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FULL LENGTH ARTICLE

Smart Home Energy Consumption Forecasting: An Engineering Approach with IoT and Al-Biruni Earth Radius Optimized LSTM Networks

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ABSTRACT

With the growing complexity of energy consumption patterns, accurate forecasting is required to maximize the benefits of demand-side management, which relies on precise forecasting and optimization. To respond to this challenge, this research suggests a new forecasting method by integrating the Al-Biruni Earth Radius (BER) optimization algorithm with the Long Short-Term Memory (LSTM) network within an Internet of Things (IoT)-based framework. The BER-optimized LSTM model processes real-time IoT sensor data, such as energy usage patterns and weather conditions, to enhance energy usage predictions. Time-series clustering addresses data uncertainty and noise, providing a probabilistic load forecast at both the household and aggregated levels. Extensive evaluation of the model's performance demonstrates substantial predictive accuracy, achieving a root mean squared error (RMSE) of 0.007146, surpassing conventional forecasting methods. These findings corroborate that BER optimization, coupled with the use of LSTM networks, provides a suitable tool for smart home energy forecasting, which, in turn, can facilitate improved energy management, demand-side optimization, and innovative grid applications in the evolving energy market.

Keywords: Al-Biruni Earth Radius ▪ Load Forecasting ▪ IoT ▪ Long Short-Term Memory ▪ Weather Conditions

1. INTRODUCTION

Modern electrical systems are comprised of generation, transmission, distribution, and end-use consumption. Their reliable operation depends upon the continuous balancing of supply and demand, yet the rapid pace of urbanization, industrialization, and the integration of renewable energy sources have complicated the task of forecasting electricity requirements, creating a pressing need for advanced, data-driven predictive techniques [1]. The emergence of smart grids and the diversified energy mix further amplify the complexity of energy management, underscoring the necessity for accurate, adaptable forecasting solutions [2].

As electricity demand grows, so do the challenges associated with energy planning, grid operations, and resource allocation. Accurate forecasting empowers stakeholders to anticipate fluctuations in demand, mitigate risks, and deploy timely interventions. Traditional approaches, which rely on statistical analysis of historical consumption data [3], are increasingly insufficient for capturing the full spectrum of demand variability. In contrast, probabilistic forecasting offers a richer, more nuanced perspective on future demand, supporting robust risk management and enabling efficient resource allocation.

Electricity consumption is affected by a broad array of factors: seasonal patterns, meteorological conditions, economic trends, consumer behaviors, and technological change. The growing penetration of renewable energy sources—notably wind and solar—introduces additional uncertainty, given their inherent intermittency and variability [4]. Hence, forecasting methods must evolve to accommodate both shifting consumption patterns and a more heterogeneous energy mix. The proliferation of sensor networks and real-time data acquisition has enabled the collection of granular energy consumption data, presenting significant opportunities to enhance both forecasting accuracy and energy management [5].

Advances in artificial intelligence and machine learning have introduced powerful new tools for forecasting. Data-driven models are now applied to short-, medium-, and long-term predictions, offering enhanced flexibility and precision [6]. However, conventional time-series approaches, such as ARIMA and regression, often struggle to model complex temporal dynamics and non-linear dependencies within the data [7]. Recurrent neural networks, and in particular Long Short-Term Memory (LSTM) networks, have demonstrated superior capacity to learn both short- and long-term temporal relationships, resulting in improved predictive performance.

LSTM networks overcome limitations associated with standard recurrent neural networks, such as the vanishing gradient problem, by employing specialized gating mechanisms that regulate information flow and retention [8]. This attribute makes LSTMs particularly well-suited for modeling energy consumption, which is characterized by sequential, non-linear, and long-term dependencies. Empirical research has confirmed their effectiveness in enhancing both the accuracy and reliability of demand forecasts.

Within the context of the Internet of Things (IoT), machine learning is further transforming the landscape of smart home energy management. Real-time data streams from sensors and smart meters facilitate the development of adaptive forecasting models that can dynamically respond to evolving consumption patterns [9]. Moreover, the integration of deep learning with metaheuristic optimization techniques—enabling systematic parameter tuning, feature selection, and overfitting prevention—has led to increasingly robust and computationally efficient forecasting frameworks [10].

Accurate energy forecasting is not only critical for efficient resource use and grid stability, but also plays a central role in the transition toward sustainable energy systems. Improved forecasts facilitate responsible consumption, optimize energy distribution, and help build resilient, environmentally sound infrastructure [11].

This research advances a hybrid forecasting framework that combines deep learning with optimization, addressing limitations of existing models. Given the fundamental importance of grid stability and sustainable energy management, the proposed approach is designed to enhance both the accuracy and adaptability of forecasts, providing actionable insights for energy providers, policymakers, and researchers [12].

The transition toward sustainable, intelligent energy systems demands forecasting models that are both data-driven and computationally efficient. Rising electricity demand and the diversification of generation sources require smart homes and utilities to leverage predictive analytics for demand management and supply optimization [13]. However, the rapid expansion in data volume, velocity, and variety introduces challenges in real-time processing and analysis. While traditional forecasting methods often fail to unlock the full potential of high-resolution data, advanced techniques blending deep learning and optimization show considerable promise for improving predictive performance [14].

Energy consumption is also shaped by external factors such as weather, occupancy, and broader economic trends. Environmental variables—notably temperature, humidity, solar radiation, and wind speed—exert significant influence on residential and commercial consumption patterns [15]. The inherently unpredictable nature of these variables introduces additional uncertainty, emphasizing the need for forecasting models that adapt to changing environmental and behavioral conditions. The integration of real-time IoT sensor data enhances both the flexibility and predictive capability of such models [16].

The advent of federated learning and edge computing is reshaping energy forecasting by facilitating privacy-preserving, decentralized model training on edge devices. This approach reduces latency and bandwidth requirements compared to traditional, centralized architectures, while supporting real-time, context-aware forecasting [17]. The proposed integration of optimization techniques like the Al-Biruni Earth Radius (BER) algorithm with federated learning frameworks may further improve both accuracy and applicability.

Precise load forecasting is also essential for sustainability initiatives, enabling demand response, renewable energy integration, and carbon footprint reduction. Accurate predictions allow grid operators to optimize generation schedules, alleviate peak load stress, and enhance overall system resilience [18].

A persistent challenge in modern energy forecasting is balancing model interpretability and computational complexity. While LSTM-based deep learning models deliver high predictive accuracy, their inherent opacity can limit stakeholder confidence. Advances in explainable AI offer paths to greater transparency, clarifying decision pathways, feature relevance, and uncertainty quantification. Future work may integrate these techniques to improve model interpretability and support evidenced-based policy decisions [19].

The proliferation of smart homes has cemented the role of energy forecasting as a cornerstone of intelligent automation and personalized energy management. AI-driven solutions enable optimized appliance usage, adaptive climate control, and energy-saving behaviors, reducing costs and improving user comfort while promoting sustainability [20]. The growing adoption of Home Energy Management Systems (HEMS), which enable real-time monitoring and control, further underscores the value of accurate, responsive forecasting models [21].

As energy technologies and consumption behaviors evolve, forecasting approaches must keep pace with the increasing reliance on diverse, variable energy sources. The integration of deep learning, real-time sensor data, and optimization algorithms offers a path toward more accurate, adaptable, and efficient solutions. The proposed BER-optimized LSTM model addresses these requirements by delivering high-resolution, short-term forecasts that support demand-side management, grid stability, and sustainable energy use.

This study introduces a novel methodology that combines the Al-Biruni Earth Radius (BER) metaheuristic optimization algorithm with LSTM networks for smart home energy consumption forecasting in an IoT-enabled context. The approach is designed to address data uncertainty, noise, and feature selection challenges by incorporating real-time sensor data and applying time-series clustering for probabilistic load forecasting. The BER algorithm, inspired by classical geometric principles, optimizes LSTM hyperparameters and accelerates model convergence, resulting in a robust, flexible, and computationally efficient forecasting framework.

