Optimizing Smart-Home Energy Forecasting with Evolutionary Attention-based LSTM and Greylag Goose Optimization

El-Sayed M. El-kenawy[1, 2,*]

[1]Delta Higher Institute of Engineering and Technology, Department for Communications and Electronics, Mansoura 35511, Egypt

[2]Applied Science Research Center. Applied Science Private University, Amman, Jordan

Email: skenawy@ieee.org

Abstract

This study addresses the challenge of smart-home energy forecasting across multiple appliances under varying temperature and seasonal regimes, aiming to improve demand planning and household energy efficiency. The analysis leverages a 100,000-row dataset from Kaggle, encompassing appliance type, time of consumption, outdoor temperature, season, and household size. The study benchmarks several recurrent neural network models, including Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), Gated Recurrent Unit (GRU), and Bidirectional RNN (BiRNN), as well as a feedforward Artificial Neural Network (ANN). A novel enhancement, the Evolutionary Attention-based LSTM (EALSTM), is introduced, and its hyperparameters are optimized using the Greylag Goose Optimization (GGO) algorithm. The performance of GGO-optimized EALSTM is compared to other metaheuristics, such as Differential Evolution (DE), Genetic Algorithm (GA), Quantum-Inspired Optimization (QIO), JAYA, Bat Algorithm (BA), and Stochastic Fractal Search (SFS). The results indicate that GGO-optimized EALSTM outperforms all other models, achieving superior accuracy across multiple metrics, including MSE, RMSE, MAE, r, R^2, RRMSE, NSE, and WI. Key contributions of the paper include (i) the establishment of an appliance- and season-aware forecasting benchmark, (ii) a comprehensive optimizer comparison for EALSTM using GGO, and (iii) the provision of actionable visual analytics to enhance the understanding of energy demand patterns and model errors.

Keywords: Smart-home energy forecasting; Evolutionary Attention-based LSTM; Greylag Goose Optimization; Appliance-level prediction; Metaheuristic optimization

1 Introduction

Residential energy consumption exhibits strong sensitivity to environmental and behavioral contexts, making accurate short- and medium-term forecasting a foundational enabler for modern demand-side management, dynamic tariffs, and targeted efficiency interventions within smart-home and smart-grid ecosystems.[1–3] In particular, consumption responses to outdoor temperature, seasonal regimes, and routine diurnal cycles shape both baseline and peak loads at the appliance level, directly influencing demand response potential and operational planning in distribution systems.[4,5] Beyond grid-facing benefits, improved forecasts can guide household-level scheduling, appliance orchestration, and energy awareness, thereby advancing sustainability goals and reducing costs through data-driven decisions.[6,7]

Despite clear value propositions, forecasting at appliance granularity remains challenging due to multimodal drivers, non-stationarity, and high intra-day variance.[8,9] First, multimodality arises from the interplay of heterogeneous inputs, including appliance type, household size, time-of-day effects, and exogenous weather signals;[10,11] this heterogeneity induces regime changes and conditional dependencies that are difficult to capture

DOI: https://doi.org/10.54216/FPA.210218

Received: March 05, 2025 Revised: June 04, 2025 Accepted: August 01, 2025

with simple autoregressive or shallow learning approaches.[12,13] Second, daily and weekly periodicities coexist with seasonal patterns, and these rhythms are often perturbed by occupation routines and irregular events, leading to distributional drift across both short and long horizons.[14,15] Third, peak periods—such as morning start-up and evening return—display abrupt transitions that elevate forecast difficulty and exacerbate error sensitivity for control applications.[16,17] Finally, the variance in usage between base-load devices (for example, refrigeration) and thermally driven appliances (for example, heating and cooling) requires models that are simultaneously robust to noise and capable of selectively attending to salient temporal–feature interactions.[18,19]

