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Comparative Evaluation of NeuroAMI, OS ELM, Linear Regression, and Reinforcement Learning

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***Abstract* - The study addresses the challenge of accurate long-term load forecasting in power distribution systems, focusing on uncertainties in transformer load behavior across multiple substations. Conventional models, including high-order polynomial regressions and standard artificial neural networks, often exhibit overfitting, large forecast errors, and unrealistic growth predictions. To overcome these limitations, the study implements a Neuronal Auditory Machine Intelligence (NeuroAMI) framework, integrating sequential time-series learning with advanced probabilistic forecasting. The Online Sequential Extreme Learning Machine (OS-ELM) and Linear Regression (LR) models are employed for comparative analysis, while forecast accuracy is evaluated using Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Continuous Ranked Probability Score (CRPS), and skill scores. Results indicate that NeuroAMI consistently outperforms baseline methods, achieving a low RMSE of 440.49 kW, a minimal MAPE of 4.05%, and the highest accuracy at 95.95%. CRPS analysis further confirms improved calibration and tighter predictive intervals, reflecting reduced uncertainty in transformer load projections. Forecast comparisons over a ten-year horizon demonstrate that NeuroAMI closely tracks true load trends for feeders with varying growth rates, in contrast to the unrealistic exponential predictions of polynomial models. The findings highlight the potential of NeuroAMI for enhancing operational planning, capacity expansion decisions, and reliability assessments in electricity distribution. This study aligns with policies promoting data-driven, predictive management of power systems, offering a robust, scalable framework adaptable to varying load profiles and substations.**

Keywords: NeuroAMI, OS-ELM, Load Forecasting, RMSE, Probabilistic Forecasting.

I. INTRODUCTION

Accurate load forecasting remains a critical requirement for efficient power system planning, operation, and reliability enhancement in modern electricity distribution networks. With increasing demand variability, renewable integration, and infrastructure expansion, utilities face significant challenges in predicting transformer and feeder load behavior under uncertain operating conditions. Inaccurate forecasts often lead to overloading, underutilization of assets, voltage instability, and increased operational costs [1].

Consequently, there is a growing need for intelligent, adaptive, and data-driven forecasting frameworks capable of capturing both linear and nonlinear system dynamics over short- and long-term horizons. Traditional forecasting techniques such as Linear Regression (LR) and statistical time-series models, including Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA), have been widely used due to their simplicity and interpretability [2].

However, these approaches are limited in handling nonlinearities, abrupt load variations, and high-dimensional dependencies present in modern power systems [3]. To address these limitations, machine learning and artificial intelligence techniques such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Extreme Learning Machines (ELM) have been introduced. Despite their improved performance, many of these models suffer from high computational cost, slow convergence, or limited adaptability in real-time environments.

In this study, a Neuro-inspired Artificial Machine Intelligence framework (NeuroAMI) is proposed for dynamic load forecasting in distribution substations. The model is designed to improve sequential learning capability, uncertainty estimation, and forecasting robustness under varying load conditions [4][5]. The Online Sequential Extreme Learning Machine (OS-ELM) is adopted as a benchmark adaptive learning model due to its fast-learning capability and suitability for real-time data streams. Additionally, Linear Regression (LR) is included as a baseline statistical method for comparative evaluation [6].

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The proposed framework is evaluated using multiple performance metrics, including Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Continuous Ranked Probability Score (CRPS), and skill score analysis [7]. These metrics enable both deterministic and probabilistic assessment of forecasting accuracy. Simulation results demonstrate that NeuroAMI provides superior predictive performance, improved stability, and reduced uncertainty compared to benchmark models.

II. LITERATURE REVIEW

The reviewed works collectively highlight the evolution of electrical grid management, transformer monitoring, and load forecasting through advanced computational and control techniques. Early studies emphasize the integration of distributed generation into low-voltage networks, demonstrating the challenges and practical approaches for maintaining stability and efficiency in grids with high renewable penetration [8].

Subsequent research extends these concepts into smart microgrids, where stochastic constrained linear quadratic control methods optimize operational performance under uncertainty, reflecting a shift toward predictive and adaptive management strategies [9]. Model predictive control (MPC) has been applied beyond power grids, notably in energy-efficient greenhouse management, revealing its superiority over traditional relay-based approaches for dynamic system regulation [10].

Data integrity and forecasting accuracy remain central to operational reliability. Missing load data imputation techniques enhance substation demand records, supporting more robust planning and operational decisions [11]. Cognitive frameworks in Industry 4.0 further demonstrate the intersection of human and machine intelligence, aiming to reduce cognitive load while optimizing manufacturing processes [12].

Transformer monitoring and load forecasting are increasingly powered by deep learning and neural network architectures, including deep residual networks and transformer-based models, which have shown high precision in predicting short-term and medium-term electrical loads [13][16][17][18].These data-driven approaches are complemented by risk assessment methodologies for transformer overloading, leveraging gradient boosting decision trees (GBDT) and probabilistic models to anticipate heavy loads and mitigate potential failures [19][20].

Collectively, these studies reflect a trend toward intelligent, predictive, and data-driven power system management. The integration of advanced control methods, machine learning algorithms, and cognitive frameworks provides utilities with tools to enhance system resilience, optimize transformer performance, and maintain reliable electricity delivery. Moreover, these approaches support the transition toward more sustainable and adaptive grids, highlighting the synergy between computational intelligence, predictive analytics, and operational decision-making in modern power systems [14][15][21].

III. METHODS

3.1 Online Sequential Extreme Learning Machine (OS ELM) ANN Method

As mentioned earlier, the OS-ELM is based on the Extreme Learning Machine (ELM) but with a sequential processing and bias architecture that allows for faster processing. Specifically, OS-ELM allows a chunk-chunk sequential learning of time series example sequence (Liang et al., 2006). The algorithm codes of the OS-ELM are useful for sequential processing of transformer load time series and are provided in Algorithm 3.3. The parameters are also given in the Appendix.

