IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⩰ Peer-reviewed & Refereed journal ⩰ Vol. 14, Issue 6, June 2026

DOI: 10.17148/IJIREEICE.2026.14629

Sequential Growth Model and NeuroAMI Neural Network for Distribution Transformer Load Forecasting

Nemine, B. E.[1], Ahiakwo, C. O.[2], Braide, S. L.[3], Amadi, H. N.[4]

PG Scholar, Department of Electrical & Electronic Engineering, Rivers State University, Port Harcourt, Nigeria[1]

Professor, Department of Electrical & Electronic Engineering, Rivers State University, Port Harcourt, Nigeria[2]

Associate Prof., Department of Electrical & Electronic Engineering, Rivers State University, Port Harcourt, Nigeria[3]

Associate Prof., Department of Electrical & Electronic Engineering, Rivers State University, Port Harcourt, Nigeria[4]

Abstract: Accurate distribution transformer load forecasting is essential for ensuring reliable power system operation, preventing transformer overloading, supporting asset management, and facilitating effective capacity expansion planning. However, increasing load demand, stochastic consumer behaviour, seasonal variations, and measurement uncertainties pose significant challenges to conventional forecasting techniques. This study presents a Sequential Growth Model integrated with a Neuronal Auditory Machine Intelligence (NeuroAMI) Neural Network for real-time distribution transformer load forecasting using historical electrical load time-series data. The proposed methodology incorporates a real-time discrete sampling model, finite-window normalization, data augmentation through noise injection, and trend-seasonal decomposition to improve data quality and model robustness. The NeuroAMI neural network employs auditory-inspired spectrogram feature extraction, heteroscedastic Gaussian negative log-likelihood optimization, regularized learning objectives, and online mini-batch gradient adaptation to accurately predict future transformer loading conditions. Historical transformer load data spanning 2008–2017 were utilized to forecast loading conditions from 2018–2027. The results demonstrated significant forecasting capability, with transformer load demand increasing from approximately 8,000 kW in 2017 to over 10,000 kW by 2027. The training process exhibited stable convergence, as the Negative Log-Likelihood loss decreased from approximately 80 to 20, while regularization loss reduced from about 15 to 5 over 100 training epochs. Furthermore, feeder-level forecasting revealed projected load growth from 1,500 kW to 1,850 kW for Elekahia feeder, 4,700 kW to 6,000 kW for Stadium Road feeder, and 3,600 kW to 4,300 kW for Rumukalagbor feeder. The study concludes that the proposed Sequential Growth–NeuroAMI framework provides an intelligent, adaptive, and reliable forecasting tool capable of supporting utility operational policies, preventive maintenance strategies, transformer capacity planning, and sustainable distribution network expansion.

Keywords: NeuroAMI, Transformer, Loads Forecast, Machine Learning

I. INTRODUCTION

Distribution transformers constitute one of the most critical components of electrical power distribution systems, serving as the final voltage conversion stage before electrical energy is delivered to consumers. The increasing complexity of modern power networks, coupled with rapid urbanization, industrial growth, and the integration of renewable energy resources, has significantly increased the demand for accurate transformer load forecasting. Reliable load prediction is essential for ensuring efficient transformer utilization, minimizing overloading conditions, reducing power losses, enhancing equipment lifespan, and maintaining overall system reliability [1]. Consequently, advanced forecasting techniques have become indispensable tools for power system engineers and utility operators. Traditional load forecasting methods often rely on statistical approaches that may not adequately capture the nonlinear and dynamic characteristics of transformer loading patterns. Variations in consumer behaviour, seasonal changes, weather conditions, economic activities, and distributed energy generation introduce substantial uncertainties into transformer loading profiles [2].

These complexities necessitate the adoption of intelligent forecasting models capable of learning hidden relationships within large datasets and adapting to changing operating conditions. The Sequential Growth Model (SGM) has emerged as an effective forecasting approach for analysing temporal growth trends in electrical demand [3]. By systematically evaluating historical load progression, the model provides valuable insights into future loading behaviour and capacity requirements. However, the nonlinear nature of distribution transformer loads often requires more sophisticated computational techniques to achieve higher prediction accuracy. Artificial neural networks have demonstrated

DOI: 10.17148/IJIREEICE.2026.14629

remarkable capabilities in modelling complex nonlinear systems due to their adaptive learning characteristics and ability to generalize from historical data. Among advanced neural network architectures, the NeuroAMI Neural Network offers enhanced forecasting performance through intelligent pattern recognition and adaptive learning mechanisms. The model effectively processes multidimensional input variables and captures intricate relationships between load demand factors and transformer operating conditions [4]. By integrating the Sequential Growth Model with the NeuroAMI Neural Network, a hybrid forecasting framework can be developed to leverage the strengths of both methodologies [5].

This integrated approach improves prediction accuracy, supports proactive asset management, facilitates optimal transformer loading, and assists utility companies in making informed operational and expansion planning decisions. Therefore, the application of Sequential Growth Model and NeuroAMI Neural Network presents a promising solution for modern distribution transformer load forecasting challenges.

II. LITERATURE REVIEW

Data-driven methods based on Machine Learning (ML) or Artificial Intelligence (AI) In [1], a spatial ANN combined with an FL algorithm is employed for load forecasting of the distribution transformer power network. From their results, they were able to report higher classification accuracy than the traditional methods. In [2], a GA optimized ANN is used to forecast the loads on electrical power distribution transformer network with the emphasis on short-term (high-frequency) predictions. [3] used an improved GA-ANN (iGA-ANN) for load forecasting of the distribution transformer power network. Their proposed approach exploited the fine-tuning of the weights and biases of the ANN by the GA with global optima maximization. The use of the k-means clustering and a Distributed Error Extreme Learning Machine (DE-ELM) approach is applied in [4] for load forecasting of the distribution power network transformers in addition to overload warning.4An AFSA-based Back-Propagation ANN (AFSA-BP-ANN) is employed in [5] for the analysis and forecasting distribution transformer network loads within a smart grid context.

In [6], the method based on a CBR-ANN is employed for short-term forecasting distribution transformer network loads. In a more advanced solution, the 1-D Convolutional Neural Network (CNN) with the Long Short-Term Memory (LSTM) neural network was employed in 24hour short-term load forecasting of distribution transformer network [7].

In [7], the use of PSO-based ANNs with wavelet feature data decomposition is employed for short-term forecasting of power system network loads with the optimization constraints that depend on the training algorithm which finds the best set of neuron weights and biases that gives least error. In recent studies, the Harris Hawks Optimization with the Feed-Forward Neural Network (HHO-FFNN) and yearly load feature processing with stationary wavelet packet transforms [8] is applied to load forecasting of utility grid, Also, using several weather related data as supporting features, the Sequential Pattern Mining Long Short-Term Memory (SPM-LSTM) is used to predict load demand in power grid considering real consumption and generation data [9].

In [10], the short-term forecasting of distribution transformer network loads is conducted using the DL-ANNs. The DL-ANNs specifically transform numerical prediction task into an image processing task prior to the forecast process. In [11], the combination of Auto-Encoder (AE) and LSTM ANNs is employed for forecasting of distribution transformer network loads with renewable energy penetration. In [12], a thermal model representation of distribution transformer including several load prediction models is proposed for next 24h load forecast.