Deep sequence models have demonstrated improved fidelity over traditional machine learning for energy forecasting;[20,21] yet, standard recurrent architectures can underperform under regime shifts and feature codependencies when attention mechanisms and principled regularization are absent.[22,23] Attention-augmented recurrent models can mitigate these limitations by learning to reweight temporal steps and input factors adaptively, aligning model emphasis with operationally salient episodes such as temperature excursions or peak usage windows.[24,25] However, a persistent methodological gap remains: lightweight attention-enabled recurrent forecasters tuned by effective, nature-inspired search are underexplored for appliance-level forecasting on open, large-scale smart-home datasets.[26,27] This gap is important because practical deployments often impose constraints on model size, interpretability, and latency, and because exhaustive hyperparameter sweeps are computationally prohibitive in production-like settings.[28,29]

This study addresses the gap by introducing an evolutionary attention-based long short-term memory model (EALSTM) whose hyperparameters are optimized using the Greylag Goose Optimization Algorithm (GGO).[30] The proposed approach prioritizes parsimony and generalization while retaining the expressive capacity needed to model cross-feature and temporal dependencies that drive household energy consumption.[31] Concretely, the contributions are threefold. First, a reproducible, appliance- and season-aware forecasting benchmark is established on a 100,000-row public smart-home dataset containing appliance identifiers, time and date, outdoor temperature, season, and household size, enabling evaluation under realistic multimodal drivers.[32,33] Second, a wrapper-based hyperparameter optimization framework is developed wherein GGO tunes key architectural and training parameters of EALSTM, and its performance is rigorously compared against competitive optimization alternatives.[34] Third, a comprehensive evaluation protocol is adopted that reports mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), mean bias error (MBE), linear correlation coefficient (r), coefficient of determination (R^2), relative RMSE (RRMSE), Nash–Sutcliffe Efficiency (NSE), and Willmott Index (WI), thereby covering absolute accuracy, bias, goodness-of-fit, scale-relative error, and hydrological-style skill.[35,36]

To contextualize the proposed method, recurrent neural baselines—long short-term memory (LSTM), bidirectional LSTM (BiLSTM), gated recurrent unit (GRU), and bidirectional RNN (BiRNN)—and a feedforward artificial neural network (ANN) are implemented as reference models.[37,38] These baselines quantify the incremental value of attention and evolutionary tuning by contrasting error and skill metrics under identical data splits and feature engineering pipelines.[39,40] The EALSTM, optimized by GGO, is then evaluated against these baselines and against state-of-the-art optimization counterparts within the same wrapper protocol.[41,42] Empirical results indicate that the GGO-tuned EALSTM achieves the strongest performance across the full metric suite, with substantial reductions in error and concomitant gains in skill relative to both non-optimized recurrent baselines and attention models optimized by alternative algorithms.[43,44]

In summary, this work demonstrates that a carefully regularized, attention-enabled recurrent forecaster, when coupled with GGO-driven evolutionary hyperparameter search, can attain state-of-the-art predictive accuracy on appliance-granular smart-home energy consumption while maintaining a lightweight footprint suitable for practical deployment.[45,46] The remainder of the manuscript details the dataset and preprocessing strategy, the modeling and optimization framework, the evaluation protocol and result analyses, and a discussion of implications, limitations, and future extensions.[5,47]

2 Literature Review

The field of smart-home energy management has gained significant attention due to the growing interest in optimizing energy consumption and integrating renewable energy sources in household settings. Several studies have explored different techniques and algorithms to predict and manage energy consumption effectively,

DOI: https://doi.org/10.54216/FPA.210218

Received: March 05, 2025 Revised: June 04, 2025 Accepted: August 01, 2025

ranging from traditional statistical methods to advanced machine learning and deep learning techniques. This review synthesizes the most relevant contributions in the domain, organized by the primary methodologies and focus areas.