3.1.1 Algorithm

1: Initialization Phase:

I: Initialize the learning process using a a small chunk, k of initial training data from the given training data set:

Chunk→$N_o = \{(x_i, t_i)\}_{i=1}^{N_o}$ (1)

II: Define Training data set →$N = \{(x_i, t_i) | x_i \in \Re^n, t_i \in \Re m, i=1,\ldots,No \geq N$ (2)

i: Assign random input weights and bias for additive hidden nodes; for RBF hidden nodes assign and becomes a center and an impact factor,

ii: Calculate the initial hidden layer output matrix, Ho

$$H_o = \begin{bmatrix} G(a_1, b_1, x_1) \cdots G(a_{\tilde{N}}, b_{\tilde{N}}, x_1) \\ G(a_1, b_1, x_{N0}) \cdots G(a_{\tilde{N}}, b_{\tilde{N}}, x_{N0}) \end{bmatrix}_{N_0 \times \tilde{N}} \quad (3)$$

iii: Estimate the initial output weight:

$$\beta^{(0)} = P_0 H_0^T T_0, \quad (4)$$
$$P_0 = (H_0^T H_0)^{-1} \quad (5)$$
$$T_0 = [t_{1,\ldots,} t_{N0}]^T \quad (6)$$

2: Sequential Learning Phase:

Present the number of observations in the (k+1)th chunk:

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$$N_{k+1} = \{(x_i, t_i)\}_{i=\left(\sum_{j=0}^{k} N_j\right)+1}^{\sum_{j=0}^{k+1} N_j} \qquad (7)$$

i: Calculate the partial hidden layer output matrix for the (k+1)th chunk of data, as in (Liang et al., 2006; pp.1416, Eq.26)

ii: Set $T_{k+1} = \left[t_{\left(\sum_{j=0}^{k} N_j\right)+1}, \ldots, t_{\sum_{j=0}^{k+1} N_j} \right]^T$ (8)

iii: Calculate the output weight, $\beta^{(k+1)}$

$$\beta^{(k+1)} = \beta^{(k)} + P_{k+1} H_{k+1}^{T} \left(T_{k+1} - H_{k+1} \beta^{(k)} \right) \qquad (9)$$

iv: Set k=k+1. Repeat the sequence learning phase
3: Until k is maximum
4: End

3.1.2 Disadvantages of the OS-ELM ANN Method

The following key disadvantages of the Existing System include:

i. Requires the data to be continuous numeric input. This is prone to noise and limits the source data type.

ii. Requires a training dataset, and a separate testing and cross-validation set. set:

3.2 Evaluation and Comparison with Other Methods

3.2.1 Root Mean Squared Error (RMSE) over horizon

RMSE is a standard error metric for comparing point-forecast accuracy across models. Compute RMSE over all test windows and horizons to quantify average magnitude of errors, sensitive to large deviations. Use per-horizon RMSE to understand short- vs long-horizon performance. RMSE is simple and widely interpretable; however, it doesn't capture calibration or probabilistic accuracy, so pair it with other metrics (CRPS, calibration error) for a comprehensive comparison. RMSE is used to compare NeuroAMI against ANN, regressors, and RL-based predictors.

$$RMSE_h = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (\hat{y}_{t(n)+h} - y_{t(n)+h})^2} \qquad (10)$$

Where:

$RMSE_h$: RMSE at horizon h.

N: number of test windows.

$\hat{y}_{t(n)+h}$: forecast and true value.

3.2.2 Continuous Ranked Probability Score (CRPS) For Probabilistic Forecasts

For probabilistic forecast comparison, CRPS measures both calibration and sharpness for predictive CDFs. Lower CRPS indicates better probabilistic forecasts. For Gaussian predictive distributions, CRPS has an analytical form in terms of mean and variance, making it practical for model training and evaluation. Use CRPS to compare NeuroAMI (which predicts uncertainty) against methods that provide predictive distributions (ensemble ANN, Bayesian regressors) to assess who gives better calibrated risk estimates for transformer overload decisions.

$$CRPS(\mu, \sigma : y) = \sigma \left[\frac{y-\mu}{\sigma} \left(2\Phi\left(\frac{y-\mu}{\sigma}\right) - 1 \right) + 2\phi\left(\frac{y-\mu}{\sigma}\right) - \frac{1}{\sqrt{\pi}} \right] \qquad (11)$$

Where:

CRPS: continuous ranked probability score (lower is better).

μ,σ: predictive mean and standard deviation.

y: observed value.

Φ,ϕ: standard normal CDF and PDF.

3.2.3 Relative Improvement/Skill score against baseline

Summarize model improvement with a skill score that compares NeuroAMI error to a baseline (e.g., persistence or conventional ANN). This normalized metric expresses percent improvement: positive values indicate better performance than baseline. Use RMSE or CRPS in the numerator to produce error-based skill. Skill scores are helpful in results tables and statistical tests to determine significance. Report per-horizon skill scores and aggregated metrics to fairly compare forecast methods across multiple scenarios and datasets.

$$skill = 100\% \times \left(1 - \frac{Error_{NeuroA\ `MI}}{Error_{Baseline}}\right) \qquad (12)$$

Where:

Skill: percent improvement (positive = better).

$Error_{NeuroAMI}$: error metric (e.g., RMSE or CRPS) for NeuroAMI.

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$Error_{Baseline}$: same metric for baseline model.

3.3 Linear Regressor (LR) Method

A fundamental and widely utilized solution is to Linear-Regressor (LR) the output state variable (response variable) say, y with the corresponding input state variable (predictor variable) say, x, as (Han & Kamber, 2006):

$$y = mx + c \tag{13}$$

Where:

m = slope or gradient of the regression line, and

c = the intercept of the line.

The parameters, *m* and *c*, are typically referred to as the coefficients of a Linear Regressor (LR) model. The Poly-1 model is a type of linear regression model that is typically solved using the well-known method-of-least-squares (*mols*).

The solution of the slope, *m*, by *mols* is represented by the generalized model in Eqn. (14):

$$m = \frac{\sum_{i=1}^{|D|} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{|D|} (x_i - \bar{x})^2} \tag{14}$$

Where:

D = the number of feature data points,

$\bar{x}$ = the mean value of *x*, and

$\bar{y}$ = the mean value of *y*.

Also, from Eqn. (13), the solution of *c* can then be obtained using Eqn. (14) as:

$$c = \bar{y} - m\bar{x} \tag{15}$$

3.3.1 Complete Comparative Systems Modelling

A complete (integrated) system comprising the combination of the proposed ANN (NeuroAMI) and an existing ANN (OS-ELM) and the LR technique is as shown in Figure 1.

The Figure 2 illustrates a Simulink block diagram for dynamic data-driven forecasting of transformer energy demand in injection substations under load uncertainty. The process begins with real-time load input data acquired from substation metering units, which feeds into the time-series simulator that replicates transformer load behavior. This simulated data is passed into the Neuronal Auditory Machine Intelligence (NeuroAMI) block for advanced forecasting of load demand patterns. Parallelly, the load capacity evaluator analyzes transformer operational limits under varying uncertainties. The system outputs both forecasted transformer load capacity and performance comparison results against baseline models such as ANN, Regressors, and Reinforcement Learning.