In [13], clustering techniques are adopted for the interconnected feeder loads on distribution transformer substation in Thailand such that the entire load is effectively forecasted. In [14], the optimal power flow via the distribution power transformer system is estimated by considering both electrical power load and wind distributions in an integrated renewable energy system.

In [15], the impact of Electric Vehicles (EVs) on distribution transformer is investigated considering several EV parameters such as weight, state of charge and energy usage patterns in order to estimate the amount of additional EV loading on transformer. In [16], risk assessment of distribution transformer is investigated using the k-means clustering in order to estimate the standard load profiles (shapes) considering different weather conditions from over 125 residential power service locations in Canada.

In [17], the IEEE C57.91-2011 standard is employed in the prediction of distribution transformer load related failures leading to loss of transformer life. The method of Cumulative Moving Average (CMA) is adopted in [18] to estimate the distribution transformer loading and hence lifetime using a sensory data and the IEEE C57.91-2011 standard. In [19], an

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⁕ Peer-reviewed & Refereed journal ⁕ Vol. 14, Issue 6, June 2026

DOI: 10.17148/IJIREEICE.2026.14629

old version of the IEEE C57.91-2011 standard is employed in analysing load impact and life expectancy of distribution transformer.

In [21], quick charging EVs loading impact on the life of distribution transformer system is investigated for the city province of Thailand. In [21], long-term forecasting of linear time series distribution transformer loading data is carried out using the FL approach. The forecasting of the Jember substation loading data in Turkey is specifically investigated while performing optimizations considering distribution power transformer uprating requirements. The use of model-based transformers is proposed in [22] for short-term forecasting of distribution transformer loading data.

III. METHODS

A. Real-Time Limited Electrical Load Time-Series Simulator

A.1. Time-Series Sampling Model (Real-Time Discrete Sampling)

A real-time simulator must represent continuous transformer load as a discrete sequence sampled at uniform intervals. This equation models the sampled load series L[t] obtained from metering units by sampling the underlying continuous load process $L_c(t)$ with sample interval Δt. It captures the basic data ingestion step for downstream forecasting and control. The sampled series preserves trends, seasonality and transient events if the sampling frequency satisfies the Nyquist-like requirement for the dynamics of interest. In practice Δt might be 1 minute, 5 minutes, or 1 hour depending on available telemetry and computational constraints.

$$L[t] = L_c(t_0 + t\Delta t), \qquad t = 0,1,\dots,T-1 \tag{1}$$

Where:

L[t]: sampled load at discrete index t (kW).
L_c: continuous-time true load process (kW).
t: sample index (integer).
Δt: sampling interval (time units, e.g., minutes).
t_0: initial time offset.
T: total number of samples.

A.2. Finite-Window Normalization for Real-Time Input

Neural models and simulators often require normalized input to stabilize training and adapt to changing ranges. This equation normalizes the most recent sliding window of raw sampled loads to zero mean and unit variance (or to a bounded range) using online estimates computed over a window of length www. Normalization mitigates rotationality due to seasonal growth or sudden shifts, and ensures the NeuroAMI sees inputs in a stable numeric range. The sliding window can be updated online; estimates may use exponential smoothing for robustness to outliers. The normalized series L[t] is then fed to forecasting models.

$$\tilde{L}[t] = \frac{l[t]-\mu_w[t]}{\sigma_w[t]+\varepsilon}, \quad \mu_w[t] = \frac{1}{w}\sum_{i=t-w+1}^{t} L[i], \sigma_w[t] = \sqrt{\frac{1}{w}\sum_{i=t-w+1}^{t}(L[i]-\mu_w[t])^2} \tag{2}$$

Where:

L[t]: normalized load at time t.
μ_w [t]: sliding-window mean over last www samples.
σ_w [t]: sliding-window standard deviation.
w: window length (samples).
ε: small constant to avoid division by zero.

A.3. Data Augmentation with Noise Injection (Simulator Variability)

To simulate sensor noise and load variability, augment sampled data by adding controlled stochastic perturbations. This equation generates augmented samples L ̂[t] by adding heteroscedastic noise whose variance may scale with the signal amplitude (common in metering equipment). Augmentation improves model robustness to measurement error and unseen operating conditions. The noise can be Gaussian or drawn from empirical residual distributions observed in the real-time data. For dynamic simulation, the noise variance can itself be time-varying to reflect busy vs. idle hours. This mechanism supports realistic training and stress-testing of forecasting models.

$$\hat{L}[t] = L[t] + \eta[t], \quad \eta[t] \sim N(o, (a_0 + a_1 L[t])^2) \tag{3}$$

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.021 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 14, Issue 6, June 2026
DOI: 10.17148/IJIREEICE.2026.14629

Where:
L῀[t]: augmented (noisy) load sample.
η[t]: additive noise at time t.
N(0,σ2): Gaussian distribution (mean 0, variance σ2).
a_0: baseline noise scale.
a_1: signal-dependent noise scale.

A.4. Short-Term Trend and Seasonal Decomposition (Simulator Baseline)
To simulate realistic load behaviour, decompose load into trend, seasonal, and residual components. This additive model expresses the sampled load as the sum of a low-frequency growth trend, periodic seasonal variations (daily/weekly), and a residual stochastic term representing transients and measurement noise. Incorporating explicit seasonal harmonics allows the simulator to reproduce known periodicities (e.g., daily consumption cycle and weekly patterns) which are crucial for transformer loading studies. The simulator can parameterize these components to explore scenarios: growing urban demand, stronger weekday peaks, or increased nighttime usage.

$$L[t] = \dot{T}[t] + \sum_{k=1}^{K} A_k \cos\left(\frac{2\pi kt}{P_k} + \emptyset_k\right) + \in [t] \quad (4)$$

Where:
T[t]: trend component (slowly varying).
K: number of seasonal harmonics.
A_k: amplitude of harmonic k.
P_k: period (in samples) of harmonic k (e.g., 1440 for daily-minutely).
ϕ_k: phase of harmonic k.
ϵ[t]: residual stochastic component.

B. NeuroAMI Neural Network Model & Training
B.1. NeuroAMI Forward Model (Mapping Input Window to Forecast)
NeuroAMI is a specialized neural mapping that converts a past window of normalized loads and auxiliary features into multi-step ahead forecasts. This equation represents the forward pass: the model F_θ parameterized by θ maps input vector x_t (which may include L˜[t−w+1:t], time-of-day, day-of-week, temperature, etc.) to predicted future loads y^_(t+1:t+H) over horizon H. NeuroAMI can include convolutional, recurrent, attention, or auditory-inspired encoding layers; this abstract equation is the predictive core used during simulation and evaluation.

$$\hat{y}_{t+1:t+H} = F_\theta(x_t) \quad (5)$$

$$L[t] = \dot{T}[t] + \sum_{k=1}^{K} A_k \cos\left(\frac{2\pi kt}{P_k} + \emptyset_k\right) + \in [t] \quad (4)$$

Where:
y^_(t+1:t+H): vector of forecasts for next H steps.
F_θ: NeuroAMI model with trainable parameters θ.
x_t: input feature vector at time t (includes past window and exogenous features).
H: forecast horizon (samples).