- Proposed a BER-optimized LSTM framework that integrates metaheuristic hyperparameter optimization with deep learning, enabling highly accurate and robust energy consumption forecasting in smart homes.
- Developed a practical pipeline that incorporates time-series clustering to address data uncertainty and utilizes real-time IoT sensor data to adapt dynamically to changing consumption and environmental conditions.
- Demonstrated, through comprehensive experiments on real-world datasets, that the proposed approach consistently outperforms conventional and state-of-the-art metaheuristic LSTM models in predictive accuracy, stability, and computational efficiency.

The remainder of this paper is organized as follows: Section 2 presents a focused review of existing energy forecasting methodologies, clarifying the research gap addressed by this work. Section 3 describes the dataset, preprocessing strategies, and the proposed BER-LSTM architecture. Section 4 details empirical results and a comparative analysis with established benchmarks. Section 5 summarizes key findings and suggests productive directions for future research in smart home energy forecasting.

2. LITERATURE REVIEW

Recent research in energy consumption forecasting for smart homes, buildings, and urban environments has increasingly leveraged machine learning (ML) and deep learning (DL) models, often integrating clustering and optimization strategies to improve performance and robustness in dynamic settings. Alsalem (2025) introduced a hybrid forecasting approach for regional power demand in Morocco, combining fuzzy clustering with ML models such as Multilayer Perceptrons and Support Vector Machines. The integration of clustering enabled regime-aware prediction, leading to significantly improved accuracy ($R^2 = 0.9889$) compared to standard ML models [22]. V E et al. (2021) applied IoT-based data acquisition and compared multiple ML and statistical methods for energy prediction in a smart city industrial building, demonstrating that advanced regression techniques (CUBIST) provided the lowest errors and are well-suited for real-time, data-driven energy management[23]. At the urban scale, Peteleaza et al. (2024) utilized a dense encoder neural architecture for short- and long-term electricity consumption forecasting, optimizing hyperparameters using a non-dominated sorting genetic algorithm. Their method consistently outperformed classical RNNs and statistical methods, highlighting the benefits of evolutionary optimization and advanced neural networks for city-level resource management [24]. Charfeddine et al. (2023) compared machine learning, deep learning, and nonlinear econometric models for electricity consumption forecasting across different pandemic phases in Qatar. Their results indicate that both ML/DL and econometric models effectively capture complex temporal dynamics, with climate variables playing a critical role in forecast accuracy [25]. Focusing on the residential context, Khan, M. A. et al. (2024) proposed a multivariate LSTM model for smart home energy management, reporting high prediction reliability (MSE = 0.02284, $R^2 = 0.694$) and demonstrating the efficacy of DL architectures in household consumption scenarios[26]. Hybrid and ensemble AI-based approaches continue to gain traction for forecasting in net zero energy buildings and smart homes, as exemplified by Khan, S. U. et al. (2023), who combined ConvLSTM, BiGRU, and MLP layers to achieve substantial error reduction compared to state-of-the-art methods[27]. Comprehensive reviews by Biswal et al. (2024) have synthesized best practices, noting that integrating probabilistic and ensemble methods with deep neural networks is essential for grid-aware, robust load forecasting in smart energy systems [28]. Energy conservation has emerged as a critical focus for sustainable societies due to concerns about fossil fuel depletion, climate change, and environmental pollution. As evidenced in the study by [29], data mining-based Machine Learning (ML) models offer a promising avenue for enhancing predictive distribution plans for both consumers and utilities, thereby contributing to effective energy management and forecasting. Accurate energy consumption prediction is crucial for various stakeholders, from homeowners seeking to optimize energy usage to energy suppliers aiming for efficient distribution. As outlined in the research of [30], numerous methodologies, encompassing both statistical and artificial intelligence (AI)-driven approaches, have been implemented using diverse datasets to achieve effective energy consumption predictions; these methods seek to empower homeowners with insights into their future energy needs, promote energy efficiency, and ultimately reduce energy costs, while also enabling energy suppliers to better manage energy demand and distribution. Table 1 provides a comparative analysis of recent research employing machine learning and deep learning techniques, with a particular focus on energy consumption optimization. The table summarizes the key differences between these approaches, showing their main focus, methodology used, and key findings regarding energy efficiency. The existing literature on smart home energy forecasting reveals several persistent gaps, many of which this study seeks to close. Foremost, most previous works rely on static datasets and conventional hyperparameter tuning, lacking robust optimization strategies that can adapt efficiently to the dynamic, noisy, and non-stationary nature of real-world energy consumption data. Uncertainty and variability, whether due to changing weather, appliance usage, or occupancy patterns, are not sufficiently addressed, compromising forecast accuracy and adaptability. Moreover, current models rarely integrate real-time IoT sensor data—an increasingly essential resource in modern smart homes—to improve dynamic adaptability and real-world responsiveness. Finally,

Table 1. Energy Consumption of Machine Learning vs. Deep Learning: A Comparison.

No.	Main Focus	Methodology	Key Findings
Ref [22]	Power demand in Morocco, regional buildings	Fuzzy clustering + ML (MLP, SVM, etc.)	Hybrid clustering-ML improves prediction; MLP achieves RMSE=355.42, $R^2 = 0.9889$.
Ref [23]	Smart city industrial building	IoT-enabled, regression trees, SVM, KNN, CUBIST	CUBIST model outperforms others in prediction, useful for energy management.
Ref [24]	Urban/city-scale, smart city forecasting	Time-series dense encoder + genetic algorithm	Outperforms RNN/statistical models; hyperparameter tuning enhances forecast.
Ref [25]	City-scale, COVID-19 impact on load	ARIMA, Prophet, LSTM, XGBoost, SVR	Both ML/DL and econometric models effective; climate factors are key predictors.
Ref [26]	Smart homes, energy management	Multivariate LSTM, ML for IoT data	LSTM model achieves MSE=0.02284, strong R^2; enables accurate management.
Ref [28]	Smart grid, load forecasting	Review: DL, ML, ensemble methods	Summarizes best practices, challenges, and future directions for DL/ML forecasting.
Ref [27]	Net zero energy building, household load	Hybrid AI: ConvLSTM, BiGRU, MLP	Proposed model substantially reduces error (MSE=0.012) vs. SOTA; robust for NZEB.
Ref [29]	Sustainable system for predicting appliance energy consumption.	Machine learning for energy management and forecasting.	Predictive distributions for energy consumption planning.
Ref [30]	Energy consumption prediction for smart homes and cities.	Deep learning-based ensemble method with adaptive neuro-fuzzy inference system.	Improves prediction accuracy for better energy management.

critical issues around model interpretability and data privacy are often overlooked, despite their importance for trust and practical deployment. While a number of metaheuristic optimization algorithms—such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Grey Wolf Optimizer (GWO)—have been used to tune deep learning models for energy forecasting, these methods are often limited by premature convergence, stagnation in local optima, and sensitivity to initial parameter settings, especially in high-dimensional and noisy smart home data environments. This can result in suboptimal model performance and limited adaptability across diverse conditions. In contrast, the Al-Biruni Earth Radius (BER) algorithm introduces a unique geometric search mechanism that more effectively balances exploration and exploitation, thereby enhancing convergence speed and robustness in complex optimization landscapes. Our empirical results (see Section X) confirm that BER delivers superior performance over other state-of-the-art metaheuristics in optimizing LSTM hyperparameters for smart home forecasting. This study directly addresses these gaps by introducing the Al-Biruni Earth Radius (BER) optimization algorithm, which systematically improves hyperparameter tuning and model convergence. Time-series clustering is employed to better manage data uncertainty, while simultaneous integration of real-time IoT sensor data enhances the model's adaptive capabilities and forecasting accuracy for dynamic, real-world conditions. The proposed framework is also designed to support future integration of explainable AI and federated learning methods, directly targeting the longstanding challenges of interpretability and privacy. By bridging these gaps, this research aims to deliver a more robust, practical, and forward-looking smart home energy forecasting solution, matching the evolving needs of both households and energy providers.