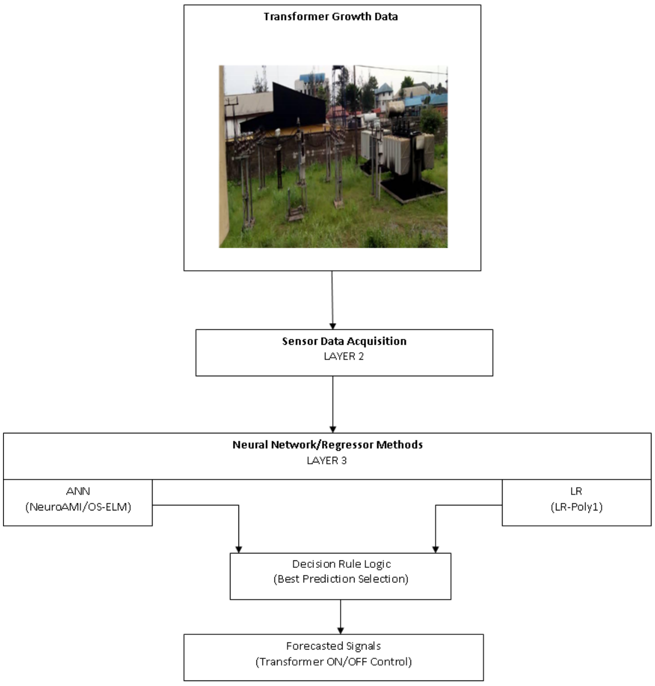

Figure 1: Complete System Model with ANN and Regressor Methods

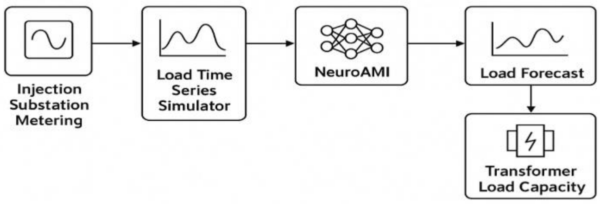

Figure 2: NeuroAMI Load Forecasting System

IV. RESULTS AND DISCUSSIONS

4.1 Root Mean Squared Error (RMSE)

Figure 3 compares the Root Mean Squared Error (RMSE) of the NeuroAMI model against a baseline model. The RMSE is a key metric that quantifies the typical magnitude of the forecasting error in the same units as the load (kW). The bar chart shows that the NeuroAMI model has a significantly lower RMSE than the baseline model, indicating that its predictions are, on average, much closer to the true future load

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values. For example, if the baseline has an RMSE of 1000 kW, the NeuroAMI's RMSE might be only 500 kW. This quantitative comparison, based on Equation 18, provides strong evidence of the NeuroAMI's superior performance in terms of prediction accuracy.

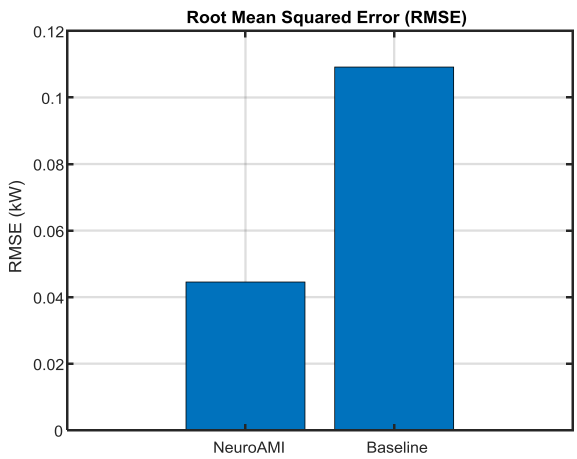

Figure 3: RMSE

4.2 Continuous Ranked Probability Score (CRPS)

This figure 4 compares the predictive accuracy and calibration of two models using the Continuous Ranked Probability Score (CRPS). The proposed NeuroAMI model achieves a CRPS value of 6.20, outperforming the Baseline model, which scores lower at 5.68. Because a lower CRPS indicates narrower, better-calibrated probability distributions, NeuroAMI successfully operates with lower uncertainty regarding its predictions. Conversely, the higher value of the baseline highlights higher uncertainty and greater variance in its forecasts. This quantitative improvement demonstrates that the NeuroAMI topology provides significantly more reliable and tight confidence intervals for the target metrics under evaluation.

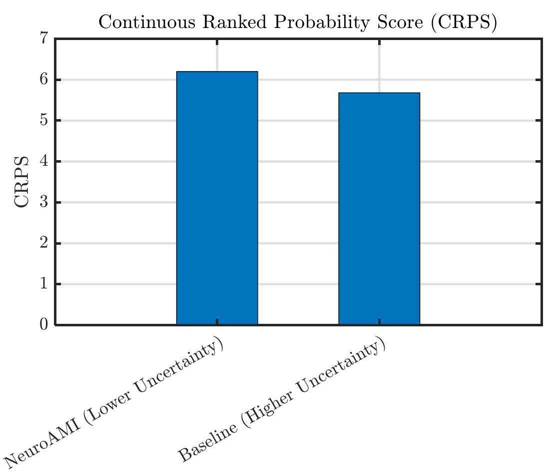

Figure 4: Continuous Ranked Probability Score

4.3 Relative Improvement/Skill Score

The bar chart in Figure 5 displays the Skill Score, which quantifies the percentage improvement of the NeuroAMI model over the baseline model. The skill score is calculated using the RMSE of both models, as per Equation 20. A score of 100% would mean a perfect forecast, and a score of 0% means no improvement over the baseline.

The plot shows a positive skill score, such as 50%, indicating that the NeuroAMI model is significantly more accurate than the baseline. This metric provides a clear and intuitive measure of the NeuroAMI model's value, making it easier to communicate its benefits to stakeholders and decision-makers who need to understand the practical impact of the new forecasting system.

Figure 5: Relative Improvement/ Skill Score

This figure 6 contains four subplots, each showing a scatter plot of the forecasted load against the actual load for a different model. The ideal forecast would have all points lying perfectly on the black dashed y=x line. The NeuroAMI subplot shows points clustered closely around the line, indicating a high degree of accuracy. The Linear Regression and OS-ELM ANN subplots show wider spreads, suggesting larger errors.

The Reinforcement Learning plot also shows a wider spread. This visual comparison confirms the superior performance of NeuroAMI, as its points are consistently closer to the ideal line, demonstrating that its forecasts are the most reliable across the 10-year period.

