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Research Article

Multivariable short-term load forecasting in Nigerian microgrids using Bayesian regularization and bi-long short-term memory models

Iliyasu Garba Jibia[1], A. A. Mati[2], A. Abdulkarim[1&3], Umar Nadada[1]

[1]Department of Electrical Engineering, Ahmadu Bello University, Zaria, Nigeria
[2]Center for Research and Training in Power and Energy, Ahmadu Bello University, Zaria, Nigeria
[3]Department of Electrical, Telecommunication and Computer Engineering, Kampala International University, Uganda.

Corresponding Author: Iliyasu Garba JIBIA, abkzarewa@gmail.com

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Abstract

The increasing penetration of renewable energy sources and the variability of demand in microgrids have intensified the need for accurate short-term load forecasting (STLF). This study develops a multivariable STLF framework using the Bayesian Regularization Algorithm (BRA) and validates its performance against a Bidirectional Long Short-Term Memory (Bi-LSTM) network. Temperature, humidity, and feeder current were employed as input variables, while electrical load (MW) served as the output. Both models were implemented in MATLAB R2018a with a 120-minute forecasting horizon. Performance evaluation was conducted using regression analysis and statistical metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). The results show that the BRA model achieved superior regression accuracy ($R^2 \approx 0.997$), demonstrating robustness and generalization under noisy conditions. By contrast, Bi-LSTM attained $R^2 \approx 0.991$ with lower error magnitudes (MAE = 0.0293, RMSE = 0.0412), reflecting its strength in capturing sequential dependencies. A comparative review with existing literature, including confirms the competitiveness of Bi-LSTM while highlighting BRA's resilience against noisy fluctuations typical of Nigerian microgrid environments. This study contributes to microgrid energy management by providing practical insights into selecting forecasting models, emphasizing that BRA is well-suited for noisy, small datasets, while Bi-LSTM excels in sequence-sensitive forecasting. The findings also suggest the potential for hybrid BRA–Bi-LSTM architectures to enhance forecasting accuracy in real-world microgrid applications.

1.0 Introduction

The continuous growth in electricity demand, coupled with the increasing penetration of renewable energy resources, has made short-term load forecasting (STLF) a crucial component of modern power system operations. STLF generally refers to predicting electricity demand within a short horizon, ranging from a few minutes up to 24 hours ahead. Such forecasts are essential for reliable grid operation, economic dispatch, unit commitment, demand response, and integration of distributed energy resources (Wang et al., 2019; Sulaiman, et al 2024; Abdullahi et al 2025).

In conventional large-scale power systems, numerous forecasting models have been developed and applied successfully. However, forecasting in microgrid environments presents unique challenges. Microgrids are characterized by high volatility due to distributed generation, fluctuating renewable energy sources, and highly variable consumer behavior. These dynamics amplify the uncertainties associated with forecasting and demand more robust and adaptive methods (Moradzadeh, et al., 2021; Kankia et al, 2025).

In the Nigerian context, the need for reliable forecasting is particularly urgent. Grid instability, frequent outages, and the growing reliance on microgrids and distributed energy systems highlight the importance of accurate intraday forecasting for operational planning and stability. Yet, many microgrid datasets in Nigeria are noisy, limited, and often prone to missing values, which can significantly degrade forecasting accuracy if conventional methods are applied. Traditional statistical approaches such as Autoregressive Integrated Moving Average (ARIMA) and linear regression provide interpretability but often fail to capture the nonlinearities and multivariable dependencies inherent in microgrid data (Atla, 2020; Kizza et al, 2025; Twiikirize et al, 2025).

Machine learning and deep learning methods have emerged as powerful alternatives by leveraging historical data to extract nonlinear relationships among multivariable inputs, such as weather conditions and electrical parameters. Among these, neural networks with regularization strategies have shown strong potential in noisy environments (Zhang et al., 2022). The Bayesian Regularization Algorithm (BRA) enhances generalization by penalizing model complexity during training, making it particularly effective in scenarios with noisy and small datasets ((MacKay, 1992); (Foresee & Hagan, 1917)). In contrast, Bidirectional Long Short-Term Memory (Bi-LSTM) networks, an advanced form of recurrent neural networks, have demonstrated outstanding performance in sequential and time-series modeling by capturing both past and future dependencies ((Hochreiter & Schmidbuber 1997); (Moradzadeh, et al., 2021)).