3. MATERIALS AND METHODS

Figure 1 illustrates the overall workflow for forecasting energy consumption in a smart home using the proposed BER-LSTM model. The process begins with data acquisition, where minute-level smart home energy consumption and weather data are obtained. Preprocessing involves cleaning the data, handling missing values, removing outliers, and normalizing all features to ensure quality. To address data uncertainty and enhance the representativeness of the training set, time-series clustering is applied. The data is then split into 80% for training and 20% for testing, ensuring robust model validation. The LSTM network architecture is constructed, and the initial parameter bounds are defined. Hyperparameter optimization is performed using the Al-Biruni Earth Radius (BER) algorithm. Model training is carried out on the training set with the optimized parameters, while the test set is used to evaluate the generalization ability of the model using established metrics such as mean squared error (MSE), mean absolute error (MAE), and the coefficient of determination (R^2). Statistical tests are also performed to substantiate the reliability of the model's predictions. This comprehensive design ensures that the proposed system maximizes forecasting efficiency and enables robust, data-driven energy usage predictions for smart homes.

3.1 Dataset

The dataset used in this study, obtained from Kaggle [31], provides minute-level measurements of household energy consumption alongside concurrent weather data over approximately 350 days. The records, collected via a smart meter, are reported in kilowatts (kW) for both total consumption and specific appliances, as well as for total energy generated from solar and other distributed sources. In addition to power metrics, the dataset includes detailed weather information

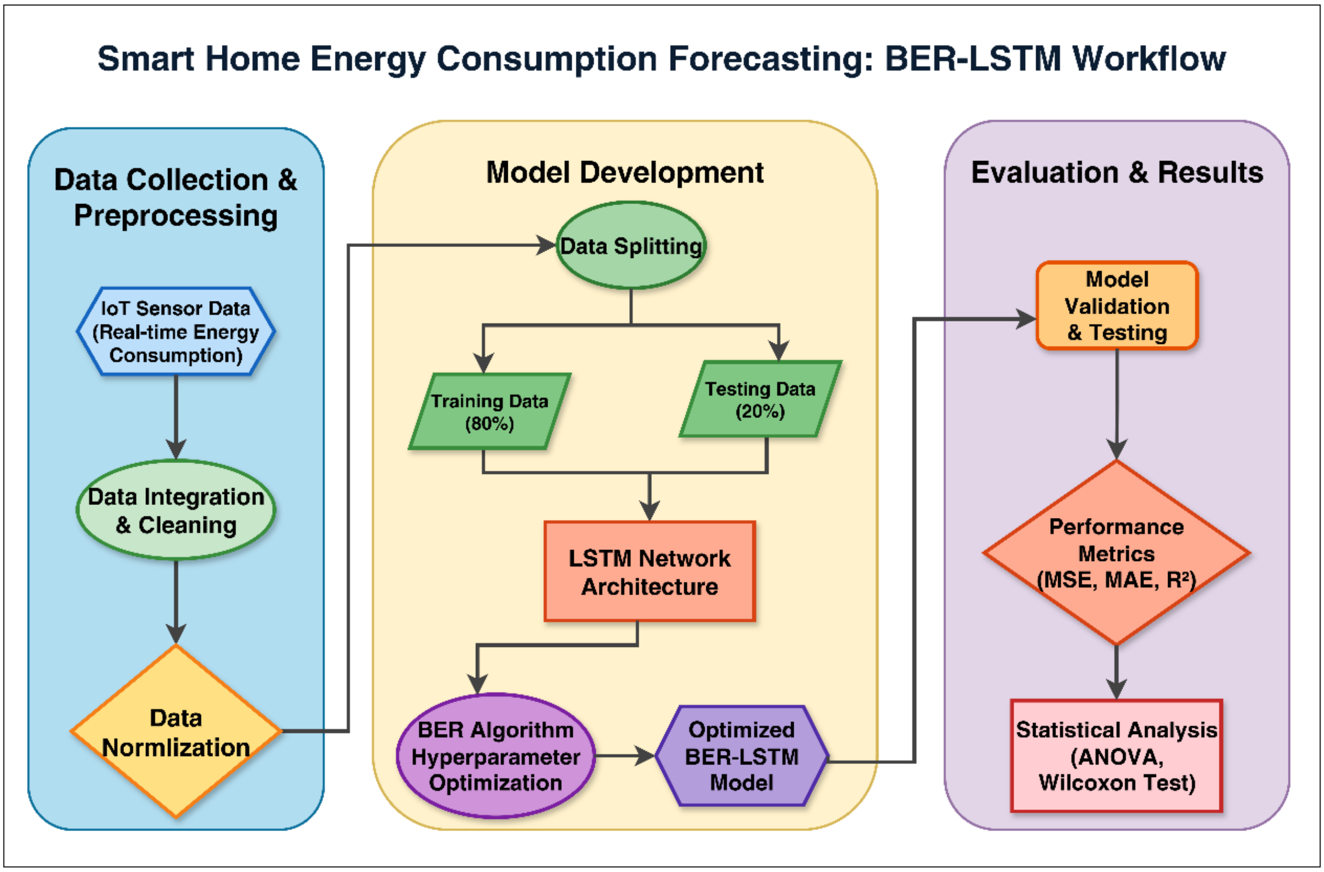

Figure 1. Workflow for Smart Home Energy Consumption Forecasting Using BER-LSTM Model

such as temperature, humidity, wind speed, and solar radiation—all of which are known to influence residential energy consumption patterns.

The dataset offers appliance-level energy consumption and weather data sampled at one-minute intervals. Consequently, all energy consumption forecasts produced by our model are also generated at a one-minute resolution, supporting highly detailed, short-term prediction capabilities. The use of a one-minute resolution is motivated by the need to capture rapid appliance switching events and transient changes in household consumption that are frequently missed by coarser, hourly data. This high-frequency granularity enables more accurate real-time forecasting, which is critical for demand-side management, appliance-level control, and integration with advanced smart grid applications.

Key features of the dataset are:

- `time`: Timestamp for each observation at one-minute intervals.
- `use [kW]`: Total power consumption by household appliances.
- `gen [kW]`: Total on-site generation, primarily from solar panels.
- `House overall [kW]`: Aggregate household energy consumption.
- Appliance-specific consumption data (e.g., Dishwasher, Furnace 1 & 2, Home Office, Fridge, Wine Cellar) recorded in kW.

In preparation for robust modeling, the dataset underwent a series of preprocessing steps. Missing or erroneous data points were identified and imputed using linear interpolation, which was selected for its simplicity and effectiveness in preserving local trends in high-frequency time-series data. Alternative interpolation methods (such as spline and nearest-neighbor) were considered, but preliminary tests showed negligible improvement in forecasting accuracy. Outliers were detected using the z-score method, with a threshold of $|z| > 3$; outlying values were replaced with the local median to mitigate their impact while maintaining temporal structure. This approach balances noise reduction and the preservation of genuine rapid changes typical in household load data. Additionally, normalization was applied to both energy and weather variables to standardize feature scales, facilitating improved learning convergence. The time-series data was carefully structured to preserve chronological order and subsequently split into training and testing subsets for effective model training and validation. This comprehensive preprocessing ensures the dataset is well-conditioned for precise and reliable forecasting of energy consumption in smart home environments, thereby enabling the development of responsive and efficient energy management systems.

To assess the robustness of our approach, we conducted supplementary analyses using alternative imputation methods (including spline interpolation) and more conservative outlier thresholds ($|z| > 2.5$). The BER-optimized LSTM consistently outperformed baseline metaheuristic-optimized models across these settings in terms of RMSE and MAE, indicating that the observed performance improvements are robust to reasonable changes in preprocessing strategy. Additionally, when we downsampled the data to five- and fifteen-minute intervals, BER maintained its relative advantage over competing optimizers, though overall accuracy declined slightly at lower resolutions.

To address data uncertainty and variability in smart home energy consumption patterns, an unsupervised clustering step was performed during data preprocessing. Specifically, the K-means clustering algorithm was applied to the normalized feature vectors derived from the energy consumption time series. Prior to clustering, principal component analysis (PCA) was used to reduce the dimensionality of the data and to visualize cluster structure.