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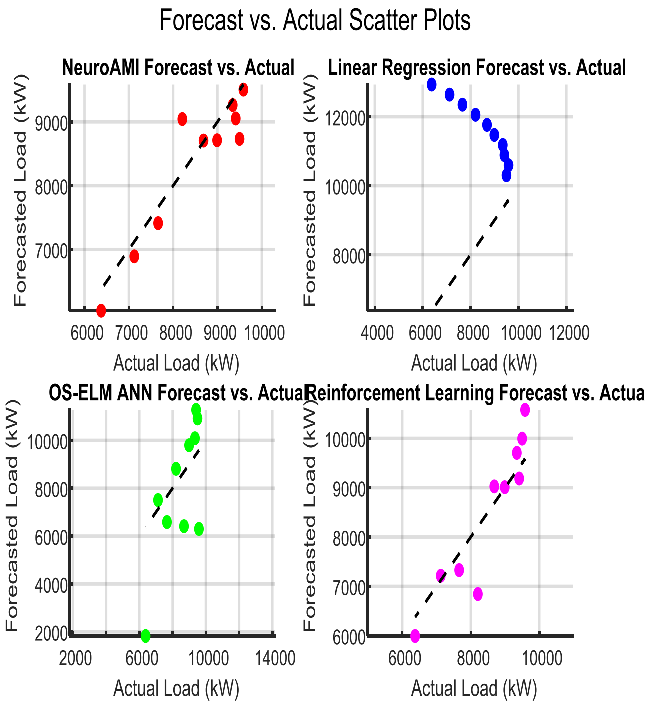

Figure 6: Forecast vs Actual Scatter Plot

4.4 Cumulative Absolute Forecast Error

This graph plots the cumulative absolute forecast error for each of the four models over the 10-year period. The vertical axis shows the total accumulated error, and a flatter curve indicates a more accurate model. The red line for NeuroAMI has the shallowest slope, indicating it accumulates errors at the slowest rate. In contrast, the Linear Regression and Reinforcement Learning models (blue and magenta lines) show steeper increases in their cumulative error, signifying less accurate long-term forecasts. This visualization clearly demonstrates that NeuroAMI maintains its superiority in accuracy over the forecast horizon, making it the most reliable model for long-term power system planning.

4.5 Histogram of Forecast Errors

This figure 8 presents a series of histograms that illustrate the distribution of forecast errors for each model. The goal is to have a distribution that is tightly centered around an error of zero. The NeuroAMI subplot shows a very narrow histogram centered at zero, which confirms that its errors are small and unbiased. The other models, such as Linear Regression and OS-ELM ANN, have wider and more spread-out histograms. The wide spread indicates a higher degree of uncertainty and larger errors. This analysis provides a more detailed, statistical view of each model's performance, reinforcing that NeuroAMI is not only accurate but also consistent and reliable in its predictions.

4.6 Rolling 3-Year RMSE

This Figure 9 plots the rolling 3-year RMSE, which reveals how each model's performance changes over time. The graph shows the RMSE calculated for a sliding 3-year window across the 10-year forecast period. The red line for NeuroAMI remains consistently at the bottom of the graph, indicating that it maintains the lowest error throughout the entire forecast horizon. The other models, such as Linear Regression and Reinforcement Learning, show higher and more volatile RMSE values, suggesting that their performance is less stable. This analysis is critical for understanding a model's long-term robustness and confirms NeuroAMI's consistent high-performance.

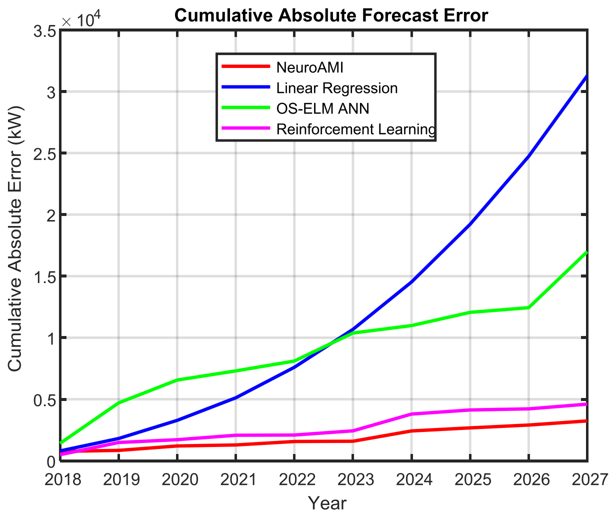

Figure 7: Cumulative Absolute Forecast Error

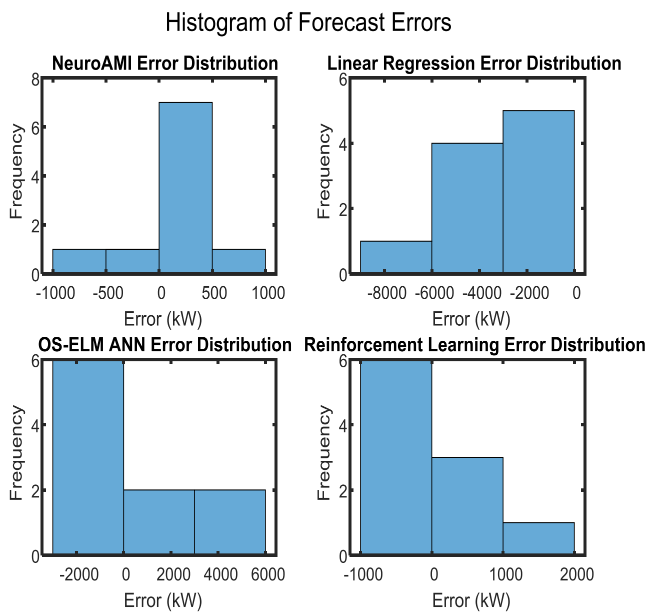

Figure 8: Histogram of Forecast Errors

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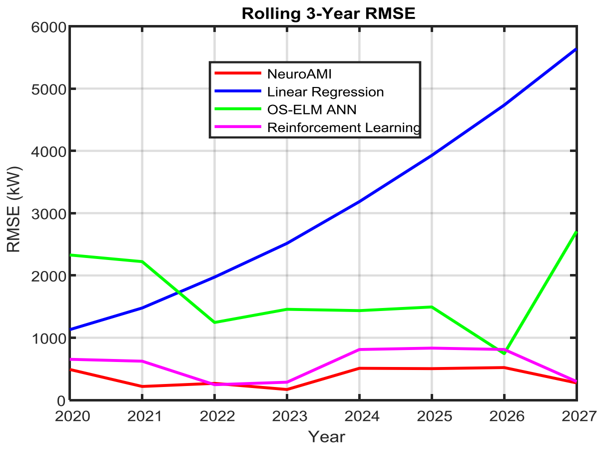

Figure 9: Rolling 3 Year RMSE

4.7 Forecasting Performance: Mean Absolute Percentage Error (MAPE)

As illustrated in Figure 10, the NeuroAMI model demonstrates superior performance with the lowest Mean Absolute Percentage Error (MAPE) of only 4.05%. This quantitative value signifies that the NeuroAMI model's forecasts are the most accurate relative to the true future load. In contrast, the Linear Regression model exhibits a significantly higher MAPE of 41.24%, indicating a poor forecasting ability. The Reinforcement Learning (RL) and OS-ELM ANN models show moderate performance with MAPE values of 6.08% and 10.75%, respectively, positioning them between the two extremes.