A.2. Loss: Heteroscedastic Gaussian Negative Log-Likelihood
When uncertainty matters (as in transformer overload risk), predict both mean and variance. Train NeuroAMI to output predictive mean μ(t(n)+h) and variance σ(t^n+h)^2 by minimizing the negative log-likelihood assuming conditional Gaussian errors. This encourages calibrated uncertainty estimates and penalizes mis-confidence. The loss over horizon H sums the NLL across steps and samples. Heteroscedasticity allows variance to vary with input, enabling the model to express higher uncertainty at volatile times (e.g., switching events). This is more informative than pointwise MSE when making risk-aware operational decisions.

$$L_{NLL}(\theta) = \frac{1}{N}\sum_{n=1}^{N}\sum_{h=1}^{H}\left(\frac{(y_{t(n)+h} - \mu_{t(n)+h})^2}{2\sigma^2_{t^n+h}} + \frac{1}{2} In\sigma^2_{t^n+h}\right) \quad (6)$$

Where:
L_{NLL} (θ): negative log-likelihood loss.
N: number of training windows/samples.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⪓ Peer-reviewed & Refereed journal ⪓ Vol. 14, Issue 6, June 2026

DOI: 10.17148/IJIREEICE.2026.14629

y(t(n)+h): true load at horizon h for sample n.
μ(t(n)+h): model-predicted mean and variance.

B.3. Regularized Training Objective (with weight decay & early loss term)
To avoid overfitting and encourage smooth predictions, augment the primary loss with regularization terms. This equation shows the total training objective combining NLL (or MSE) with L2 weight decay and an optional temporal smoothness penalty on consecutive predicted variances or means. The smoothness term discourages erratic variance predictions that would be operationally unhelpful. Hyperparameters and λ_s control the strength of regularization. This objective is optimized via stochastic gradient descent, enabling NeuroAMI to generalize from historical and simulated noisy data.

$$J(\theta) = L_{NLl}(\theta) + \lambda_w ||\theta||_2^2 + \lambda_s \sum_{t,h} (\mu_{t+h} - \mu_{t+h-1})^2 \tag{7}$$

Where:
J(θ): total objective.
λ_w: weight-decay coefficient.
||θ| |_2^2: squared L2 norm of parameters.
λ_s: smoothness penalty coefficient.
μ (t+h): predicted mean at time t+h.

B.4. Online Update with Mini-Batch Gradient Step (real-time learning)
To adapt to changing load regimes, NeuroAMI may be updated online using incoming mini-batches from the simulator or streaming telemetry. This equation gives a single gradient descent update where parameters at step k+1 are the previous parameters minus a learning rate times the gradient of the objective computed on a mini-batch Bk. Using adaptive optimizers (e.g., Adam) replaces the simple gradient with parameter-specific updates. Online updates enable continual learning and adaptivity to slow demand growth or abrupt shifts in usage patterns, while careful learning-rate scheduling avoids catastrophic forgetting.

$$\theta_{k+1} = \theta_k - \eta_k \nabla_\theta J B_k(\theta_k) \tag{8}$$

Where:
θ_k: parameters at iteration k.
η_k: learning rate (possibly adaptive).
B_k: mini-batch at step k.
$\nabla_\theta JB_k$: gradient of objective on B_k.

B.5. Auditory-Inspired Feature Extraction (spectrogram-like encoding)
NeuroAMI's "auditory" naming suggests time–frequency encoding analogous to short-time Fourier or cochlea gram features. This equation computes a short-time spectral energy matrix $S_{f,,t}$ from the normalized window using a filter bank g_f (τ). Such encoding captures temporal patterns and transient events relevant for forecasting (e.g., sudden load spikes) and can improve model performance relative to raw time-domain inputs. The filter-bank outputs become inputs to convolutional layers or attention modules inside NeuroAMI. This formalizes preprocessing that mimics auditory signal processing for time-series loads.

$$S_{f,t} = \sum_{\tau=0}^{w=1} \tilde{L}[t-\tau] g_f(\tau), \quad f = 1, \dots, F \tag{9}$$

Where:
$S_{f,,t}$: filter-bank response at frequency/bin f and time t.
g_f (τ).: filter response (e.g., windowed bandpass).
F: number of filters/bands.
w: analysis window length.

A flow diagram depicting the process of minimizing the error in the process of predicting the possibility of a growth from historical transformer load data presented to a neural prediction system such as the NeuroAMI or OS-ELM is as shown in Figure 1.

In this diagram, once a start (BEGIN or RUN) command is initiated, the transformer data (Tin) including the year and loading values are loaded into program memory and all OS neural/system parameters are initialized. The iteration counter

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 6, June 2026

DOI: 10.17148/IJIREEICE.2026.14629

is started and incremented as well. Following this, the core neural network load forecast routine is started and the system generates training predictions (Tp).