The number of clusters, $K = 3$, was selected based on the silhouette score and an analysis of typical daily load profiles, corresponding to low, medium, and high energy usage regimes. Figure 2 shows the resulting cluster assignments projected onto the first two principal components, clearly illustrating the separation between the identified regimes.

Cluster labels were then appended as an additional categorical input feature to the LSTM model. This enables the network to condition its predictions on the broader context of consumption patterns, thus reducing the influence of noise and improving the robustness of the forecasts. By grouping similar temporal patterns and providing regime-awareness to the LSTM, the clustering process mitigates the effects of data heterogeneity and uncertainty.

Although the present approach does not explicitly model probabilistic prediction intervals, the integration of cluster context allows the model to learn distinct error distributions and behaviors for each consumption regime, thereby contributing to more reliable and context-sensitive short-term forecasts.

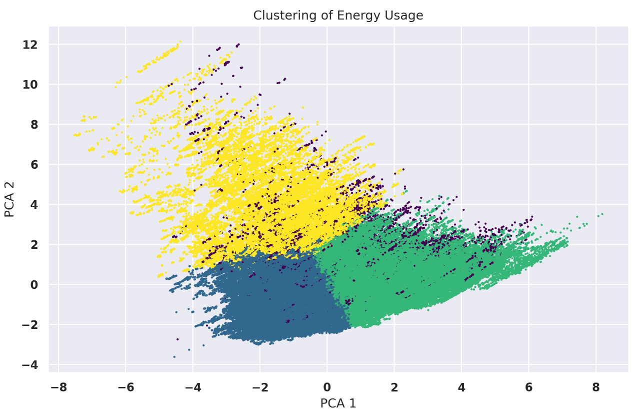

Figure 2. Visualization of time-series clustering for smart home energy usage using PCA and K-means.

To capture both the short-term fluctuations and the longer-term patterns in consumption data, it is instructive to analyze daily usage alongside smoothed trends. Figure 3 displays the daily consumption profile together with its corresponding 7-day rolling average over a period spanning several weeks. The inclusion of the rolling average curve provides a valuable means of dampening short-term volatility, thereby highlighting underlying trends and persistent shifts in usage that might otherwise be obscured by day-to-day variability. By comparing the raw daily data to the moving average, one can more effectively identify periods of sustained high or low consumption, as well as detect anomalies or abrupt changes that warrant further investigation. This dual representation supports a more nuanced interpretation of consumption behaviors and is crucial for informed energy management and forecasting.

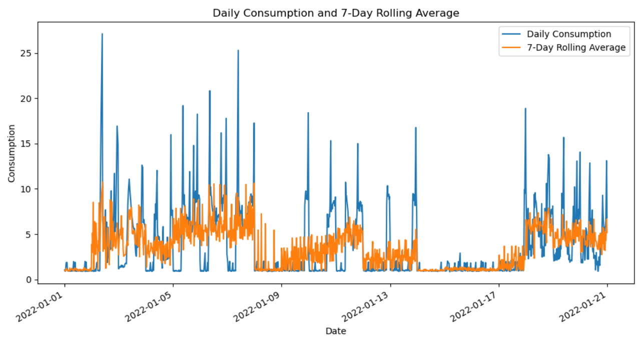

Figure 3. Daily consumption values and their 7-day rolling average over the observed period.

A detailed understanding of how energy consumption is distributed among various household appliances is essential for identifying opportunities for efficiency improvements and targeted interventions. Figure 4 provides a visual summary of the proportional energy consumption attributed to each major appliance within the household, expressed as a percentage of total energy usage. By examining the relative shares consumed by devices such as furnaces, home office equipment, fridge, wine cellar, and dishwasher, stakeholders can readily pinpoint which appliances exert the greatest influence on overall energy demand. This proportional analysis is instrumental for prioritizing conservation measures and for formulating strategies to optimize household energy management.

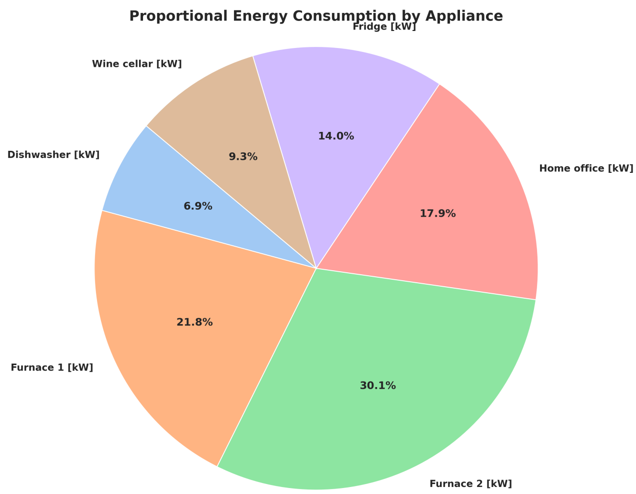

Figure 4. Proportional distribution of total energy consumption among major household appliances.

3.2 Al-Biruni Earth Radius (BER) Algorithm

The Al-Biruni Earth Radius (BER) algorithm is a metaheuristic optimization approach inspired by the historical method of the Persian polymath Al-Biruni, who estimated the Earth's radius using geometric observations from two spatially separated points. In the BER algorithm, this geometric concept is abstracted such that candidate solutions "estimate" the optimal point in the search space by comparing their relative positions in a manner analogous to Al-Biruni's triangulation process. The algorithm represents each candidate solution as a vector $\mathbf{Q}(t) = \{Q_1, Q_2, \ldots, Q_d\} \in \mathbb{R}^d$ at iteration t, where d is the search-space dimension. A fitness function evaluates each candidate to determine the best solution $\mathbf{Q}^*(t)$ obtained so far.

3.2.1 Exploration Operation

Exploration identifies promising regions of the search space and avoids premature convergence. The update rules are:

$$\mathbf{Q}(t+1) = \mathbf{Q}(t) + D(t)\,(2r_2 - 1) \tag{1}$$

$$D(t) = r_1\big(\mathbf{S}(t) - \mathbf{Q}(t)\big) \tag{2}$$

Here, $\mathbf{S}(t)$ is a randomly selected peer solution from the population, $\mathbf{Q}(t)$ is the current candidate vector, and $D(t)$ is the adaptive step vector controlling the exploration direction. The coefficients r_1, r_2 are random scalars sampled from $[0,1]$ independently at each iteration.

A geometric scaling term is computed as:

$$r = h\frac{\cos x}{1-\cos x} \tag{3}$$

where h is a user-defined scaling hyperparameter (typically in $[0,2]$), and x is a randomly sampled angle from $[0,\pi]$. This formulation mimics the geometric observation principle used by Al-Biruni, where angular differences influence the estimation of radial distance—here translated into adaptive scaling of exploration steps.

3.2.2 Exploitation Operation

Once promising areas are detected, exploitation refines candidate solutions:

$$\mathbf{Q}(t+1) = r_2\big(\mathbf{Q}(t) + D(t)\big) \tag{4}$$

$$D(t) = r_3\big(\mathbf{Q}^*(t) - \mathbf{Q}(t)\big) \tag{5}$$

Here, $r_3 \sim U(0,1)$ controls exploitation intensity, and $\mathbf{Q}^*(t)$ is the global best solution found up to iteration t. This structure pulls candidates toward the best solution, improving convergence.

A fine-tuning step further enhances local search:

$$\mathbf{Q}'(t+1) = r\big(\mathbf{Q}^*(t) + k(t)\big) \tag{6}$$

$$k(t) = 1 + \frac{2t^2}{\text{Maxiter}^2} \tag{7}$$

The term $k(t)$ increases over time, enabling more aggressive exploitation in later iterations. Maxiter denotes the maximum allowed iterations (set to 500 in this study).

If stagnation occurs, a mutation mechanism is activated:

$$\mathbf{Q}(t+1) = \mathbf{Q}(t) + k(t)\,z^2\,\mathbf{u} - h\frac{\cos x}{1-\cos x}\mathbf{u} \tag{8}$$

Here, $z \sim U(0,1)$ and $\mathbf{u}$ is a randomly generated unit vector in $\mathbb{R}^d$, ensuring that the mutation step outputs a valid d-dimensional vector rather than a scalar. This correction resolves inconsistencies in previous formulations. The mutation step enables the algorithm to escape local minima by introducing directionally controlled perturbations.