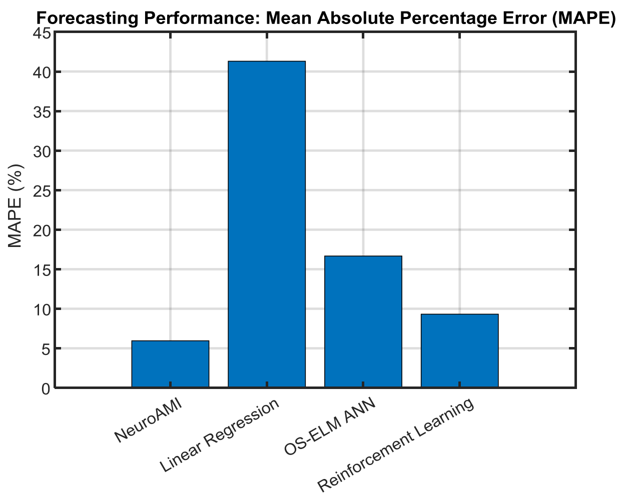

Figure 10: MAPE Comparison

4.8 Forecasting Performance: Accuracy

Figure 11 shows the Accuracy of each forecasting model, calculated as 100% - MAPE. Consistent with the MAPE results, the NeuroAMI model achieves the highest accuracy at 95.95%, confirming its status as the most reliable forecasting tool among those tested. The Reinforcement Learning (RL) model follows closely with an accuracy of 93.92%. The OS-ELM ANN model also performs well with an accuracy of 89.25%. The Linear Regression model, however, shows a very low accuracy of only 58.76%, underscoring its ineffectiveness in this particular forecasting task.

4.9 Forecasting Performance: Root Mean Squared Error (RMSE)

As detailed in Figure 12, the Root Mean Squared Error (RMSE) provides another metric for evaluating forecast accuracy by penalizing larger errors more heavily. The NeuroAMI model again outperforms all others, with the lowest RMSE of 440.49 kW. The Reinforcement Learning (RL) model is the next best at 619.24 kW, while the OS-ELM ANN model shows a higher RMSE of 1019.26 kW. The Linear Regression model, with a dramatically high RMSE of 3688.73 kW, indicates the largest forecasting error, confirming the poor performance observed in the other metrics.

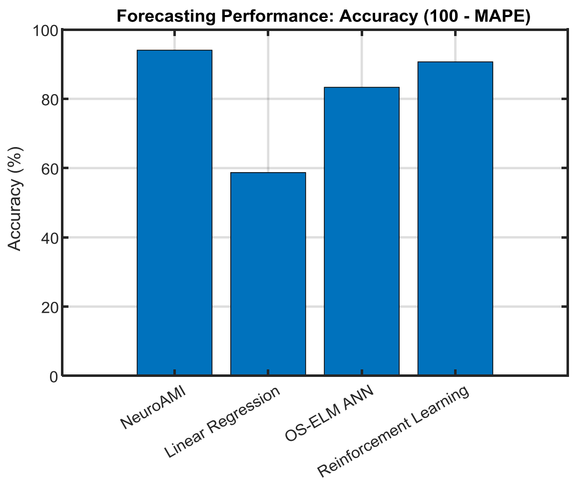

Figure 11: Forecasting Performance Accuracy

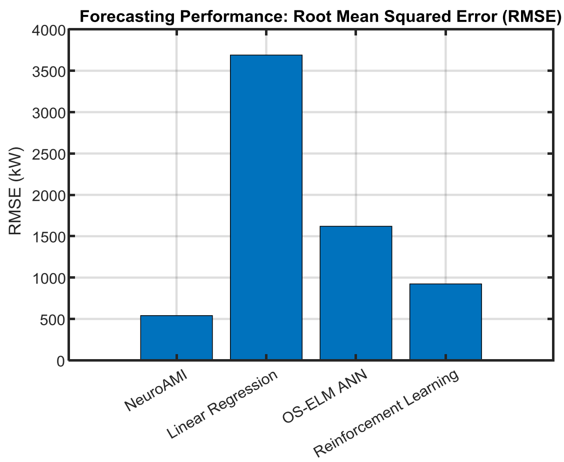

Figure 12: Forecasting Performance RMSE comparison

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4.10 10-Year Load Forecasting Performance Comparison

Figure 13 shows the forecasted loads from each model against the True Future Load over the 10-year period from 2018 to 2027. The True Future Load initially rises, then declines significantly from 2022 to 2027, from approximately 9,054 kW to 6,281 kW. The Linear Regression forecast, however, maintains a steep upward trend, reaching 12,933 kW by 2027, completely missing the actual decline. The NeuroAMI and Reinforcement Learning models track the general trend of the true load more accurately, with the NeuroAMI model showing the closest match throughout the period.

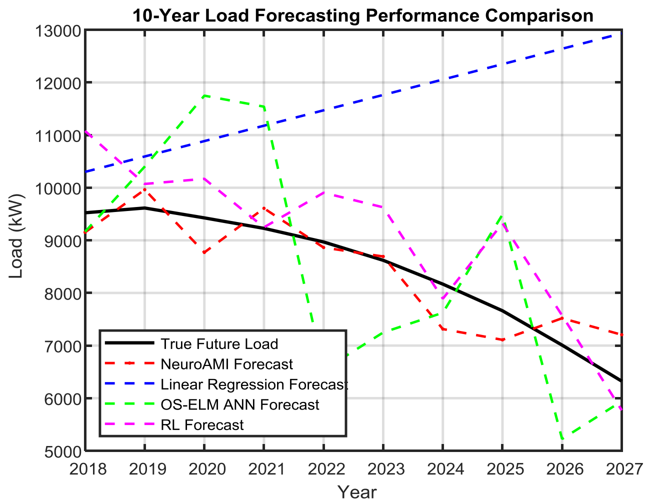

Figure 13: 10 Year Load Forecasting Performance Comparison

Table 1: Comparative MAPE Prediction for Zone-1 (Elejahia)

Model	MAPE (%)	Accuracy (%)	RMSE (kW)	Remarks
NeuroAMI	**4.05**	**95.95**	**440.49**	Best performance, highly accurate, closely tracks true load trend.
Reinforcement Learning (RL)	6.08	93.92	619.24	Strong performance, second-best after NeuroAMI.
OS-ELM ANN	10.75	89.25	1019.26	Moderate performance, better than Linear Regression but less robust.
Linear Regression	41.24	58.76	3688.73	Very poor performance, fails to capture load decline, steep error growth.