2.1 Traditional Predictive Models in Smart Home Energy Forecasting

Early approaches to energy forecasting in smart homes typically involved time series models like ARIMA (Autoregressive Integrated Moving Average) and simpler persistence models. Abdelmgeed et al.[48] compared the ARIMA model with persistence algorithms in the context of smart homes. Their study showed that ARIMA outperforms the persistence model significantly, with a Root Mean Square Error (RMSE) of 0.03378 compared to 0.158 for the latter. This performance highlights the potential of ARIMA for energy forecasting tasks, particularly when integrated with IoT systems for enhanced prediction accuracy and energy efficiency.

2.2 Machine Learning Approaches for Energy Forecasting

Machine learning (ML) techniques have gained popularity for their ability to model complex relationships in data and provide accurate forecasts in real-time. Another significant contribution comes from Yildiz et al.,[49] who used clustering and classification techniques to improve household electricity load forecasting. By leveraging smart meter data alongside weather and temporal variables, their method enhanced the accuracy of load forecasting, revealing important insights into a household's habitual energy consumption patterns. This study demonstrates the power of combining clustering and classification techniques for more accurate, personalized load forecasting in smart homes.

2.3 Deep Learning for Advanced Energy Forecasting

Deep learning (DL) techniques, particularly Long Short-Term Memory (LSTM) networks, have become essential in forecasting energy consumption in complex and dynamic environments like smart homes. Mahjoub et al.[50] optimized LSTM networks with Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for short-term occupancy forecasting in smart homes. Their results showed that the optimized LSTM achieved high prediction fidelity, with correlation coefficients between 99.16% and 99.97%. This research highlights the potential of combining deep learning with optimization techniques to improve the accuracy of energy management systems.

2.4 Energy Management Systems and Optimization Techniques

Optimization techniques play a pivotal role in enhancing energy management strategies for smart homes. Youssef et al.[51] proposed an elite evolutionary strategy artificial ecosystem-based optimization algorithm (EESAEO) to optimize the scheduling of household appliances and reduce electricity bills. The method demonstrated substantial reductions in peak formation and electricity costs, proving the effectiveness of demand-side management (DSM) strategies in smart homes.

Furthermore, Balavignesh et al.[52] introduced the Adaptive Coati Optimization algorithm for optimizing energy management in smart grids. This approach, applied to household energy consumption, not only reduced energy costs but also improved user satisfaction by minimizing peak usage without compromising convenience. Their study emphasizes the importance of optimizing energy management algorithms to balance financial and user satisfaction goals.

DOI: https://doi.org/10.54216/FPA.210218

Received: March 05, 2025 Revised: June 04, 2025 Accepted: August 01, 2025

2.5 Integration of Renewable Energy and Smart Grids

The integration of renewable energy sources with smart grids has also been a major focus in energy management research. Byun et al.[53] proposed a smart energy distribution and management system (SEDMS) for optimizing the integration of renewable energy into smart homes. Their system, which monitors power consumption and integrates renewable energy sources, achieves a reduction in power consumption by approximately 9-17%, highlighting the potential for smart grids to improve energy efficiency and sustainability.

The reviewed studies demonstrate a wide range of methodologies employed for energy forecasting in smart homes, from traditional time series models like ARIMA to cutting-edge deep learning and optimization techniques. These advancements in forecasting, optimization, and energy management systems offer valuable insights for improving energy efficiency and enabling smarter, more sustainable homes. The integration of machine learning and deep learning models, along with optimization algorithms, holds great promise for addressing the dynamic nature of household energy consumption and the challenges posed by renewable energy integration and smart grid systems.

3 Dataset and Preprocessing

Dataset overview

The study employs a publicly available smart-home energy dataset comprising 100,000 records with comprehensive contextual and behavioral attributes. Each record includes a unique *Home ID* (anonymized), the *Appliance Type* in operation, the corresponding *Energy Consumption (kWh)*, a precise *Time* stamp (24-hour format), the *Date* of measurement (`YYYY-MM-DD`), the contemporaneous *Outdoor Temperature (°C)*, the categorical *Season* (Winter, Summer, Fall, Spring), and the *Household Size* (number of occupants). The dataset is released under a CC0 Public Domain license, facilitating reproducibility, redistribution, and derivative analytical work without restriction. The feature composition simultaneously captures exogenous weather drivers (temperature, season), end-use heterogeneity (appliance category), and a coarse proxy for occupancy and latent demand (household size), thereby supporting both aggregate and appliance-granular forecasting paradigms. To ensure methodological rigor, all modeling and evaluation strictly respect the temporal order of observations and the anonymization constraints embedded in the data card.