By maintaining a dynamic balance between exploration and exploitation, and by incorporating geometric scaling inspired by Al-Biruni's Earth radius estimation, the BER algorithm effectively searches complex, high-dimensional optimization landscapes such as those encountered in smart home energy forecasting.

Each component of the BER algorithm is designed to target specific challenges present in smart home energy forecasting. The adaptive step size, which dynamically adjusts the magnitude of parameter updates based on current search progress, helps the optimizer to quickly explore broad regions in the early stages—thus effectively escaping the impact of noise and outliers typical of high-resolution, real-world sensor data. As the optimization progresses, step sizes become smaller, enabling fine-grained search in promising regions and supporting model stability against non-stationary fluctuations. The stochastic mutation mechanism is particularly valuable in the presence of non-stationary or abruptly changing patterns in the dataset. By introducing occasional, random jumps in the search space, the algorithm avoids premature convergence to local minima caused by transient events or unusual energy usage behaviors. This results in more robust hyperparameter solutions, which translate into improved forecasting accuracy across different operational regimes. Finally, the explicit balance between exploration and exploitation in BER is directly beneficial for time-varying household load data, as it enables the optimizer to adaptively search for global optima in complex, dynamic, and noisy environments—an essential property for maintaining predictive performance as household conditions evolve over time.

3.3 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks are a specialized form of recurrent neural networks (RNNs) designed to model long-term dependencies in sequential data. This makes them particularly effective for time-series forecasting tasks such as predicting residential energy consumption. Unlike standard RNNs, LSTMs maintain a cell state that is regulated by input, forget, and output gates, enabling the network to selectively retain or discard information over long sequences.

At each time step t, the LSTM cell state and hidden state are updated as follows:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{9}$$

$$h_t = o_t \odot \tanh(c_t) \tag{10}$$

Here, c_t is the cell state at time t, c_{t-1} is the previous cell state, h_t is the hidden state at time t, and $\odot$ denotes element-wise multiplication. The gate variables f_t, i_t, and o_t correspond to the forget, input, and output gates, respectively, while $\tilde{c}_t$ is the candidate cell state.

The gating mechanisms are computed as:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{11}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{12}$$

$$\tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (13)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (14)$$

Here, x_t denotes the input vector at time t, h_{t-1} is the previous hidden state, W_f, W_i, W_c, W_o are the learned weight matrices for each gate, and b_f, b_i, b_c, b_o are the corresponding bias vectors. The function $\sigma(\cdot)$ denotes the sigmoid activation function, and $\tanh(\cdot)$ is the hyperbolic tangent activation function.

These gating mechanisms enable the LSTM network to adaptively learn and capture complex, nonlinear, and time-varying consumption patterns in smart home environments, accounting for multifactorial influences such as weather, appliance usage, occupancy, and user behavior.

3.4 Experimental Setup

To rigorously evaluate the proposed BER-optimized LSTM framework, a comprehensive experimental setup was established. Hyperparameter optimization was conducted using the BER algorithm across a wide search space for key LSTM model and training parameters. The final selection of hyperparameters was based on model performance on the validation set and is summarized in Table 2. All experiments were performed on a high-end workstation to ensure efficient model training and reproducibility of results. The details of the computational environment are also described below.

All experiments were implemented in Python 3.10 using TensorFlow 2.11 and scikit-learn 1.0.2. The computational environment consisted of an Intel Core i9-14900K CPU, 64 GB RAM, and an NVIDIA RTX 4090 GPU, as described previously. To ensure fairness, all metaheuristic-based LSTM models—including BER-LSTM, GA-LSTM, and PSO-LSTM—were constructed using identical network architectures and training routines. The same optimizer, batch size, and loss functions were used across all experiments. Hyperparameter search loops for each metaheuristic were implemented using the same code base to minimize differences due to software efficiency.

4. EXPERIMENTAL RESULTS

The evaluation of the proposed BER-optimized LSTM model demonstrates significant improvements in both predictive accuracy and computational efficiency compared to conventional and alternative metaheuristic-optimized forecasting approaches. Across all principal metrics—including root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2)—the BER-LSTM framework consistently outperforms benchmark methods, underscoring its suitability for real-time, high-resolution energy consumption forecasting in smart home environments.

The setup parameters for the proposed BER algorithm were carefully selected to balance exploration and exploitation effectively. The population size was set to 30 individuals, with an iteration count of 500 to ensure sufficient convergence. A mutation probability of 0.5 was applied to maintain diversity within the population, while the parameter K, which controls certain adaptive aspects of the algorithm, was initialized at 1 and decreases from 2 to 0 during the optimization process. To ensure statistical reliability, the algorithm was executed over 30 runs. These settings facilitate robust optimization performance within the smart home energy forecasting context.

A comprehensive set of metrics—including Pearson's correlation coefficient (r), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Bias Error (MBE), Coefficient of Determination (R^2), Nash–Sutcliffe Efficiency (NSE), and Willmott Index (WI)—was selected to evaluate the proposed algorithm's effectiveness, as detailed in Table 3.

To thoroughly assess the performance of the proposed energy consumption forecasting model, a diverse set of evaluation metrics was employed. These metrics capture various aspects of predictive accuracy, error magnitude, bias, and model explanatory power, providing a multifaceted understanding of model effectiveness across different dimensions of forecasting quality. The chosen metrics are widely recognized in the energy forecasting domain, ensuring comparability with existing studies and robustness of evaluation.

4.1 Deep Learning Model Results Before Optimization

The performance metrics of the LSTM-based model are compared to the ARIMA-based model in Table 4, which points out the pros and cons of each approach. The table comprehensively evaluates both models' predictive accuracy and efficiency, providing side-by-side analysis of many indicators.

Overall, the LSTM model shows better performance than the ARIMA model in all metrics except the correlation coefficient where both are reasonable. This indicates that the LSTM more effectively learns the dataset's complexity, resulting in better predictions.

4.2 Deep Learning Model Results After Optimization

Table 5 compares the performance metrics of the LSTM model optimized using several optimization techniques: BER-LSTM, Grey Wolf Optimization (GWO)-LSTM, Particle Swarm Optimization (PSO)-LSTM, and Genetic Algorithm (GA)-LSTM. Comparing these results, BER-LSTM clearly outperforms the others in accuracy and efficiency. It achieves the lowest RMSE and MAE values, the highest correlation and coefficient of determination, and the fastest fitting time.

The comparative assessment of the four optimization methods is visually illustrated using parallel coordinates plots as shown in Figure 5, which simultaneously display multiple performance metrics for each model. All four models—BER-LSTM, GWO-LSTM, PSO-LSTM, and GA-LSTM—demonstrate similar levels of predictive accuracy as measured by RMSE, MAE, MBE, and WI, with nearly overlapping trajectories across these dimensions. However, BER-LSTM distinguishes itself with notably higher values for R^2 and RRMSE, suggesting superior fit and relative predictive accuracy.