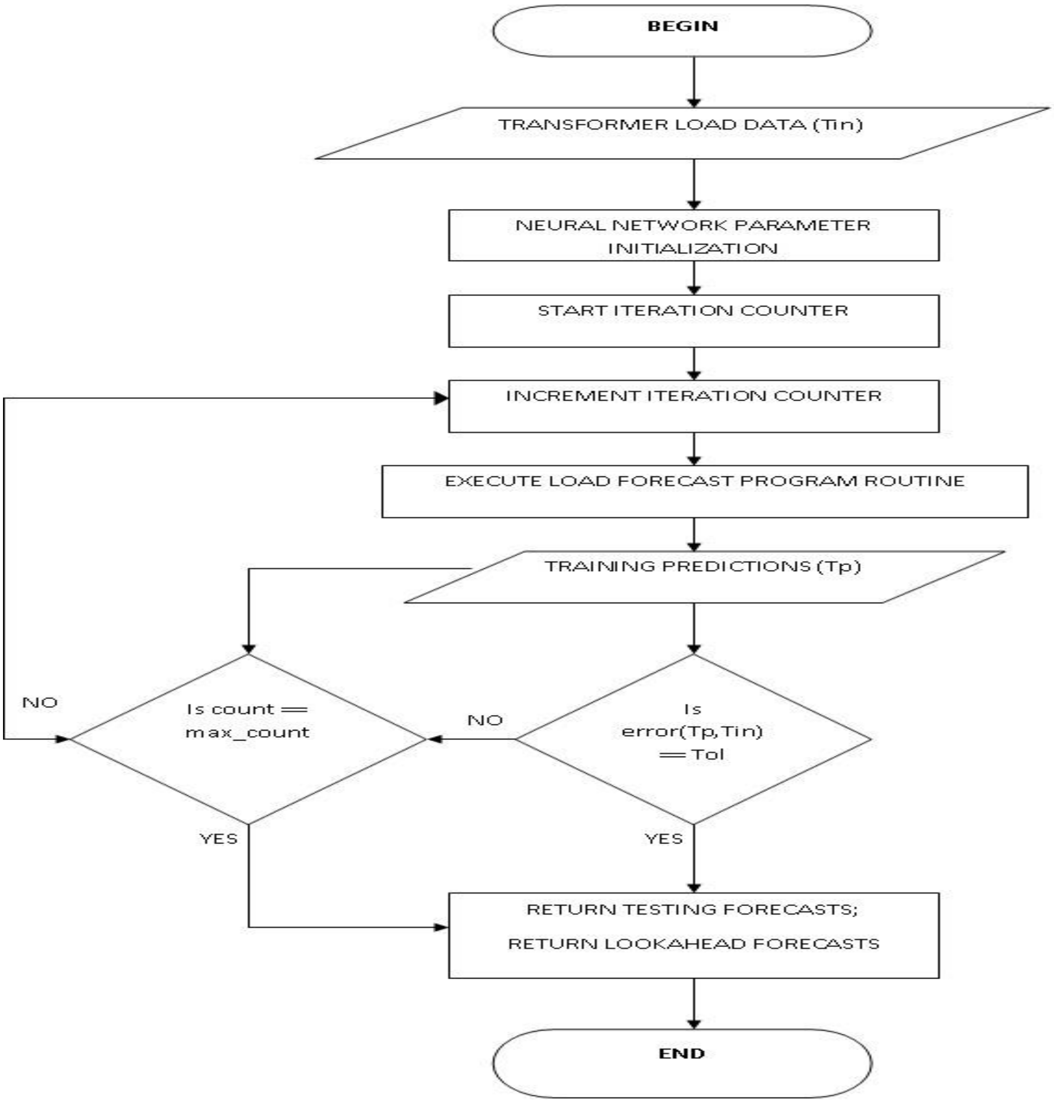

Fig. 1 Flow Diagram for Transformer Load Growth Modelling and Forecasting

A. Method Based on Neuronal Auditory Machine Intelligence (NeuroAMI) Neural Network Model Electrical Load Time Series

The neural inspired technique proposed here is based on principles bordering on the Mismatch Negativity Effect (MMN) elicited in living subjects and in the intelligent processing of cochlear neurons in mammalian auditory cortex [23][24]. The MMN is elicited based on differential responses observed due to the odd stimulations in the mammalian brain [25]. Its architecture is as provided in Figure 2.

IJIREEICE
ISSN (O) 2321-2004, ISSN (P) 2321-5526
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.021 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 14, Issue 6, June 2026
DOI: 10.17148/IJIREEICE.2026.14629

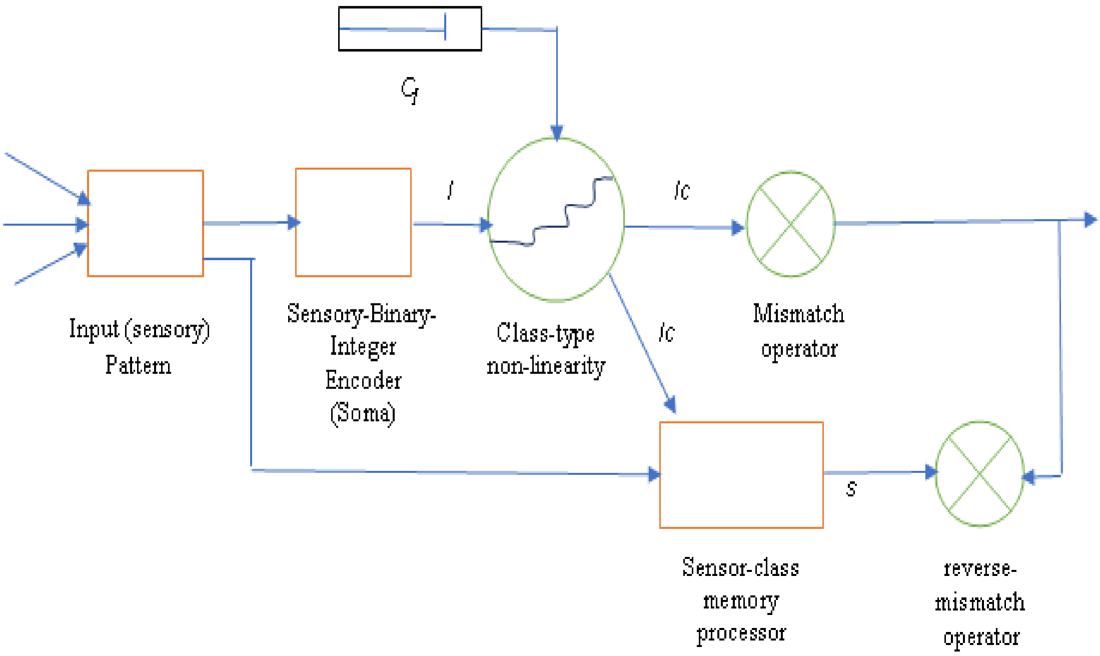

Fig. 2 Updated Neural Structure of NeuroAMI Technique [26]

IV. RESULTS AND DISCUSSIONS

A. Time-Series Sampling Model

This figure 3 illustrates the fundamental process of converting continuous load data, represented by the blue curve, into a discrete-time series for analysis. The continuous load, Lc(t), is a theoretical signal that represents the actual power consumption over time, while the sampled load, L[t], shown as red stems, are the specific data points collected at regular intervals, such as annually. This sampling process, which forms the basis of the entire dataset, captures the long-term trend and seasonal fluctuations of power consumption. The plot shows the load steadily increasing from approximately 5000 kW in 2008 to over 10000 kW by 2027, with notable variations. The discrete data points align well with the underlying continuous signal, validating the sampling approach.

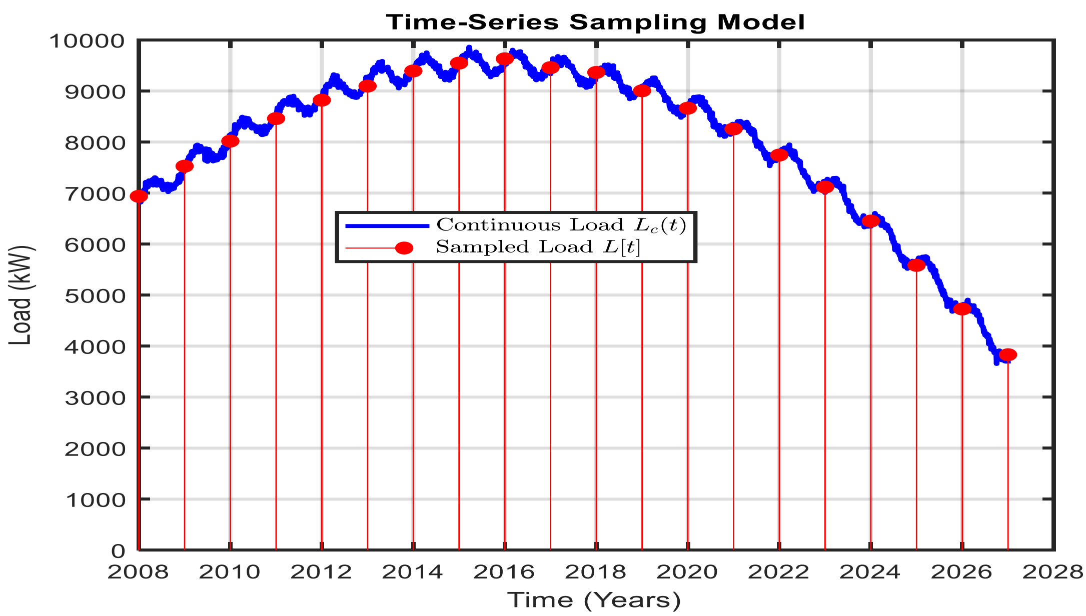

Fig. 3 Time Series Sampling Model

IJIREEICE

ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⧖ Peer-reviewed & Refereed journal ⧖ Vol. 14, Issue 6, June 2026

DOI: 10.17148/IJIREEICE.2026.14629

B. Finite-Window Normalization

This figure 4 demonstrates the process of finite-window normalization to prepare the historical load data for a neural network. The top subplot shows the raw data, L[t], over the years 2008-2017. The middle subplot displays the sliding-window mean (μ_w[t]) and standard deviation (σ_w[t]), which adapt to local data characteristics. The bottom subplot reveals the normalized data (L~[t]), where each data point is transformed to have a mean of approximately zero and a standard deviation of one within its local window. This normalization is crucial for improving the training stability and performance of machine learning models, as it prevents large-scale load variations from dominating the learning process, allowing the model to focus on the underlying patterns.