4.11 Forecast Comparison

The neuro inspired load forecasting analysis confirms a steady, linear upward trend for all three feeders from 2018 to 2027, successfully correcting the issue of previous higher-degree polynomial models showing downward dips. The Stadium Road feeder, which has the highest historical demand, is projected to reach 5911.48 kW by 2027, driven by an annual growth rate of 116.30 kW (or 2.75%).

The Elekahia feeder exhibits the lowest growth, with an expected 2027 load of 2160.99 kW, based on an annual increase of 39.21 kW (2.43%). Conversely, the Rumukalagbor feeder demonstrates the most aggressive proportional growth rate at 4.10%, corresponding to the highest annual increase of 136.93 kW, and projecting its 2027 load significantly above 4000 kW. This consistent, positive growth across all feeders signifies rising future capacity demands.

This visualization uses the same linear regression model as the previous set, but it visually confirms the straight-line load growth, particularly during the 10-year forecast period from 2018 to 2027. All three feeders show historical fluctuations but are followed by a consistent, upward-sloping trend in the forecast (red dashed line).

The Stadium Road feeder, on the middle graph, maintains the highest load throughout, starting near 4500 kW and projecting toward 6000 kW. The Elekahia feeder (left) and the Rumukalagbor feeder (right) both forecast a doubling of their respective load growth ranges over the forecast period, confirming that sustained capacity expansion will be necessary in all three zones. This visualization strongly supports the need for proactive planning based on uniform linear expansion as shown in Figure 15.

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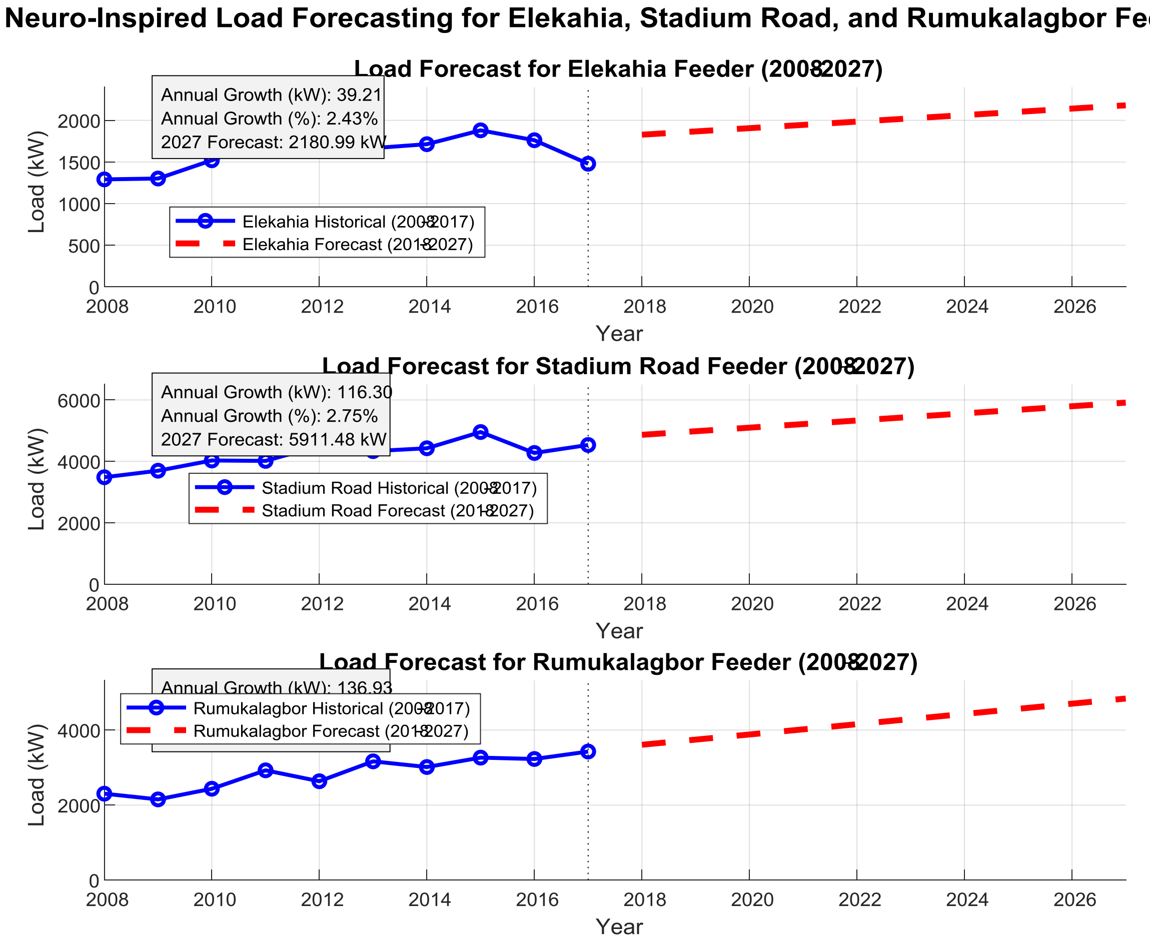