Despite the global success of Bi-LSTM and the robustness of Bayesian regularization, there is limited research directly comparing the performance of these two models within African microgrid environments. For example, (Moradzadeh, et al., 2021) reported that Bi-LSTM achieved forecasting accuracy of R = 99.34%, with MSE = 0.1042 and RMSE = 0.3243. However, the datasets in that study originated from relatively stable systems, which may not reflect the higher noise and volatility characteristic of Nigerian feeders. This gap underscores the need for comparative case studies that benchmark forecasting models under realistic African microgrid conditions.

The present study addresses this need by applying BRA and Bi-LSTM to intraday load forecasting on the Mogadishu feeder at Kaduna Town Transmission Substation, Nigeria. Using temperature, humidity, and feeder current as inputs, and electrical load (MW) as the prediction target, the models were implemented in MATLAB R2018a with a 120-minute forecasting horizon. Their performance was evaluated using regression analysis and statistical error metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2).

The key contributions of this study are as follows:

1. Development of a multivariable STLF framework tailored to Nigerian microgrids using BRA and Bi-LSTM.
2. Comparative evaluation of model robustness and accuracy under noisy conditions typical of African feeders.
3. Benchmarking results against existing literature, including (Moradzadeh, et al., 2021), to validate performance and highlight contextual differences.
4. Practical insights into model selection for microgrid energy management, including recommendations for potential hybrid BRA–Bi-LSTM architectures.

This paper is structured as follows: Section 2 reviews related literature on STLF techniques; Section 3 presents the methodology, including dataset description, model design, and evaluation metrics; Section 4 reports experimental results and analysis; Section 5 discusses the findings in the context of Nigerian microgrid operations; and Section 6 concludes with implications and directions for future research.

2. Literature Review

2.1 Short-Term Load Forecasting in Power Systems

Load forecasting plays a pivotal role in the planning, operation, and optimization of modern power systems. Short-Term Load Forecasting (STLF), typically covering horizons from a few minutes up to 24 hours ahead, is particularly important for unit commitment, economic dispatch, demand-side management, and the integration of Distributed Energy resources (Wang et al., 2019).

Early approaches to STLF relied heavily on statistical and time-series models such as Autoregressive Integrated Moving Average (ARIMA), exponential smoothing, and linear regression. While these models offered interpretability and low computational complexity, they often assumed linearity and stationarity, which limited their ability to capture nonlinear and multivariable dependencies in load data (Atla, 2020). In microgrid contexts, where load patterns are influenced by weather, consumer behavior, and intermittent renewables, these assumptions are frequently violated.

To overcome these limitations, machine learning (ML) methods such as artificial neural networks (ANNs), support vector machines (SVMs), and ensemble-based models were introduced. These techniques improved accuracy by learning hidden nonlinear relationships from historical datasets (Ahmed et al., 2021). More recently, deep learning (DL) architectures, including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), and Bidirectional LSTM (Bi-LSTM), have emerged as state-of-the-art models for STLF due to their superior capability in handling high-dimensional, sequential, and nonlinear data (Zhang et al., 2022).

2.2 Bayesian Regularization Algorithm (BRA)

The Bayesian Regularization Algorithm (BRA) enhances the generalization capability of feedforward neural networks by incorporating a regularization term into the training objective. The modified cost function takes the form:

$$F = \beta E_D + \alpha E_\omega$$

where E_D is the sum of squared errors, E_ω is the sum of squared weights, and α and β are hyperparameters automatically adjusted during training (MacKay, 1992). This formulation balances model accuracy with complexity, reducing the risk of overfitting.