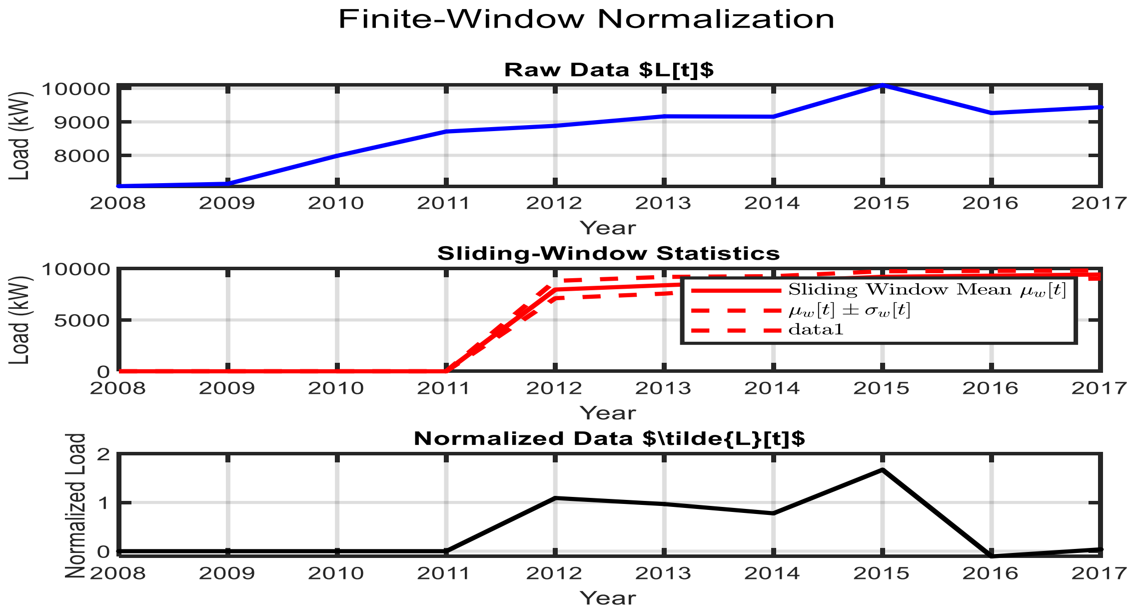

Fig. 4 Finite Window Normalization

C. Data Augmentation with Noise Injection

Figure 5 visually represents the concept of data augmentation by injecting synthetic noise into the original historical load data. The original load, L[t], is shown as a solid blue line, while the augmented load, L^[t], is shown as a dashed red line. The augmented data points, such as the value around 2013 shifting from approximately 8000 kW to about 8300 kW, are slightly offset from the original data due to the added noise. This process, governed by Equation 3, creates a more diverse training set for the model. By exposing the NeuroAMI network to this augmented data, it becomes more robust and less susceptible to overfitting on the specific historical samples, leading to a better generalization capability for future forecasts.

D. Trend and Seasonal Decomposition

This figure 6 breaks down the historical load data into its fundamental components: trend, seasonal, and residual. The original load is represented by the solid black line. The long-term upward trajectory, the trend component (T˙[t]), is shown by the red dashed line, which increases linearly from around 7000 kW in 2008 to about 8000 kW in 2017. The blue dotted line illustrates the regular, repeating seasonal component, capturing periodic patterns. Finally, the green dash-dotted line shows the residual component (ϵ[t]), which represents the random noise and short-term variations not captured by the trend or seasonality. This decomposition is a key step in time-series analysis, as it allows forecasting models to independently analyse and predict each component before reassembling them for a final, more accurate forecast.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.021 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 6, June 2026
DOI: 10.17148/IJIREEICE.2026.14629