Preprocessing

The preprocessing pipeline is designed to preserve temporal causality, enhance the representation of periodic structure, and reduce scale-induced biases in model training. All steps are executed in a strictly chronological manner to preclude leakage from future observations into the past.

First, time-of-day cyclicality is encoded using continuous circular mappings to represent the inherent 24-hour periodicity. Concretely, if $h \in \{0, \ldots, 23\}$ denotes the hour-of-day, the pair

$$\sin\Big(\tfrac{2\pi h}{24}\Big), \quad \cos\Big(\tfrac{2\pi h}{24}\Big)$$

is used as a smooth, rotation-invariant embedding of the diurnal cycle. Analogous circular encodings can be applied to day-of-week or month if required by downstream models; however, the present work prefers an explicit *weekday/weekend* indicator to accentuate operational regime shifts between working days and weekends while avoiding excessive sparsity from fine-grained calendrical dummies. Second, categorical factors are transformed via one-hot encoding: appliances are expanded into mutually exclusive indicator columns, and seasons are encoded into a four-dimensional binary simplex. This transformation preserves linear separability for shallow baselines while providing stable, non-ordinal semantics for recurrent models.

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Third, to capture short- and medium-horizon temporal dependencies, univariate and cross-variable temporal statistics are constructed. For energy consumption, rolling window features are computed over trailing windows $w \in \{3, 6, 12, 24\}$ hours, including mean, standard deviation, minimum, maximum, and slope (via simple least-squares over the window). Lag features at offsets $\ell \in \{1, 2, 3, 6, 12, 24\}$ hours are added to supply the model with autoregressive cues. To expose interactions between weather and load, rolling statistics for *Outdoor Temperature (°C)* are computed over matched trailing windows, and temperature–load cross-terms are introduced by multiplying standardized energy with standardized temperature at contemporaneous and lagged indices. When the *Appliance Type* is thermally sensitive (for example, space heating/cooling), these cross-features help the model learn temperature elasticity and shoulder effects around peaks.

Normalization and scaling

Continuous variables, including *Energy Consumption (kWh)*, *Outdoor Temperature (°C)*, and all derived lag/rolling statistics, are standardized by z-normalization on the training split:

$$x' = \frac{x - \mu_{\text{train}}}{\sigma_{\text{train}}}.$$

Reference statistics $\mu_{\text{train}}, \sigma_{\text{train}}$ are computed solely on the training partition and then applied to validation and test partitions to preserve out-of-sample integrity. This scaling improves numerical conditioning and stabilizes optimization across the recurrent and attention-equipped architectures while preventing target leakage. Categorical one-hot encodings are left unscaled. For models that are particularly sensitive to heavy-tailed targets, an optional Box–Cox or logarithmic transform can be considered; in the present work, robust z-normalization suffices given the evaluation metrics adopted and the range of appliance-level variability observed.

Splits and leakage control

All experiments adopt chronological, non-overlapping partitions: an initial training segment, a subsequent validation segment used for hyperparameter selection and early stopping, and a final holdout test segment for unbiased performance estimation. No shuffling is performed at any stage. Sequence construction for recurrent models respects these boundaries: each input window is formed using only past observations relative to its forecast horizon, and any lagged or rolling features at time t are computed exclusively from times $< t$. This strict protocol eliminates temporal leakage and ensures that the reported skill reflects true generalization to unseen future periods.