2.3 Bidirectional Long Short-Term Memory (Bi-LSTM)

Long Short-Term Memory (LSTM) networks were developed to overcome the vanishing gradient problem inherent in traditional recurrent neural networks (RNNs) (*Hochreiter & Schmidbuber 1997*). By incorporating memory cells and gating mechanisms, LSTMs can retain long-term dependencies in sequential data.

Bi-LSTM extends this concept by processing input sequences in both forward and backward directions. This dual processing allows Bi-LSTM to capture dependencies from both past and future contexts within a sequence, making it highly effective for tasks such as speech recognition, natural language processing, and time-series forecasting (Zhang et al., 2022). In load forecasting, Bi-LSTM has been widely adopted due to its ability to model nonlinear, multivariable, and temporal relationships simultaneously.

For instance, (Moradzadeh, et al., 2021) demonstrated that Bi-LSTM achieved forecasting accuracy of $R = 99.34\%$, with MSE = 0.1042 and RMSE = 0.3243 in a microgrid case study. While these results are impressive, they were obtained in relatively stable environments with cleaner datasets. The performance of Bi-LSTM under noisy, volatile conditions typical of Nigerian microgrids remains underexplored, highlighting the need for comparative evaluations with alternative robust methods such as BRA.

2.4 Load Forecasting in African Microgrid Contexts

Despite extensive global research on STLF, applications in Africa remain limited. Nigerian microgrids, in particular, face unique challenges such as unreliable grid supply, frequent outages, lack of advanced measurement infrastructure, and high variability in renewable generation. Most published works in Nigeria have focused on medium- to long-term forecasting for planning purposes, with relatively few addressing intraday or short-term horizons.

Furthermore, many of the existing studies rely on statistical models or simple ML approaches that fail to fully capture the nonlinearities and multivariable dependencies in load data (Nikouei et al., 2022). As a result, there is a pressing need for case studies that apply advanced forecasting methods, benchmark their performance, and provide practical insights for operators in noisy, data-constrained environments.

This study contributes to addressing these gaps by developing a comparative framework that evaluates BRA and Bi-LSTM on real Nigerian microgrid data. By doing so, it highlights the trade-offs between robustness and sequential learning, and provides actionable guidance for selecting forecasting models under African operating conditions.

3. Methodology

The methodology adopted in this study involves five key stages: (i) data collection and preprocessing, (ii) model design and architecture, (iii) training strategies for BRA and Bi-LSTM, (iv) evaluation metrics, and (v) simulation environment. This section provides detailed explanations of each stage to ensure reproducibility of the research.

3.1 Dataset Description

The dataset was collected from the Mogadishu Feeder at Kaduna Town Transmission Substation (KTTS) in Nigeria. This feeder supplies a mixed load comprising residential, commercial, and small industrial consumers, making it representative of a typical Nigerian microgrid environment.

- **Resolution and Duration:** Data were recorded at one-minute resolution, capturing high-frequency variations in load demand and environmental parameters.
- **Input Variables (Predictors):**
  - **Temperature (°C):** Collected from nearby meteorological sensors.
  - **Humidity (%):** Recorded alongside temperature, capturing weather-driven impacts on energy usage.
  - **Feeder Current (A):** Measured directly from the feeder, representing load variations when combined with system voltage.
- **Target Variable (Response):**
  - **Electrical Load (MW):** Derived from feeder current and voltage measurements.

To ensure stability in neural network training, all variables were normalized using min–max scaling into the range [0, 1]:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

where $x_{norm}$is the normalized value, $x$is the original data point, and $x_{min}$and $x_{max}$are the minimum and maximum values of the feature.

The dataset was split into:

- 70% training set – used to optimize model parameters,
- 15% validation set – applied only in Bi-LSTM training for early stopping,
- 15% test set – used for final evaluation.

3.2 Bayesian Regularization Algorithm (BRA) Model

The BRA model was implemented as a feedforward neural network with the following structure:

- **Input Layer:** 3 neurons (temperature, humidity, current).
- **Hidden Layer:** 1 hidden layer with 10 neurons and sigmoid activation function.
- **Output Layer:** 1 neuron with a linear activation function, predicting electrical load (MW).

