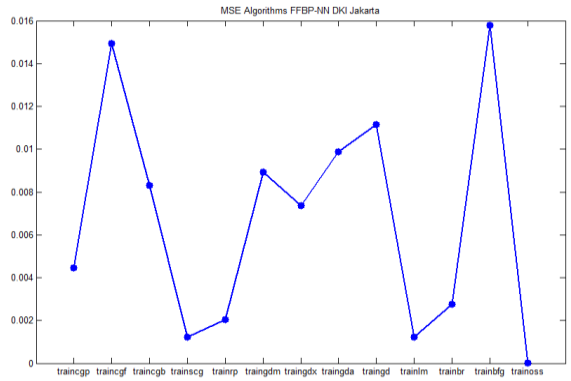


Fig. 3. MSE of 13 Combined Models of FFBP-NN and Training Function Algorithms

Based Table VIII In 2018, the target value of 32,779.20 was compared with an output of 32,779.54, shows in a difference of 0.34. In 2019, the difference was 0.59, from a target of 34,107.98 to an output of 34,108.57. In 2020 showed a difference of 1.01, from a target of 32,166.71 to an output of 32,167.72. Then, 2021, the difference was 14.53, from 32,709.30 to 32,723.83. Next, in 2022, the output was 34,578.11, very close to the target of 34,578.29, with only a 0.18 difference. In 2023, the difference was 4.22, from a target of 36,992.35 to an output of 36,988.13. The TRAINOSS forecasting output and the target data can be compared in Table VIII. The reported performance metrics reflect in-sample fitting performance, not out-of-sample predictive accuracy. Therefore, extremely low MAPE and MSE values should be interpreted as indicators of model capability to capture historical nonlinear patterns, rather than as guaranteed future forecasting accuracy.

It should be noted that PLN's RUPTL forecasting is not designed as a pure statistical prediction model, but as a long-term planning instrument incorporating policy targets, scenario assumptions, and regulatory considerations. Therefore, the comparison in this study does not aim to discredit RUPTL, but to illustrate how alternative data-driven forecasting approaches may complement existing planning frameworks by providing additional quantitative insight.

TABLE VIII. TRAINOSS OUTPUT DAN ACTUAL DATA

Actual (GWh)	RUPTL (GWh)	TRAINOSS (GWh)	MAPE RUPTL (%)	MAPE TRAINOSS (%)
32,779	36,444	32,779.2	11.18	0.00244
34,107	38,111	34,108.5	11.74	0.00299
32,166	39,821	32,167.7	23.8	0.00401
32,709	41,870	32,723.8	28.01	0.04494
34,578	44,000	34,578.1	27.25	0.00083
36,992	46,194	36,988.1	24.87	0.01175
	MAPE		21.14	0.06696

It is important to distinguish between statistical prediction accuracy and planning effectiveness. While improved forecasting accuracy reduces informational uncertainty, it does not automatically translate into optimal infrastructure investment decisions. Load forecasting should be viewed as a supporting analytical component within a broader decision-making framework that includes generation adequacy, transmission reliability, policy constraints, and risk management. Therefore, the contribution of this study is limited to improving the forecasting input of the planning process rather than replacing comprehensive power system planning methodologies.

This study also addresses the recent large-scale blackout in Bali on May 2, 2025, caused by the failure of the undersea power cable connecting Java and Bali. The Bali case study is presented as an illustrative application rather than an independent model development exercise. The TRAINOSS algorithm is re-trained using Bali-specific input data to evaluate whether the same optimization strategy remains effective under different regional characteristics. This transfer is not intended as direct domain generalization, but as a robustness check of the training function when applied to another province using the same indicator structure as RUPTL.

The outage halted electricity from Java, while Bali's local plants could not meet demand, disrupting power across the island [53]. Beyond the cable failure, this research examines whether suboptimal load planning contributed to the event. Using the best-performing algorithm, TRAINOSS FFBP-NN, with the same inputs as RUPTL, simulations are conducted to evaluate planning accuracy. After the simulation using the input and target variables from Tables IV, V, and VI, Table IX shows the MAPE comparison between the FFBP-NN TRAINOSS method and RUPTL for Bali Province.

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TABLE IX. MAPE TRAINOSS VS RUPTL BALI PROVINCE

Actual (GWh)	RUPTL (GWh)	TRAINOSS (GWh)	MAPE RUPTL (%)	MAPE TRAINOSS (%)
5,302.67	5,866	5,299	10.62	0.06921
5,706.72	6,221	5,754	9.01	0.82850
4,946.86	6,630	4,781	34.02	3.35280
4,708.02	7,105	4,708	50.91	0.00042
5,470.51	7,595	5,419	38.84	0.94159
6,354.53	8,101	6,354	27.48	0.08341
	MAPE		**28.48**	**0.87932**

The comparison in Table VIII shows that the TRAINOSS FFBP-NN method, with a MAPE of only 0.88%, is far more accurate than the RUPTL projection's 28.48%,. This inaccuracy, coupled with the recent blackout caused by a submarine cable failure, highlights that planning plays a critical role alongside technical reliability. More precise forecasting methods and stronger local generation capacity are essential to make sure optimal load planning and reduce the risk of future blackouts.

Although TRAINOSS exhibits the lowest MSE and MAPE among the tested algorithms, this superiority should be interpreted cautiously. The observed performance differences are descriptive and based on numerical convergence behavior rather than formal statistical significance testing. Given the identical data and network structure used across algorithms, the results indicate robustness in optimization efficiency rather than definitive dominance. Statistical hypothesis testing and robustness checks are recommended for future work with larger datasets. The Bali blackout case is discussed not to imply a direct causal relationship between forecasting error and the outage event, which was primarily caused by submarine cable failure, but to emphasize the importance of accurate demand estimation in ensuring sufficient local generation margins under contingency conditions.

IV. CONCLUSION

Using the FFBP-NN model with the TRAINOSS algorithm in PLN's RUPTL planning demonstrates improved in-sample fitting performance for electricity consumption forecasting under limited data conditions. This leads to more realistic load planning, reducing prediction errors and the risk of over or under-supply, which ultimately enhances efficiency and cost-effectiveness in energy planning and infrastructure investment. While the TRAINOSS-based FFBP-NN demonstrates strong in-sample performance, further studies using higher-resolution data (monthly or hourly) and proper out-of-sample validation are required before operational deployment. Nevertheless, the results show that AI-based forecasting models have strong potential to complement PLN's existing RUPTL framework in improving long-term electricity demand planning.

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