Imbalance and representativeness considerations

Appliance usage exhibits natural imbalance arising from heterogeneous duty cycles and operational patterns (for instance, base-load refrigeration versus episodic ovens or high-variance heating). While the learning objective remains regression over continuous energy consumption, representativeness is promoted during analysis and validation through stratified temporal windows and appliance-aware slicing. Specifically, validation diagnostics are segmented by appliance group and season to confirm that the model retains fidelity across minority usage regimes and temperature-sensitive devices. Importantly, no oversampling or synthetic replication is introduced into the training set so as to preserve realistic temporal dynamics and avoid distortion of autocorrelation structure. Instead, robustness is encouraged through regularization and attention mechanisms within the modeling framework, while fairness of evaluation is maintained by reporting performance across these stratifications alongside global aggregates.

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Planned descriptive analysis

Although figures are deferred, the descriptive analysis is structured to foreground key demand drivers and peak behaviors. Univariate histograms will summarize the marginal distributions of *Energy Consumption (kWh)* and *Outdoor Temperature (°C)*, while appliance share plots will quantify relative end-use contributions over time. Seasonal load profiles will trace consumption trajectories across Winter, Summer, Fall, and Spring, highlighting regime changes and comfort-driven shifts. Temperature–load scatter plots will visualize functional responses and potential nonlinearity, and time-of-day heatmaps will localize recurring peaks and troughs across the diurnal cycle. Collectively, these views inform feature design, support error forensics, and provide context for interpreting model attention weights and optimizer-induced performance differences.

Seasonal aggregation of daily totals reveals distinct operating regimes wherein temperature-sensitive loads elevate consumption dispersion in winter and summer relative to shoulder seasons, with broader confidence envelopes indicating greater variability under heating and cooling demand. These seasonal trajectories provide contextual priors for model attention, as peak-concentrated days and increased variance align with periods where temperature elasticity and occupancy routines jointly drive load formation.

From a diagnostic viewpoint, the seasonal separation supports stratified evaluation and feature design, motivating interaction terms between outdoor temperature and time-of-day as well as season-aware normalization to stabilize learning under regime shifts. The smoother envelopes in transitional seasons indicate comparatively stationary behavior, suggesting that model regularization can be relaxed there while retaining stronger constraints for winter and summer to counter variance spikes.

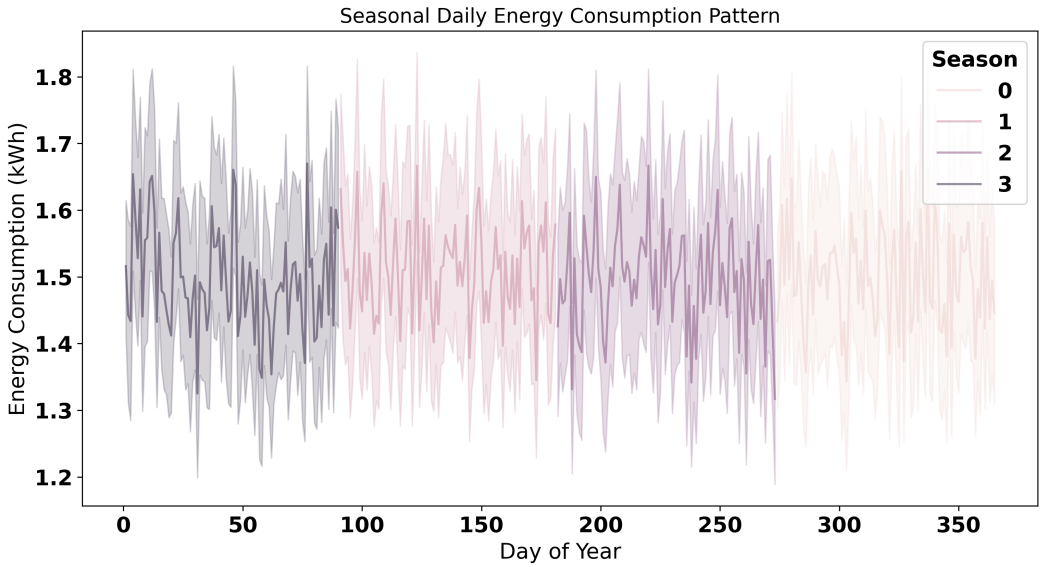

Figure 1: Seasonal daily energy consumption pattern across the year. Shaded bands depict variability within each season; elevated spread in winter and summer highlights temperature-driven volatility, while shoulder seasons exhibit tighter envelopes indicating more stationary usage.