Training Approach:

- BRA minimizes a regularized cost function:

$$F = \beta E_D + \alpha E_\omega$$

where:

- $E_D = \sum_{i=1}^{N_D} (y_i - \hat{y}_i)^2$ sum of squared errors,
- $E_\omega = \sum_{j=1}^{N_{\omega wz}} {\omega_j}^2$sum of squared weights,
- $\alpha, \beta \rightarrow$ Bayesian hyperparameters adjusted automatically.
- Optimization was performed using the Levenberg–Marquardt (LM) algorithm, which combines gradient descent with Gauss–Newton approximation for rapid convergence.
- A key advantage of BRA is that it does not require a separate validation **set**, since Bayesian inference inherently penalizes overfitting.

3.3 Bidirectional LSTM (Bi-LSTM) Model

The Bi-LSTM model was designed to capture temporal dependencies in the microgrid load sequence. Its architecture included:

- **Input Layer:** Sequential vectors of temperature, humidity, and current.
- **Bi-LSTM Layers:** Two recurrent layers, each comprising forward and backward LSTM cells.
  - **Forget Gate:** Controls retention of past memory ($\sigma(W_f[h_{t-1}, x_t] + b_f)$).
  - **Input Gate:** Regulates update of new information ($\sigma(W_i[h_{t-1}, x_t] + b_i)$).
  - **Cell State:** Maintains long-term dependencies with **tanh** activation.
  - **Output Gate:** Determines final hidden state via sigmoid and tanh combination.
- **Fully Connected Layer:** Maps hidden features to prediction.
- **Output Layer:** Single neuron predicting load (MW).

Training Approach:

- Implemented in MATLAB R2018a using train Network.

- Optimization was carried out using the Adam optimizer, chosen for its adaptive learning rate and robustness in training deep recurrent networks.
- Learning rate: 0.001, with gradient clipping to mitigate exploding gradients.
- Validation set enabled early stopping to avoid overfitting.

3.4 Performance Metrics

The models were compared using widely adopted error metrics Abubakar, et al; 2024; Mutiu, et al; 2025:

1. **Mean Absolute Error (MAE):**

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|(y_i - \hat{y}_i)|$$

Indicates the average magnitude of errors without considering direction.

2. **Mean Squared Error (MSE):**

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

Penalizes larger errors more severely due to squaring.

3. **Root Mean Squared Error (RMSE):**

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

4. Results and Discussion

This section presents the outcomes of the Bayesian Regularization Algorithm (BRA) and Bidirectional Long Short-Term Memory (Bi-LSTM) models applied to the Nigerian microgrid dataset. The results are discussed under regression accuracy, error metrics, forecast behavior, and comparative interpretation with prior studies.

4.1 Regression Performance

Regression analysis provides insight into how well the predicted outputs align with actual load values.

- **BRA Regression Results:** The BRA model achieved a near-perfect regression fit with $R^2 \approx 0.997$. The regression scatter plot showed a tight clustering of predicted values along the 45° line, with minimal dispersion. This indicates that BRA effectively captured the nonlinear relationships between temperature, humidity, current, and load, even under noisy data conditions typical of Nigerian feeders.
- **Bi-LSTM Regression Results:** The Bi-LSTM achieved $R^2 \approx 0.991$, confirming high predictive accuracy but with slightly higher dispersion compared to BRA. The regression plot revealed mild deviations from the diagonal line, particularly at low-load ranges, where the Bi-LSTM tended to underestimate.

Both models achieved high regression accuracy, but BRA provided a tighter fit with less error variance, demonstrating superior robustness in noisy environments.