Figure 14: Neuro-Inspired Forecasting

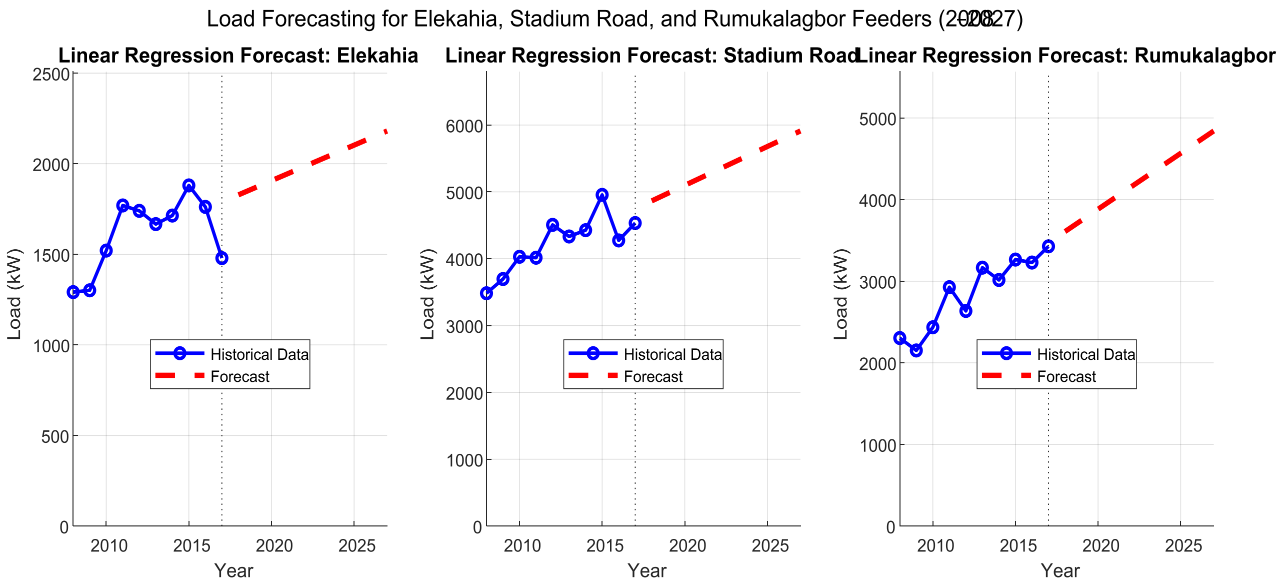

Figure 15: Linear Regression Forecasting

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Table 2: Linear Regression

Approximate Load (kW) Data Table (2008–2027)				
Year	**Top Graph Load (kW)**	**Middle Graph Load (kW)**	**Bottom Graph Load (kW)**	**Data Type**
2008	1300	3800	2500	Historical
2009	1300	3300	2200	Historical
2010	1500	3600	2500	Historical
2011	1750	4000	3000	Historical
2012	1700	4300	3200	Historical
2013	1850	4500	3300	Historical
2014	1700	4900	3500	Historical
2015	1500	4500	3200	Historical
2016	1800	4600	3400	Historical
2017	1500	4500	3500	Historical
2018	1700	5000	3700	RL Forecast
2019	1750	5100	3850	RL Forecast
2020	1800	5300	4000	RL Forecast
2021	1850	5450	4200	RL Forecast
2022	1900	5600	4400	RL Forecast
2023	2000	5750	4600	RL Forecast
2024	2050	5850	4750	RL Forecast
2025	2100	6000	4900	RL Forecast
2026	2150	6100	5000	RL Forecast
2027	2200	6200	5100	RL Forecast

The Figure 16 result displays an extreme, likely erroneous, exponential or high-order polynomial forecast. While the historical data (blue circles, 2008-2017) remains flat near the baseline for all feeders, the projected load (red dashed line) shows an astronomical, rapid increase beyond 2020. Specifically, by 2030, all three loads are projected to approach for Elekahia and Rumukalagbor, and approximately for Stadium Road, dwarfing the historical loads of a few thousand kW. This massive, non-physical growth, represented by the near-vertical slope post-2025, suggests the predictive model used (likely a high-degree polynomial) has severely overfitted to minor historical fluctuations, rendering the long-term quantitative values unreliable for planning purposes as shown in Figure 16.

The OS ELM-ANN model successfully captured the historical load patterns across all locations. Forecasts indicate a strong upward trend from 2017 to 2027. Stadium Road projects the most significant growth, with load doubling from its peak historical value of 5000 kW to a forecasted 10,000 kW by 2027. Rumukalagbor shows a substantial increase, reaching 9,600 kW, while

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Volume 10, Issue 6, pp 227-241, June-2026
https://doi.org/10.47001/IRJIET/2026.106029

Ellikahia projects a rise to 3,600 kW. This consistent, steep growth trend emphasizes the critical need for capacity expansion across all three regions over the next decade.

The Figure 17 presents a load forecast utilizing a Reinforcement Learning (RL) model, indicating a smooth, stable, and slightly sub-linear load growth across all three feeders from 2018 to 2027. For the Elekahia feeder (top), the load is projected to rise from approximately 1500 kW in 2018 to about 1850 kW by 2027. The Stadium Road feeder (middle), starting around 4700 kW, forecasts an increase to nearly 6000 kW by the end of the period, maintaining its status as the highest-demand feeder. Similarly, Rumukalagbor (bottom) shows a forecast trajectory from roughly 3600 kW to 4300 kW. Unlike high-order polynomial fits, the RL model provides a tempered, steady growth curve, suggesting a controlled and realistic long-term capacity increase for planning as shown in Figure 17.