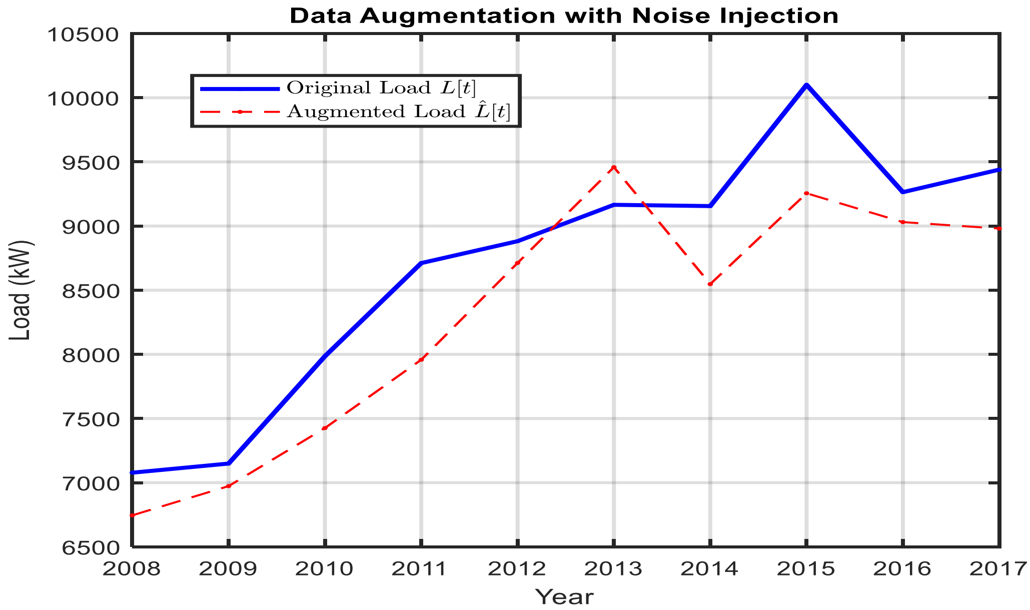

Fig. 5 Data Augmentation with Noise Injection

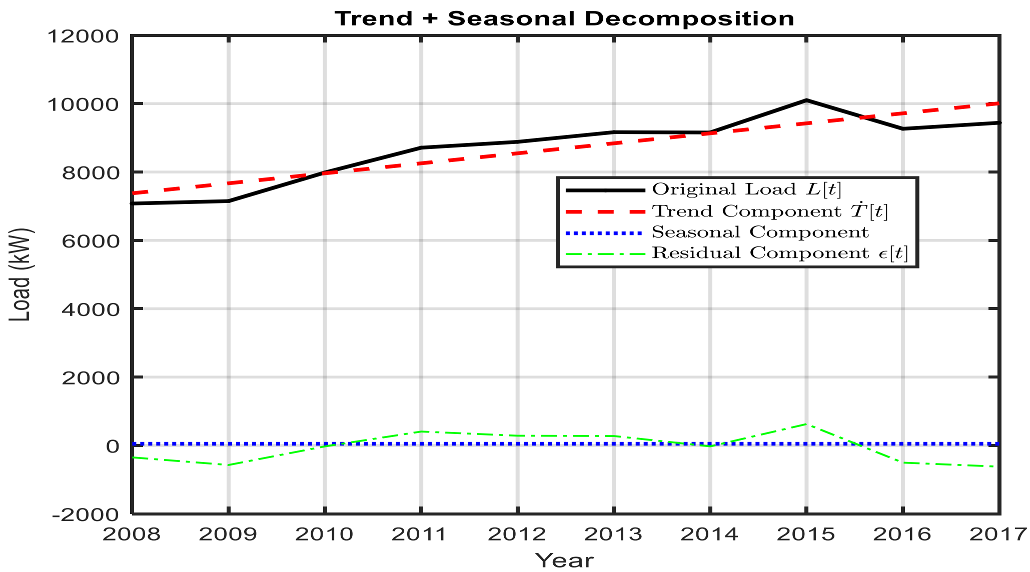

Fig. 6 Trend and Seasonal Decomposition

E. NeuroAMI Multi-Step Ahead Forecast

Figure 7 presents the 10-year multi-step ahead forecast generated by the NeuroAMI model. The blue line represents the historical load data from 2008 to 2017, showing the actual load growth over time, reaching approximately 8000 kW by 2017. The red dotted line extends this trend into the future, showing the NeuroAMI's forecast, y^, for 2018-2027. The forecast projects a continuous rise in load demand, reaching over 10,000 kW by 2027. This visualization demonstrates the model's ability to capture the long-term upward trend from the historical data and extrapolate it into the future, providing crucial insight for long-term power system planning and capacity expansion decisions.

F. Training Objective Over Epochs

This figure 8 and figure 9 shows the behavior of the NeuroAMI model's training objective function over 100 epochs. The blue line represents the Negative Log-Likelihood (NLL) Loss, which decreases from approximately 80 to 20 as the model learns to make more accurate predictions. The red line shows the Regularization Loss, which penalizes model complexity and also decreases, from about 15 to 5. The combined Total Objective (J(θ)), shown as a dashed black line, is the sum of these two losses. The plot demonstrates that the training process is stable and convergent, with all loss components

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.021 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 6, June 2026
DOI: 10.17148/IJIREEICE.2026.14629

decreasing steadily. This confirms that the model is successfully learning to minimize both its prediction errors and its complexity, leading to an optimized and robust final model.