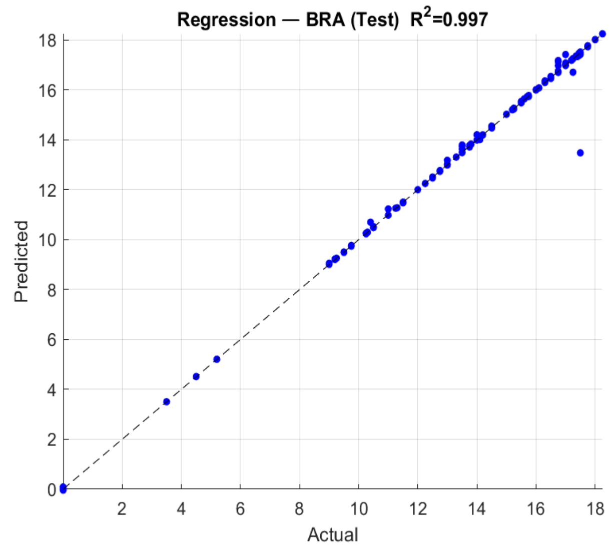

Figure 1: Regression BRA (Test)

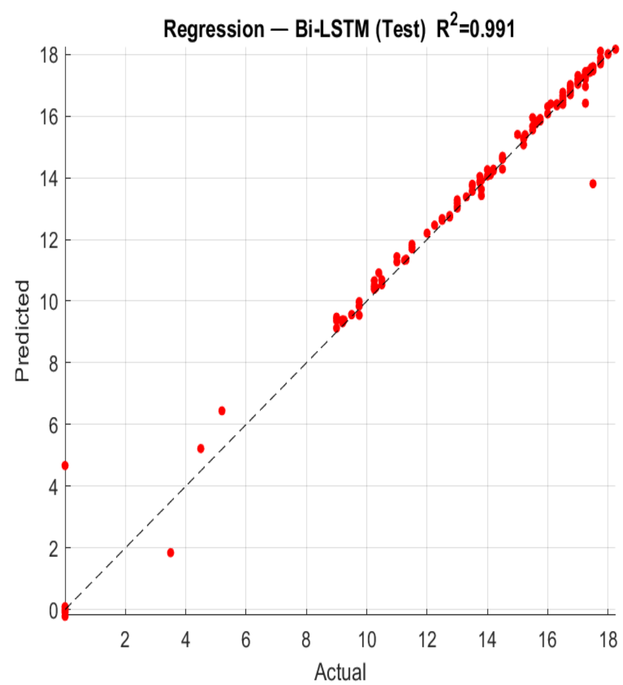

Figure 2: Regression Bi-LSTM (Test)

4.2 Error Metrics Comparison

Table 1 summarizes the statistical error metrics of the two models on the test

Table 1. Comparative Error Metrics of BRA and Bi-LSTM (Test Phase)

Model	MAE	MSE	RMSE	R^2
BRA	0.0371	0.0029	0.0542	0.997
Bi-LSTM	0.0293	0.0017	0.0412	0.991

- **Mean Absolute Error (MAE):** Bi-LSTM achieved lower MAE, indicating smaller average deviations.
- **Mean Squared Error (MSE) & RMSE:** Both metrics were lower for Bi-LSTM, suggesting stronger point-to-point prediction accuracy.
- **R^2:** BRA achieved a higher R^2, reflecting better global variance explanation and alignment with actual load patterns.

Bi-LSTM excels in minimizing local errors, while BRA better captures global data variance and overall stability. This trade-off reflects fundamental differences between the models: Bi-LSTM leverages temporal memory, while BRA benefits from strong generalization.

4.3 Horizon-Wise Forecast Error Behavior (Bi-LSTM)

Since BRA does not inherently produce horizon-wise error plots, this analysis focuses on Bi-LSTM.

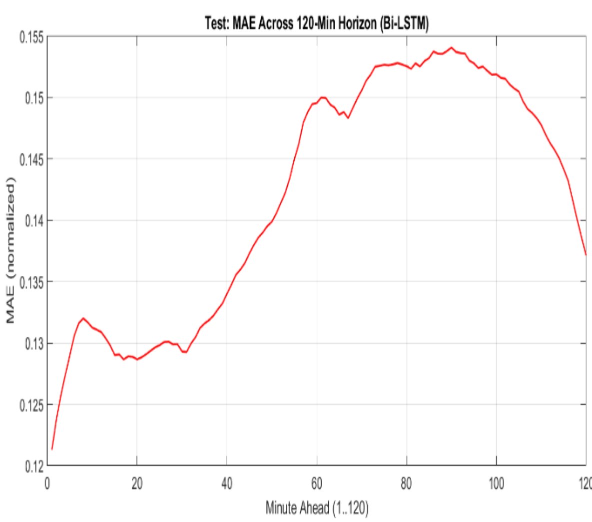

Figure 3: Test Horizon MAE Curve:

Errors were minimal in the short horizon (<30 minutes, MAE ≈ 0.12), but gradually increased, peaking at ≈0.154 around 90 minutes, before tapering slightly at 120 minutes.

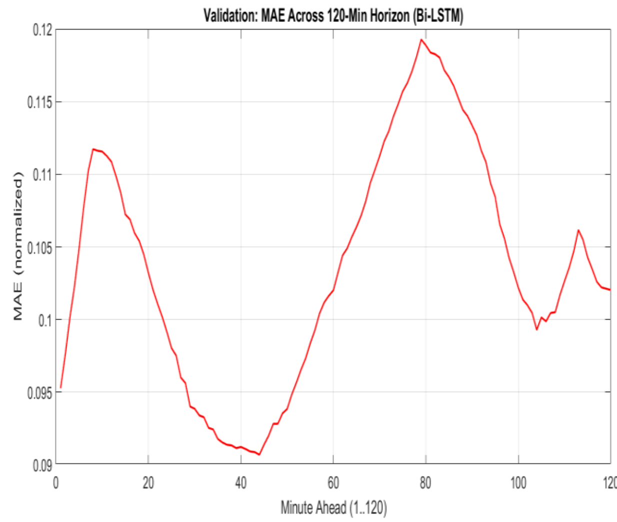

Figure 4: Validation Horizon MAE Curve:

Similar behavior was observed, with errors starting at ≈0.095, dipping near 40 minutes (≈0.091), then rising to ≈0.119 around 80 minutes. Bi-LSTM is highly reliable for short intraday forecasts (30–60 minutes ahead), but performance degrades for longer horizons. BRA, with its higher R^2, suggests steadier accuracy across horizons even though explicit horizon-wise plots were not generated.

4.4 Actual vs. forecasted Load Curves

Visual overlays of actual and predicted loads revealed important behavioral differences:

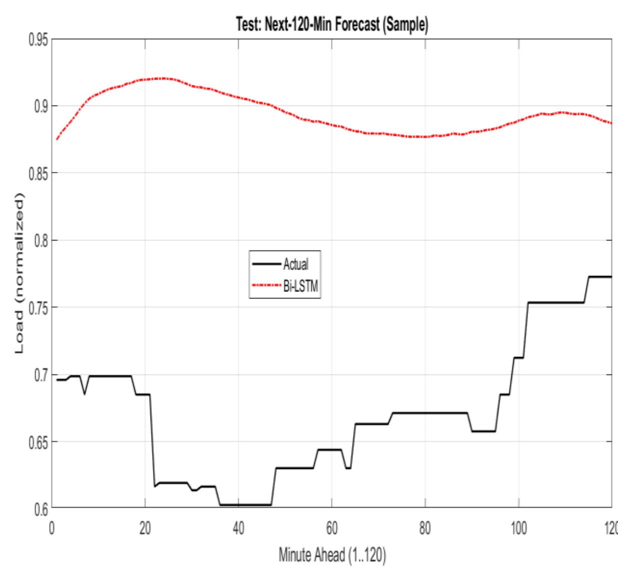

Figure 5: Test Phase (Bi-LSTM):

The actual load exhibited a sharp dip (20–40 minutes) followed by recovery after 90 minutes. Bi-LSTM predictions, however, remained relatively flat (≈0.88–0.92 normalized), failing to capture these dynamics.