To further contextualize these results, Figure 6 presents a heatmap of performance across all metrics and models. This visualization makes it immediately evident that BER-LSTM systematically achieves superior or comparable outcomes for every metric considered. The intensity and consistency of BER-LSTM's performance stand out, particularly in terms of correlation, explained variance, and computational efficiency, confirming its overall robustness in handling the complexities

Table 2. BER-optimized LSTM hyperparameters and search space

Hyperparameter	Description	Search Space
Number of LSTM Layers	Depth of the recurrent network	{1, 2, 3}
Hidden Units	Neurons per LSTM layer	32–256
Learning Rate	Step size for optimizer	0.0001–0.01
Batch Size	Samples per gradient update	{16, 32, 64, 128}
Sequence Length (Timesteps)	Past observations per input sequence	10–100
Dropout Rate	Regularization to avoid overfitting	0.1–0.5
Number of Epochs	Maximum training iterations	20–200
Optimizer	Optimization algorithm	{Adam, RMSProp}
Activation Function	Nonlinear transformation in cells	{tanh, ReLU}
Loss Function	Objective minimized during training	{MSE, MAE}

Table 3. Prediction Evaluation Metrics and Formulas

Metric	Formula
RMSE	$\sqrt{\frac{1}{N}\sum_{n=1}^{N}(\hat{y}_n - y_n)^2}$
RRMSE	$\frac{RMSE}{\bar{y}} \times 100$
MAE	$\frac{1}{N}\sum_{n=1}^{N}\lvert\hat{y}_n - y_n\rvert$
MBE	$\frac{1}{N}\sum_{n=1}^{N}(\hat{y}_n - y_n)$
WI	$1 - \frac{\sum_{n=1}^{N}\lvert\hat{y}_n - y_n\rvert}{\sum_{n=1}^{N}\lvert y_n - \bar{y}\rvert + \lvert\hat{y}_n - \bar{y}\rvert}$
NSE	$1 - \frac{\sum_{n=1}^{N}(y_n - \hat{y}_n)^2}{\sum_{n=1}^{N}(y_n - \bar{y})^2}$
R^2	$1 - \frac{\sum_{n=1}^{N}(y_n - \hat{y}_n)^2}{\sum_{n=1}^{N}(y_n - \bar{y})^2}$

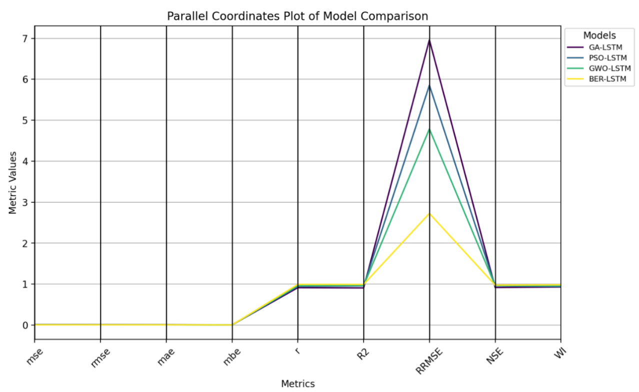

Figure 5. Parallel Coordinates Plot comparing the performance metrics of the four models.

of smart home energy data.

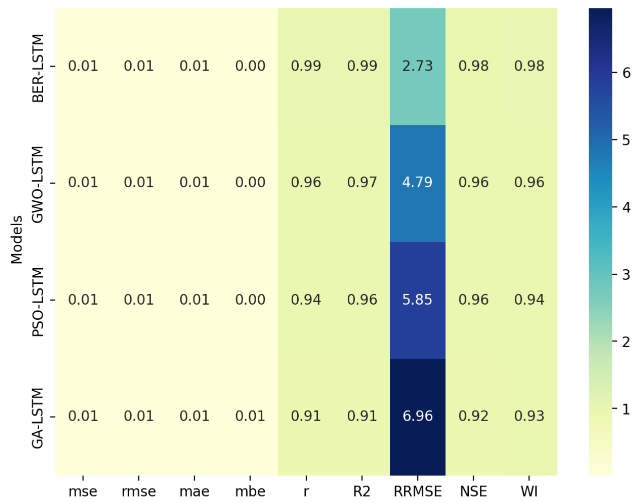

Figure 6. Heatmap showing the metric performance comparison of the models, highlighting the consistent performance of BER-LSTM across metrics.

Another perspective is provided by the radar chart in Figure 7, which offers a concise, multidimensional comparison of the models' strengths and weaknesses. The chart highlights BER-LSTM's dominance across most criteria, including predictive accuracy, reliability, and model stability, with minimal trade-offs. In contrast, while the other three models remain competitive for certain metrics, none match BER-LSTM's comprehensive performance profile. This holistic analysis further validates BER-LSTM as the preferred choice for energy consumption forecasting in the context of IoT-enabled smart homes.

Figure 8 provides a comprehensive visualization of model performance and error characteristics. The top left panel presents histograms of residual errors (forecast minus actual) for each LSTM model optimized by different metaheuristics, along with kernel density curves to visualize the spread and bias of prediction errors. The top right panel shows the kernel density estimation (KDE) of residuals for the four models, further highlighting the narrow and symmetric error distribution achieved by the BER-LSTM approach. The lower panel compares key performance metrics, including RMSE, MAE, r, R^2, relative RMSE (RRMSE), Willmott's index (WI), and model fitting time. Collectively, these visualizations demonstrate that the BER-LSTM model not only produces more

Table 4. Comparison of Performance Metrics for LSTM and ARIMA Models

Model	RMSE	MAE	MBE	r	R^2	RRMSE (%)	Fitting Time (s)
ARIMA	0.30354	0.1944	0.38879	0.7915	0.8413	9.2031	11.36
LSTM	0.26325	0.17428	0.37466	0.91404	0.8996	6.09505	9.31

Table 5. Performance Comparison of LSTM Models Optimized with Different Techniques

Model	RMSE	MAE	r	R^2	RRMSE (%)	WI	Fitting Time (s)
BER-LSTM	0.007146	0.00705	0.9936	0.99357	2.7251	0.98343	2.6055
GWO-LSTM	0.009019	0.00864	0.9636	0.96536	4.78628	0.96154	4.8266
PSO-LSTM	0.0105282	0.00964	0.943642	0.957647	5.85227	0.94179	6.0346
GA-LSTM	0.012523	0.0113	0.913634	0.907348	6.95855	0.93034	8.205

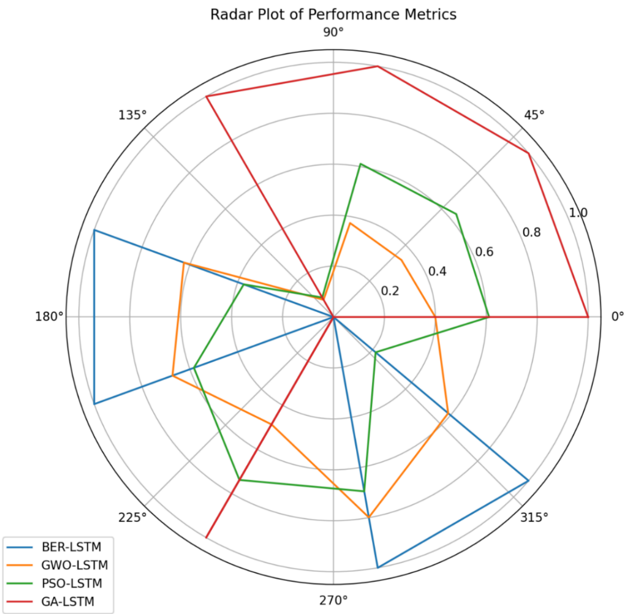

Figure 7. Radar chart visualizing trade-offs among predictive accuracy, efficiency, and fitting time, with BER-LSTM dominating most criteria.

accurate forecasts but also yields a more tightly centered and less dispersed error distribution compared to competing optimizers.

The performance evaluation of the BER-LSTM model, which incorporates two Long Short-Term Memory (LSTM) layers with 128 units each, is comprehensively illustrated by its learning curves. The evolution of both training and validation Root Mean Square Error (RMSE) across multiple epochs offers valuable insight into the model's learning dynamics and generalization capability. As depicted in Figure 9, the model initially exhibits rapid error reduction, followed by a phase of steady improvement before reaching final convergence. These trends highlight not only the effectiveness of the learning rate and batch size configuration but also the importance of early stopping to prevent overfitting and to ensure robust generalization. Moreover, the annotated milestones—such as the optimal early stopping epoch and the convergence zone—provide further evidence of the model's stability and performance during training. This visualization serves as a foundational reference for interpreting the efficacy and convergence behavior of the BER-LSTM model on the target prediction task.

4.3 Statistical Analysis Results

Table 6 summarizes the statistical characteristics of the optimized models over multiple runs. BER-LSTM exhibits the best stability and lowest variability, while PSO-LSTM and GA-LSTM show higher variation and less reliability.