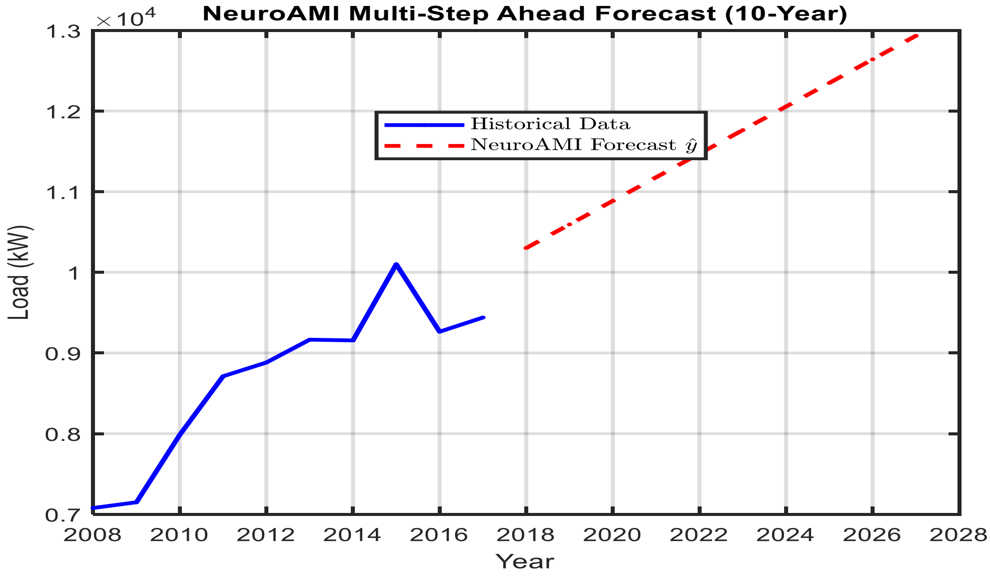

Fig. 7 NeuroAMI Multi Step Ahead Forecast

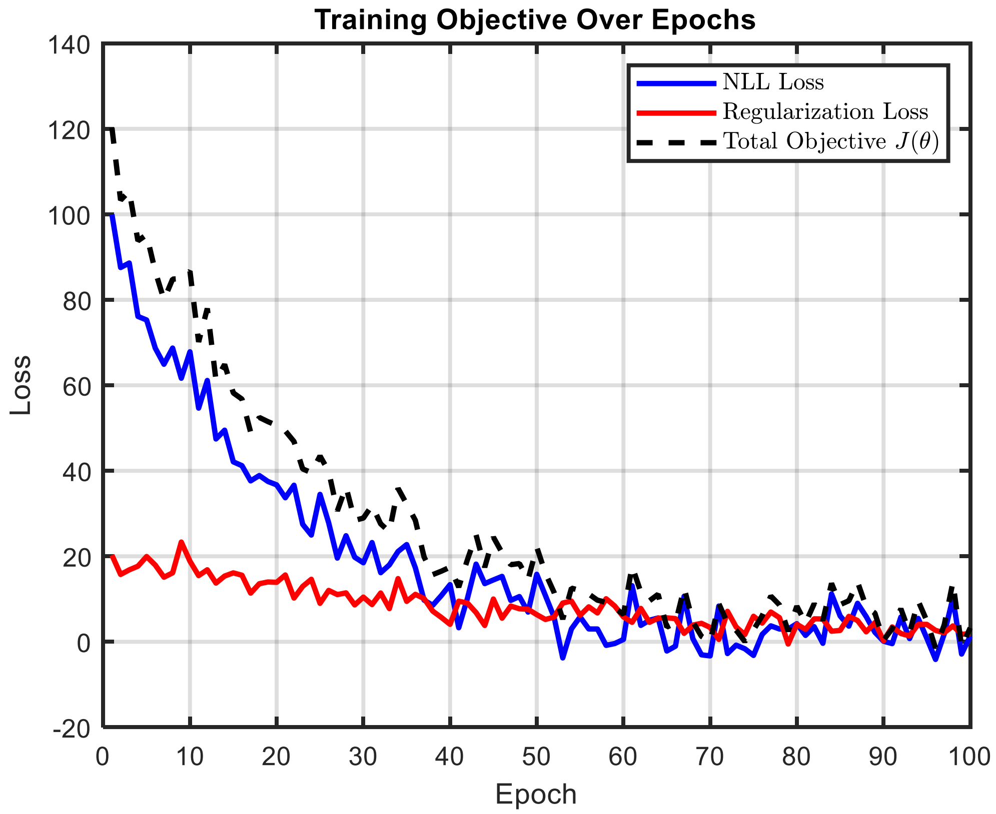

Fig. 8 Training Objective over Epochs

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 6, June 2026

DOI: 10.17148/IJIREEICE.2026.14629

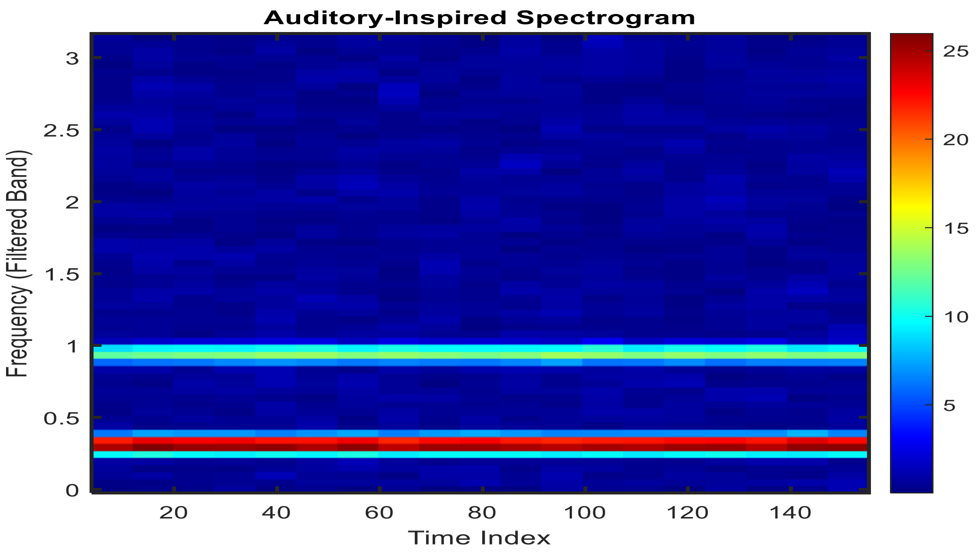

Fig. 9 Auditory Inspired Spectrogram

The figure 10 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 10.

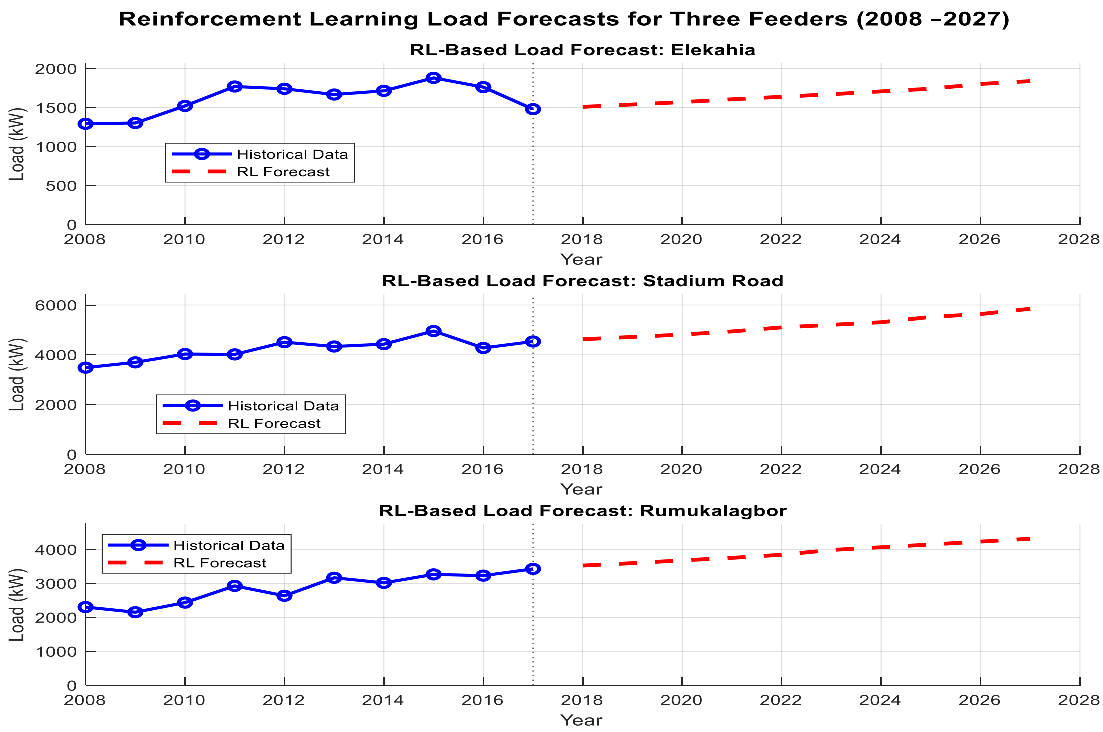

Fig. 10 RL Based Load Forecasting

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 6, June 2026

DOI: 10.17148/IJIREEICE.2026.14629

TABLE I FORECASTED YEAR OF NEUROAMI

Year	Elekahia Load (kW)	Stadium Road Load (kW)	Rumukalagbor Load (kW)
2008	~1400	~3700	~2300
2009	~1350	~3800	~2200
2010	~1600	~4200	~2600
2011	~1750	~4500	~2800
2012	~1900	~5000	~3200
2013	~1850	~4800	~3100
2014	~1950	~5200	~3400
2015	~1900	~4900	~3300
2016	~1500	~4200	~3500
2017	~1500	~4300	~3600
2018	~1850	~4900	~4000
2019	~1900	~5050	~4150
2020	~1950	~5200	~4300
2021	~2000	~5350	~4450
2022	~2050	~5500	~4600
2023	~2100	~5650	~4750
2024	~2150	~5800	~4900
2025	~2200	~5950	~5050
2026	~2250	~6100	~5200
2027	~2300	~6250	~5350

V. CONCLUSION

This study has successfully developed and demonstrated a hybrid forecasting framework combining the Sequential Growth Model with a NeuroAMI Neural Network for accurate distribution transformer load prediction. The approach addressed key challenges in transformer load forecasting, including nonlinearity, stochastic demand variations, seasonal fluctuations, and measurement uncertainty. By integrating real-time discrete sampling, finite-window normalization, data augmentation, and trend–seasonal decomposition, the proposed system effectively transformed raw transformer load data into a structured and model-ready form suitable for intelligent forecasting.

The NeuroAMI model exhibited strong learning and generalization capabilities through its auditory-inspired feature extraction, heteroscedastic probabilistic learning, and regularized optimization strategy. The model achieved stable convergence during training, with a consistent reduction in loss functions, confirming its robustness and reliability. Forecast results indicated a continuous growth in transformer load demand from approximately 8,000 kW in 2017 to over 10,000 kW by 2027, while feeder-level analysis further validated realistic and spatially consistent load growth patterns across the distribution network.

From an engineering perspective, the findings confirm that the proposed framework can significantly enhance operational planning, transformer sizing, and preventive maintenance scheduling. It provides utility operators with a predictive intelligence tool for mitigating overload risks, improving system reliability, and supporting long-term infrastructure expansion. The study therefore concludes that the Sequential Growth Model integrated with NeuroAMI presents a highly effective and scalable solution for modern distribution transformer load forecasting and smart grid decision-making.