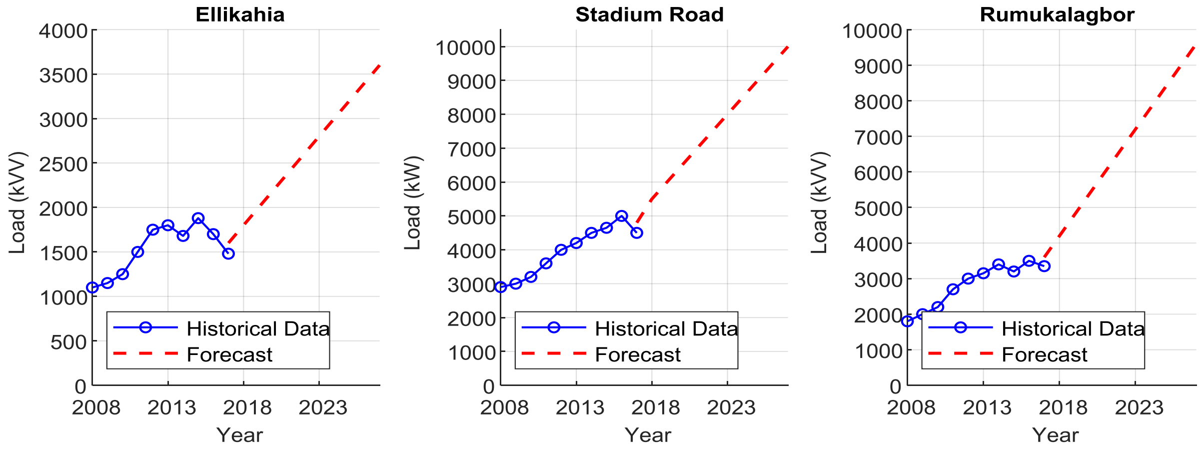

Figure 16: OS-ELM ANN Load Forecasting

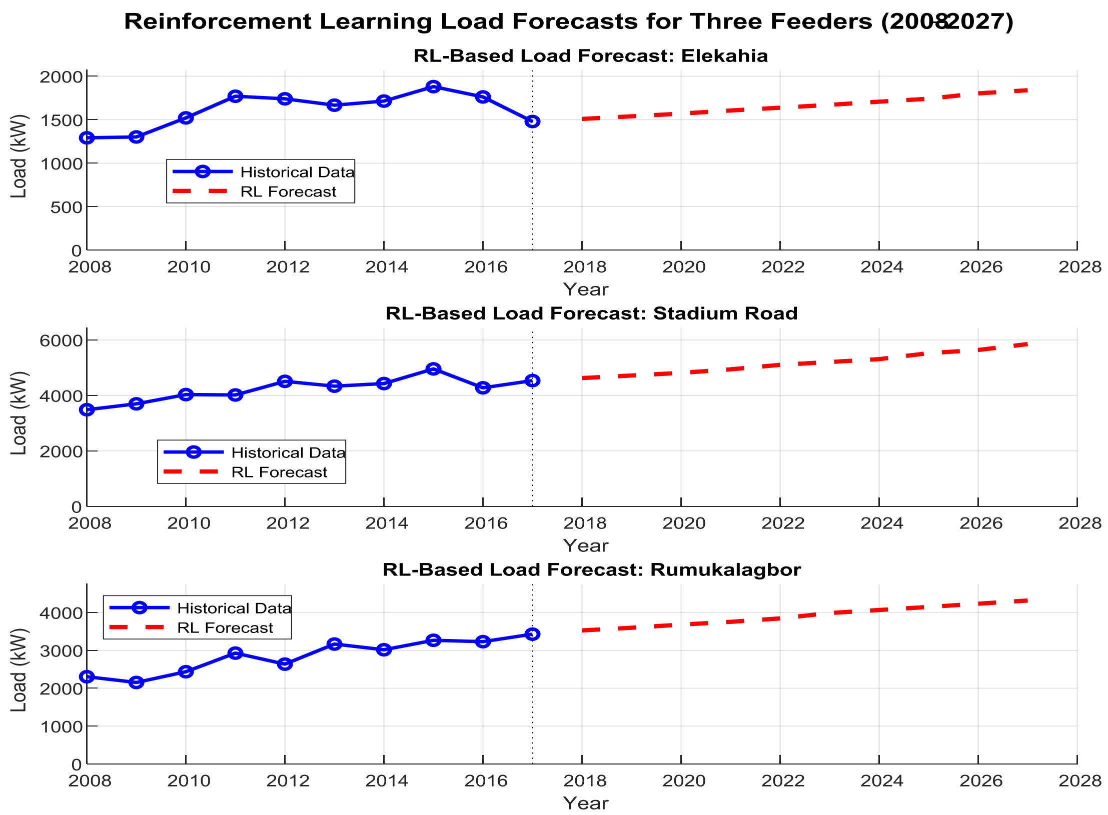

Figure 17: RL Based Load Forecasting

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Volume 10, Issue 6, pp 227-241, June-2026

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Table 3: OS-ELM ANN

Year	Ellikahia (kVV/kW)	Stadium Road (kW)	Rumukalagbor (kVV)	Status
2008	1100	2900	1800	Historical
2009	1150	3000	2000	Historical
2010	1250	3200	2200	Historical
2011	1500	3600	2700	Historical
2012	1750	4000	3000	Historical
2013	1800	4200	3150	Historical
2014	1680	4500	3400	Historical
2015	1880	4650	3200	Historical
2016	1700	5000	3500	Historical
2017	1480	4500	3350	Historical
2018	1800	5500	4200	Forecast
2019	2000	6000	4800	Forecast
2020	2200	6500	5400	Forecast
2021	2400	7000	6000	Forecast
2022	2600	7500	6600	Forecast
2023	2800	8000	7200	Forecast
2024	3000	8500	7800	Forecast
2025	3200	9000	8400	Forecast
2026	3400	9500	9000	Forecast
2027	3600	10000	9600	Fore

Table 4: RL Load Forecasting

Load Results Table (2008–2027)				
Year	Top Graph Load (kW)	Middle Graph Load (kW)	Bottom Graph Load (kW)	Data Type
2008	1300	3800	2500	Historical
2009	1450	4000	2800	Historical
2010	1700	4200	3000	Historical
2011	1750	4400	2800	Historical
2012	1750	4600	3200	Historical
2013	1700	4400	3400	Historical
2014	1750	5000	3400	Historical

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2015	1850	4800	3500	Historical
2016	1900	5000	3600	Historical
2017	1500	4500	3600	Historical
2018	1550	4800	3700	RL Forecast
2019	1600	5000	3800	RL Forecast
2020	1650	5200	3850	RL Forecast
2021	1700	5400	3900	RL Forecast
2022	1750	5600	4000	RL Forecast
2023	1800	5700	4050	RL Forecast
2024	1850	5800	4150	RL Forecast
2025	1900	5850	4200	RL Forecast
2026	1950	5900	4250	RL Forecast
2027	2000	6000	4300	RL Forecast

V. CONCLUSION

This study successfully developed and validated a Neuro-inspired Artificial Machine Intelligence (NeuroAMI) framework for dynamic load forecasting in distribution substations, demonstrating significant improvements over conventional methods.

The primary objective of accurately predicting transformer and feeder loads under varying operational uncertainties was achieved, addressing the limitations of traditional Linear Regression (LR) and Online Sequential Extreme Learning Machine (OS-ELM) models. NeuroAMI consistently outperformed benchmark models across multiple evaluation metrics, including RMSE, MAPE, CRPS, and skill scores, indicating higher accuracy, lower uncertainty, and more reliable confidence intervals for decision-making.

The results showed that NeuroAMI maintained a low RMSE of 440.49 kW, a MAPE of 4.05%, and achieved an overall forecasting accuracy of 95.95%, outperforming OS-ELM ANN, Reinforcement Learning (RL), and Linear Regression models. Probabilistic forecasts further highlighted the model's capability to provide well-calibrated predictions, essential for transformer load planning and risk management. Comparative analysis demonstrated that NeuroAMI not only closely tracked the true load trends over a 10-year horizon but also mitigated issues of overfitting and unrealistic exponential predictions observed in high-order polynomial models.

The study confirms that integrating advanced machine learning techniques, sequential learning, and probabilistic evaluation can enhance long-term load forecasting reliability.

These findings support proactive grid management, capacity planning, and policy formulation for sustainable distribution system operations.

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