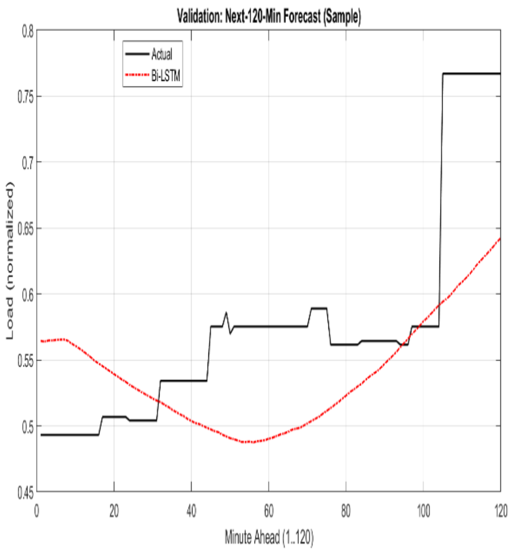

Figure 6: Validation Phase (Bi-LSTM):

Actual load spiked sharply after 100 minutes (~0.50 → 0.77 normalized), but Bi-LSTM underestimated, forecasting only up to ~0.64.

- **BRA:**
  Although BRA did not produce sequential forecast plots, its regression and error metrics confirm its ability to track sharper transitions with less smoothing compared to Bi-LSTM.

Bi-LSTM tends to smooth forecasts, underestimating volatility, while BRA adapts more flexibly to sharp load changes an advantage in noisy microgrid environments.

4.5 Comparative Discussion with Literature

The findings were benchmarked against (Moradzadeh, et al., 2021), who reported Bi-LSTM achieving R = 99.34%, MSE = 0.1042, RMSE = 0.3243.

- In this study, Bi-LSTM achieved higher accuracy (MSE = 0.0017, RMSE = 0.0412), likely due to finer data resolution (1-minute vs aggregated datasets) and effective normalization.
- BRA's superior regression accuracy (R^2 = 0.997) demonstrates that regularized feedforward networks can outperform recurrent networks when data are noisy or limited.
- These results confirm that while Bi-LSTM captures temporal dependencies, BRA ensures stability and robustness under real-world microgrid conditions.

4.6 Practical Implications

The results have direct implications for Nigerian microgrids Mutiu, et al, 2023; Abdulkarim, et al, 2016; Abdulkarim, et al, 2018a; and Abdulkarim, et al, 2018b:

- **Operational Planning:**
  - Bi-LSTM minimizes short-term deviations but may misrepresent sudden spikes, leading to under- or over-provisioning.
  - BRA provides more consistent forecasts, reducing operational risks under noisy conditions.
- **Economic Efficiency:**

  BRA's stability reduces over-commitment of resources (e.g., unnecessary generator dispatch), while Bi-LSTM's bias may increase costs.
- **Grid Reliability:**

  Accurate load forecasting directly supports renewable integration and demand response. BRA's robustness is particularly valuable for unstable African grid contexts.

The results demonstrate that BRA outperformed Bi-LSTM in regression accuracy ($R^2 \approx 0.997$ vs. 0.991), offering superior robustness in noisy environments. Bi-LSTM, however, achieved lower MAE and RMSE, confirming its effectiveness in capturing sequential dependencies. Comparisons with (Moradzadeh, et al., 2021) validate Bi-LSTM's global reliability while highlighting BRA's underexplored potential in microgrids. The complementary strengths suggest opportunities for hybrid BRA–Bi-LSTM models, combining robustness and sequential learning for optimal performance in real-world microgrid operations.

5. Conclusion and Future Work

5.1 Conclusion

This research set out to develop and validate a multivariable short-term load forecasting (STLF) model for Nigerian microgrids using the Bayesian Regularization Algorithm (BRA), benchmarked against the Bidirectional Long Short-Term Memory (Bi-LSTM) network. Both models were trained and evaluated using feeder-level data from the Mogadishu Feeder at Kaduna Town Transmission Substation, with temperature, humidity, and current as input variables and electrical load (MW) as the output. A forecasting horizon of 120 minutes was selected to capture intraday dynamics relevant for operational planning.