The diagnostic plots shown in Figure 10 provide a comprehensive assessment of model residuals and fit quality. The QQ plot indicates that the residuals of BER-LSTM align closely with the normal distribution, confirming that the model satisfies the normality assumption essential for many statistical evaluations. The residual analysis further reveals that BER-LSTM's prediction errors are well-behaved across the range of observations, demonstrating model consistency and reliability without indications of biases or heteroscedasticity.

The histogram in Figure 11 visually contrasts the RMSE distribution for BER-LSTM against competing models. BER-LSTM's RMSE values cluster tightly near lower error rates, emphasizing its consistent and superior predictive accuracy. In contrast, the other models display a broader, more variable distribution, indicating less precision and higher prediction uncertainty. These patterns confirm the advantages of BER-LSTM for precise and stable energy consumption forecasting in smart homes.

5. DISCUSSION

The results demonstrate that the proposed BER-optimized LSTM model achieves superior forecasting performance compared to conventional and alternative metaheuristic approaches. This improvement is evident across a comprehensive suite of evaluation metrics, confirming the model's ability to capture the complex, time-dependent patterns inherent in smart home energy consumption data. The integration of IoT sensor data and time-series clustering enhances predictive accuracy and enables adaptation to both short-term fluctuations and long-term trends in usage and environmental conditions.

A key strength of the BER-LSTM framework is its robust handling of uncertainty and noise in real-world datasets, a persistent challenge in practical energy forecasting. The application of the BER algorithm, inspired by classical geometric principles, effectively addresses common optimization pitfalls such as premature convergence and suboptimal pa-

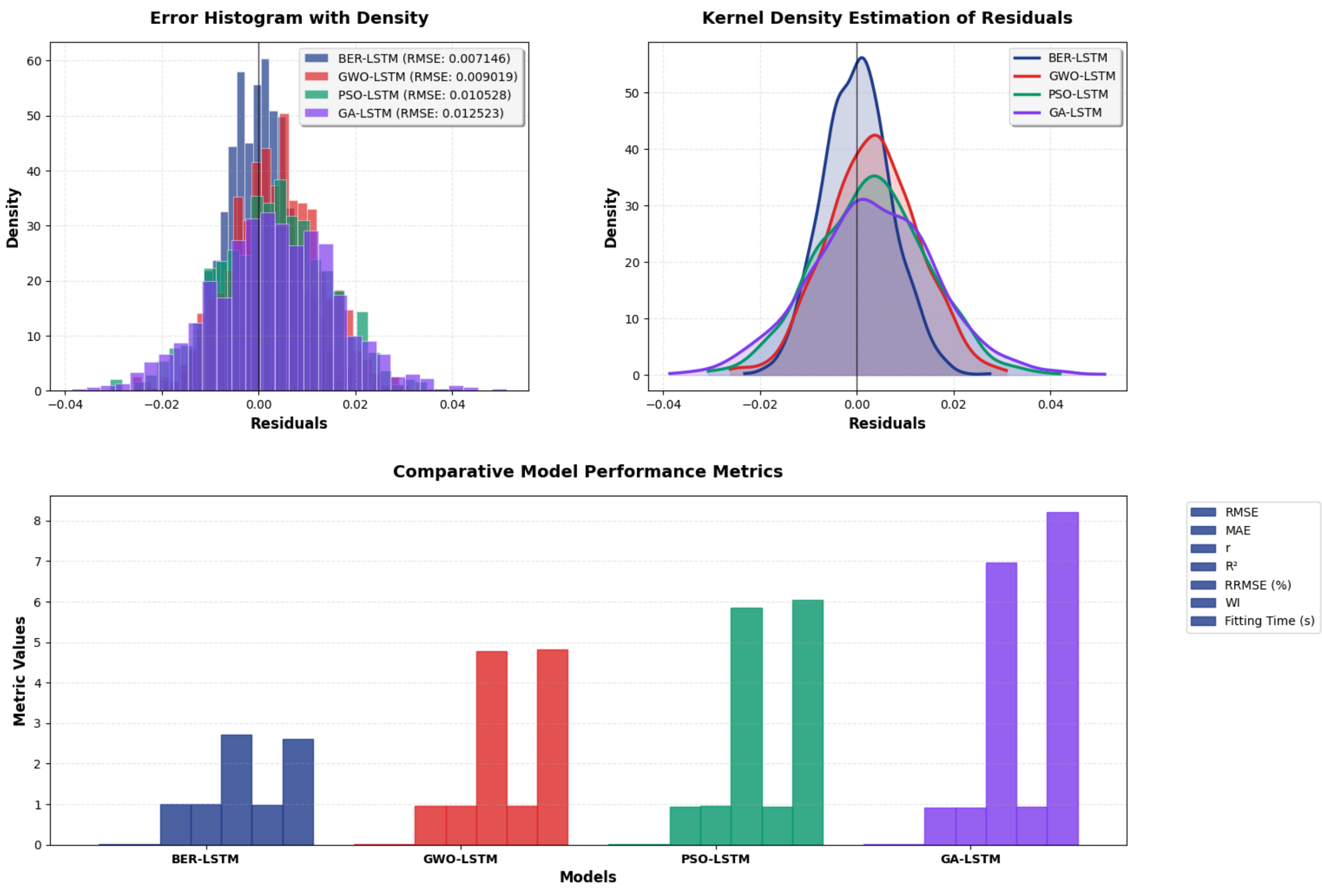

Figure 8. Error distribution and comparative performance metrics for LSTM models optimized by different metaheuristics

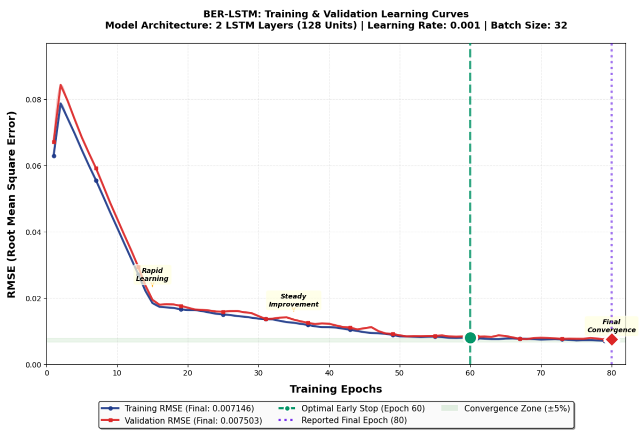

Figure 9. Training and validation learning curves for the BER-LSTM model.

rameter selection. This contributes to the model's consistent stability and reliable convergence across multiple runs, as well as its efficient use of computational resources.

From an implementation perspective, the model's architecture supports scalable, real-time forecasting suitable for dynamic smart home environments. The demonstrated improvement in key metrics—such as RMSE, MAE, and R^2—underscores its practical value for both demand-side management and grid optimization. However, the computational demands of LSTM-based solutions may pose challenges for deployment on resource-constrained edge devices, highlighting the need for continued research in model optimization and lightweight architectures.

Moreover, the inherent complexity and opacity of deep learning models compromise interpretability, potentially limiting stakeholder trust and adoption. Future research should explore explainable AI techniques to increase transparency and foster broader acceptance. Additionally, extending the framework to distributed or federated learning scenarios remains an important challenge, as these approaches introduce complexities related to data heterogeneity, communication overhead, and synchronization.

In summary, this study advances the state-of-the-art in smart home energy forecasting by developing a robust, adaptable, and accurate predictive framework. While substantial progress has been made, addressing challenges related to computational cost, scalability, and interpretability will be essential for realizing the full practical potential and broader adoption of the proposed approach.