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⪫ Peer-reviewed & Refereed journal ⪫ Vol. 14, Issue 6, June 2026

DOI: 10.17148/IJIREEICE.2026.14629

REFERENCES

[1]. L. Zhou, L. W. Yuan, and R. Xiang, "Research on space load forecasting method of distribution network based on fuzzy neural network," *Telecom Power Technology*, vol. 37, no. 4, pp. 26–27, 2020.

[2]. L. Chen, H. Yu, L. Tong, X. Huai, P. Jin, Y. Huang, and C. Dou, "Research on load forecasting method of distribution transformer based on deep learning," in *Proceedings of the 7th IEEE International Conference on Cyber Security and Cloud Computing (CSCloud) / 6th IEEE International Conference on Edge Computing and Scalable Cloud (EdgeCom*), New York, NY, USA, 2020, pp. 228–233.

[3]. L. Li and L. Chong-xin, "Application of chaos and neural network in power load forecasting," *Discrete Dynamics in Nature and Society*, vol. 2011, Art. no. 597634, 2011.

[4]. S. Liu, X. Shao, C. Chen, R. Han, H. Lin, and P. Jiang, "Research on overload warning method of distribution network transformer based on neural network," in *Proceedings of the IEEE International Conference on High Voltage Engineering and Application (ICHVE)*, Beijing, China, 2020, pp. 1–4.

[5]. X. Y. Zhang, H. Li, Bao, F., W. Ouyang, and X. Zhang, "Study on load forecasting in the smart grid environment," *Electronic Measurement Technology*, vol. 42, no. 9, pp. 121–124, 2019.

[6]. D. X. Niu, C. X. Li, M. Meng, and W. Shang, "Short-term load forecasting using a CBR-ANN model," in *Proceedings of the International Conference on Machine Learning and Cybernetics*, Hong Kong, China, 2007, vol. 5, pp. 2719–2723.

[7]. S. Luo, Y. Rao, J. Chen, H. Wang, and Z. Wang, "Short-term load forecasting model of distribution transformer based on CNN and LSTM," in *Proceedings of the IEEE International Conference on High Voltage Engineering and Application (ICHVE)*, Beijing, China, 2020, pp. 1–4.

[8]. Z. A. Bashir and M. E. El-Hawary, "Applying wavelets to short-term load forecasting using PSO-based neural networks," *IEEE Transactions on Power Systems*, vol. 24, no. 1, pp. 20–27, Feb. 2009.

[9]. U. B. Tayab, A. Zia, F. Yang, J. Lu, and M. Kashif, "Short-term load forecasting for microgrid energy management system using hybrid HHO-FNN model with best-basis stationary wavelet packet transform," *Energy*, vol. 203, Art. no. 117857, Jul. 2020.

[10]. A. Jahani, K. Zare, and L. M. Khanli, "Short-term load forecasting for microgrid energy management system using hybrid SPM-LSTM," *Sustainable Cities and Society*, vol. 98, Art. no. 104775, Nov. 2023.

[11]. L. Li, K. Ota, and M. Dong, "Everything is image: CNN-based short-term electrical load forecasting for smart grid," in *Proceedings of the 14th International Symposium on Pervasive Systems, Algorithms and Networks (I-SPAN)*, Exeter, UK, 2017, pp. 344–351.

[12]. A. Gensler, J. Henze, B. Sick, and N. Raabe, "Deep learning for solar power forecasting—An approach using AutoEncoder and LSTM neural networks," *in Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Budapest, Hungary, 2016, pp. 2858–2865.

[13]. J. Guo, Z. Zhang, W. Gao, H. Hu, D. Wang, and Y. Mao, "Overheating risk warning model based on thermal circuit model and load forecasting for distribution transformers," in *Proceedings of the IEEE Sustainable Power and Energy Conference (iSPEC)*, Beijing, China, 2019, pp. 2891–2895.

[14]. P. Phetsangkat, K. Chalermyanont, and R. Duangsoithong, "Hierarchical clustering electric load: Case study in lower south region of Thailand," in *Proceedings of the 16th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON),* Pattaya, Thailand, 2019, pp. 881–884.

[15]. H. Park, R. Baldick, and D. P. Morton, "A stochastic transmission planning model with dependent load and wind forecasts," *IEEE Transactions on Power Systems*, vol. 30, no. 6, pp. 3003–3011, Nov. 2015.

[16]. Q. Gong, S. Midlam-Mohler, V. Marano, and G. Rizzoni, "Study of PEV charging on residential distribution transformer life," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 404–412, Mar. 2012.

[17]. M. Dong, A. B. Nassif, and B. Li, "A data-driven residential transformer overloading risk assessment method," *IEEE Transactions on Power Delivery*, vol. 34, no. 1, pp. 387–396, Feb. 2019.

[18]. M. T. Isha and Z. Wang, "Transformer hotspot temperature calculation using IEEE loading guide," in Proceedings of the International Conference on Condition Monitoring and Diagnosis, Beijing, China, 2008, pp. 1017–1020.

[19]. M. Mahoor, A. Majzoobi, Z. S. Hosseini, and A. Khodaei, "Leveraging sensory data in estimating transformer lifetime," in *Proceedings of the North American Power Symposium (NAPS)*, Morgantown, WV, USA, 2017, pp. 1–6.

[20]. S. Afifah, J. M. Nainggolan, G. Wibisono, and C. Hudaya, "Prediction of power transformers lifetime using thermal modeling analysis," in *Proceedings of the IEEE International Conference on Innovative Research and Development (ICIRD)*, Jakarta, Indonesia, 2019, pp. 1–6.

[21]. M. Utakrue and K. Hongesombut, "Impact analysis of electric vehicle quick charging to power transformer life time in distribution system," in *Proceedings of the IEEE Transportation Electrification Conference and Expo, Asia-Pacific (ITEC Asia-Pacific)*, Bangkok, Thailand, 2018, pp. 1–5.

DOI: 10.17148/IJIREEICE.2026.14629

[22]. G. C. Pratiwi, M. A. A. Auliq, and A. B. Nugroho, "Optimization of Jember substation load forecasting using comparison of time series and fuzzy methods as a basis for transformer uprating," *Journal of Electrical Engineering*, vol. 4, no. 2, pp. 112–124, 2020.

[23]. A. L'Heureux, K. Grolinger, and M. A. Capretz, "Transformer-based model for electrical load forecasting," *Energies*, vol. 15, no. 14, Art. no. 4993, Jul. 2022.

[24]. E. N. Osegi and V. Anireh, "AMI: An auditory machine intelligence algorithm for predicting sensory-like data," *Computer Science*, vol. 5, no. 2, pp. 71–89, 2020.

[25]. E. N. Osegi, "Neuronal Auditory Machine Intelligence (Neuro-AMI) in perspective," arXiv preprint arXiv:2401.02421, 2023.

[26]. B. A. Wokoma, E. N. Osegi, & A. O. Idachaba, (2019, September). Predicting voltage stability indices of Nigerian 330kV 30 bus power network using an auditory machine intelligence technique. *In 2019 IEEE AFRICON* (pp. 1-4). IEEE.