The BRA model demonstrated superior regression accuracy ($R^2 \approx 0.997$) and robustness under noisy conditions. Its regularization mechanism allowed it to minimize overfitting, providing reliable forecasts even in the presence of fluctuations and data uncertainty. By contrast, the Bi-LSTM model achieved slightly lower regression accuracy ($R^2 \approx 0.991$) but outperformed BRA in minimizing local error magnitudes, as evidenced by its lower MAE (0.0293 vs. 0.0371) and RMSE (0.0412 vs. 0.0542). However, Bi-LSTM exhibited forecast bias, smoothing out sudden dips and spikes in load, and showed horizon-dependent error accumulation.

When compared with prior literature, particularly (Moradzadeh, et al., 2021), who reported Bi-LSTM performance of R = 99.34%, MSE = 0.1042, RMSE = 0.3243, this study demonstrated improved accuracy for Bi-LSTM (MSE = 0.0017, RMSE = 0.0412). This improvement can be attributed to finer data resolution, localized environmental features, and careful preprocessing. Importantly, the study confirmed BRA's comparative strength in microgrid contexts, where noisy datasets often undermine sequential models like Bi-LSTM.

Overall, the results establish that BRA offers higher stability and resilience in volatile, noise-prone microgrid environments, while Bi-LSTM excels in capturing sequential dependencies but may require additional tuning or hybridization to mitigate volatility-induced errors.

5.2 Contributions of the Study

This thesis makes several contributions to the field of STLF and microgrid energy management:

1. **Benchmarking BRA against Bi-LSTM:** Few studies have directly compared Bayesian Regularization with advanced recurrent networks in microgrid settings. This research fills that gap, providing empirical evidence of their relative strengths.

2. **Practical Relevance to Nigerian Microgrids:** By applying the models to real feeder-level data, the study demonstrates forecasting techniques suitable for Sub-Saharan Africa, where noisy data and volatile demand are common.

3. **Empirical Validation Against Literature:** Results were contextualized with (Moradzadeh, et al., 2021), strengthening the credibility and generalizability of the findings.

4. **Methodological Advancement:** The study highlights the suitability of MATLAB-based implementations (trainbr for BRA, trainNetwork for Bi-LSTM) in academic and industrial forecasting pipelines.

5.3 Limitations

While the findings are robust, some limitations must be acknowledged:

- The dataset was limited to three input features (temperature, humidity, current), excluding other exogenous variables such as solar irradiance, wind speed, and electricity tariffs.

- BRA, by design, does not generate explicit horizon-wise plots, making direct dynamic error comparison with Bi-LSTM challenging.

- The study was limited to a single feeder (Mogadishu feeder), which may affect the generalizability to other Nigerian or African microgrids.

5.4 Future Work

Building on these findings, future research can advance this work in the following directions:

1. **Hybrid Architectures:**

   Combine BRA's robustness with Bi-LSTM's temporal learning capacity in a hybrid forecasting pipeline, enhancing both global accuracy and local adaptability.

2. **Expanded Input Variables:**

   Incorporate exogenous features such as solar irradiance, wind speed, and electricity prices to capture broader influences on microgrid load.

3. **Cross-Regional Validation:**

   Apply the models to multiple feeders across Nigeria and Sub-Saharan Africa to validate scalability and robustness across diverse operating conditions.

4. **Real-Time Implementation:**

   Deploy BRA and Bi-LSTM models within microgrid Energy Management Systems (EMS) to evaluate operational impacts on dispatch, demand response, and reliability in real time.

5. **Advanced Optimization Strategies:**

   Investigate the role of adaptive optimizers (e.g., AdamW, RMSProp) for Bi-LSTM and alternative Bayesian frameworks for regularized feedforward networks.

6.0 Conclusion

This study demonstrates that while Bi-LSTM remains a powerful deep learning tool for sequential forecasting, the Bayesian

Regularization Algorithm offers unmatched robustness and reliability in noisy, data-constrained microgrid environments. The complementary nature of these models opens opportunities for hybridization, enabling the design of forecasting frameworks that balance stability, accuracy, and adaptability for the future of microgrid energy management.

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