6. CONCLUSION AND FUTURE WORK

A smart home energy forecasting approach was introduced in which the Al-Biruni Earth Radius (BER) algorithm and LSTM, supported by IoT, are combined. The developed BER-LSTM model overcomes difficulties in energy forecasting such as data noise and uncertainty, and selects useful features that improve both the accuracy and efficiency of the prediction. BER draws upon the historical principles of geometry used by Al-Biruni to identify and improve the main parameters of the LSTM model, allowing it to better handle complex energy consumption details. As a result, the BER-LSTM

Table 6. Summary Statistics of Optimized LSTM Models

Metric	BER-LSTM	GWO-LSTM	PSO-LSTM	GA-LSTM
Count	10	10	10	10
Min	0.006146	0.008019	0.009905	0.009252
25% Percentile	0.007146	0.009019	0.01053	0.01202
Median	0.007146	0.009019	0.01053	0.01252
75% Percentile	0.007146	0.009019	0.01103	0.01402
Max	0.009315	0.009919	0.01905	0.02325
Range	0.003169	0.0019	0.009148	0.014
Mean	0.007263	0.009009	0.01152	0.01367
Std. Deviation	0.0007864	0.0004483	0.002734	0.004119
Skewness	2.065	-0.334	2.84	1.726
Kurtosis	6.661	4.555	8.314	2.849

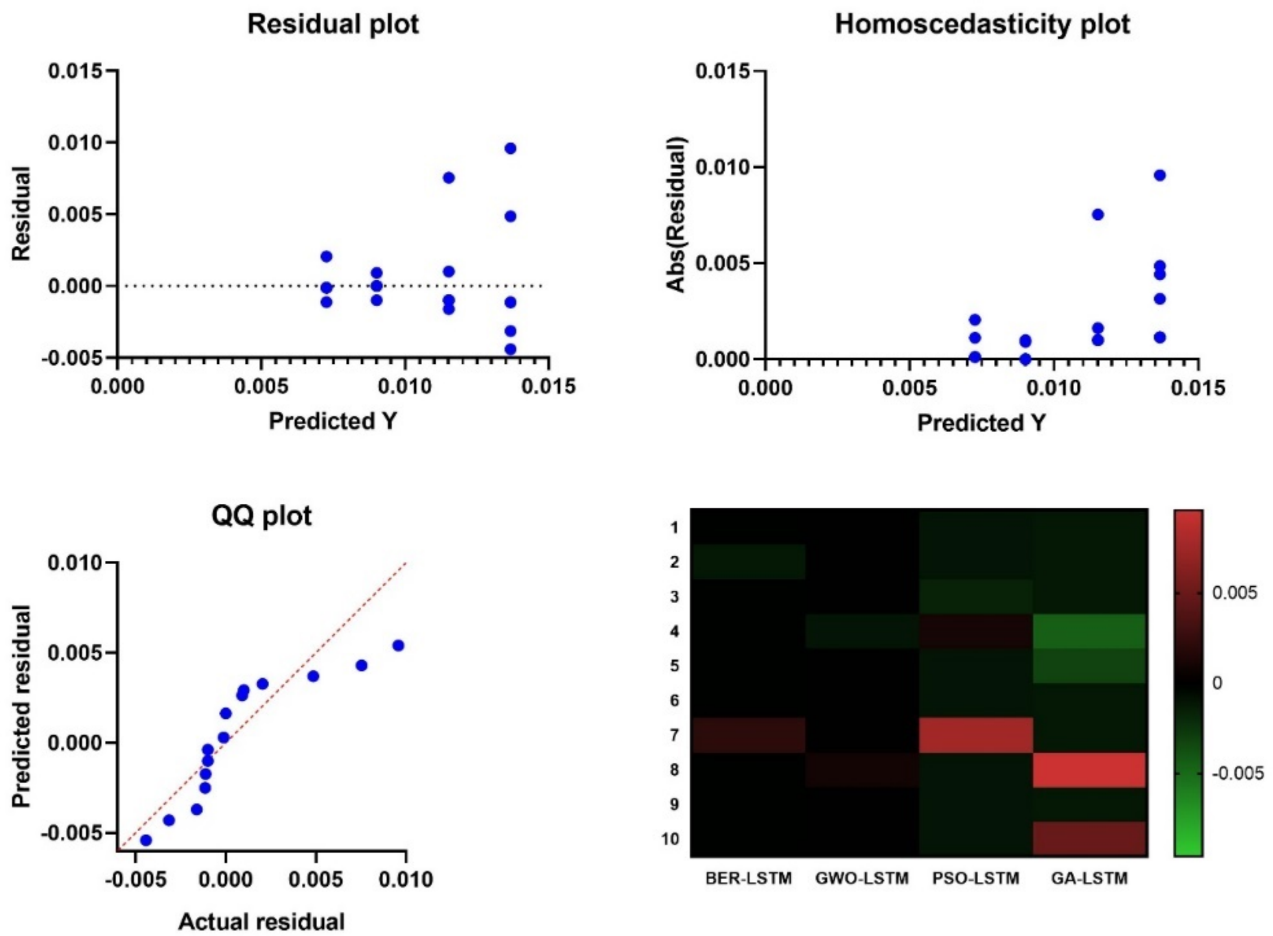

Figure 10. Diagnostic plots including QQ plot and residual analysis for the proposed models.

achieved a root mean squared error (RMSE) of 0.007146, outperforming GWO, PSO, or GA-based LSTM variants. The study improved upon existing models by introducing time-series clustering to manage data variability, enabling accurate probabilistic forecasting at both the household and aggregate levels. Incorporating real-time weather, energy usage, and additional features further enhanced the model's forecast accuracy. Comprehensive analysis demonstrates that BER-LSTM consistently achieves the lowest RMSE and best R^2 scores among the tested forecasting models, supporting its confident integration into smart home energy management systems. Moreover, BER-LSTM's scalability and flexibility make it a strong candidate for intelligent energy management. It effectively captures long-term dependencies in energy usage, enhances forecast reliability, and adapts to evolving consumption patterns. The approach's utility may extend beyond smart homes to the broader grid and urban energy planning, forecasting, and management.

Although the proposed framework offers superior accuracy and robust performance, its computational cost is non-negligible: a typical hyperparameter optimization and training cycle required approximately 6 hours on an NVIDIA

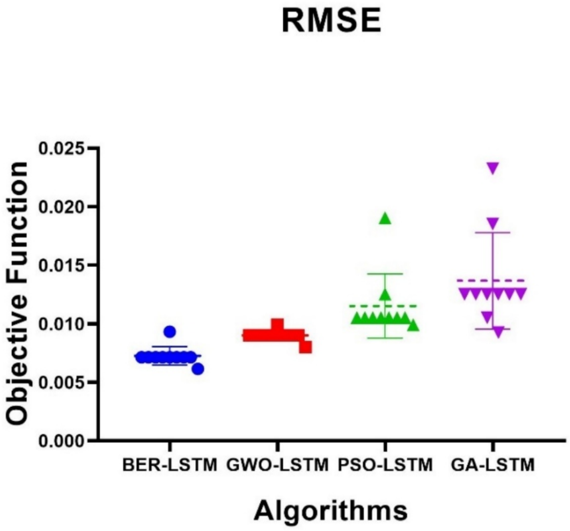

Figure 11. Histogram depicting the distribution of RMSE values across the considered models.

RTX 4090 GPU, with memory usage peaking at 40 GB RAM. This may limit deployment on edge devices or resource-constrained environments, highlighting the need for model compression and lighter architectures in future work.

Interpretability remains an essential challenge. For practical adoption in smart home and grid applications, explainable AI (XAI) tools should be integrated with BER-LSTM to increase transparency and user trust. Feasible approaches include applying post hoc explanation techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) to quantify the impact of individual features—such as appliance usage, temperature, or cluster label—on each forecast. Attention mechanisms, if incorporated into the LSTM framework, could highlight the most influential time steps or input features in energy usage sequences, while integrated gradients or saliency mapping may provide additional insights into temporal dependencies. Future research will systematically evaluate these methods for BER-LSTM-based forecasting to deliver actionable interpretability for energy managers and end users.

In conclusion, the BER-LSTM framework presented here provides a robust, adaptive, and scalable solution for energy consumption forecasting in smart homes. By bridging theoretical advances and real-world applications, it supports the transition toward smarter, energy-efficient homes and cities. As the demand for intelligent energy systems grows, this approach lays the groundwork for future innovation in predictive analytics, smart grid optimization, and sustainable energy management.

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