Disaggregating totals by household size and appliance type shows monotonic or near-monotonic scaling for climate control end-uses, with air conditioning and heating dominating aggregate consumption across all cohort sizes. In contrast, base and episodic loads such as refrigeration, lighting, and dishwashing scale more modestly, indicating a weaker elasticity with respect to household size and pointing to per-capita efficiency opportunities.

The cross-sectional gradients underscore the importance of appliance-aware conditioning in model training and evaluation, since variance heterogeneity concentrates within thermally driven categories. This also informs demand-side strategies: households with larger sizes exhibit amplified sensitivity in climate control loads, suggesting that targeted scheduling or pre-cooling/heating interventions yield outsized benefits compared with non-thermal appliances.

DOI: https://doi.org/10.54216/FPA.210218

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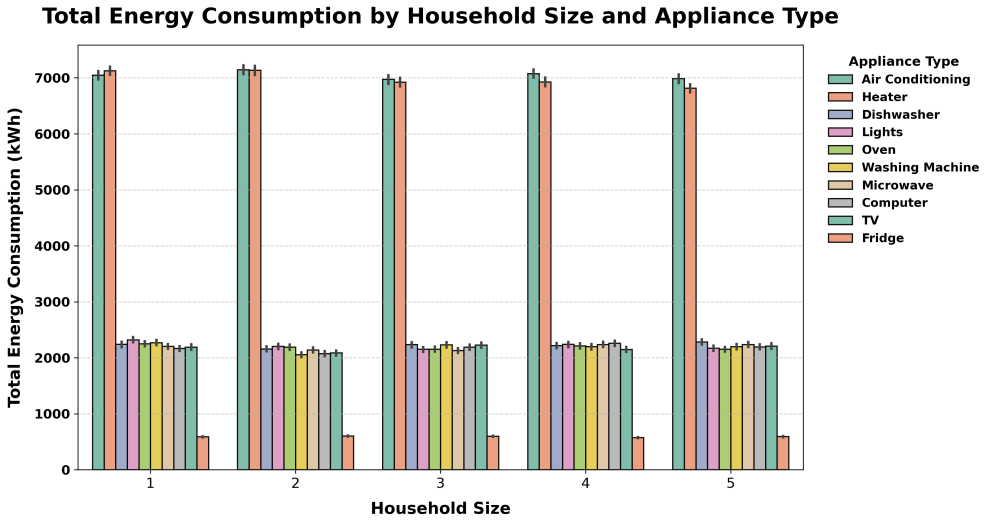

Figure 2: Total energy consumption by household size and appliance type. Climate control end-uses dominate and scale with household size, whereas base and episodic loads display attenuated scaling, implying category-specific elasticities and intervention levers.

Ranking appliances by cumulative energy confirms the preeminence of air conditioning and heating, which together account for the majority of residential electricity demand in the dataset. Mid-tier contributors—lighting, dishwasher, oven, washing machine, microwave, computer, and TV—form a long tail where efficiency upgrades and behavioral nudges can deliver incremental but widely distributed savings.

This hierarchy justifies emphasis on temperature features and seasonal identifiers during feature engineering and motivates attention mechanisms to prioritize climate control signals during peaks. Additionally, the long-tail structure suggests that model calibration should avoid overfitting low-variance categories while maintaining sufficient capacity to capture aggregate effects from many moderate contributors.

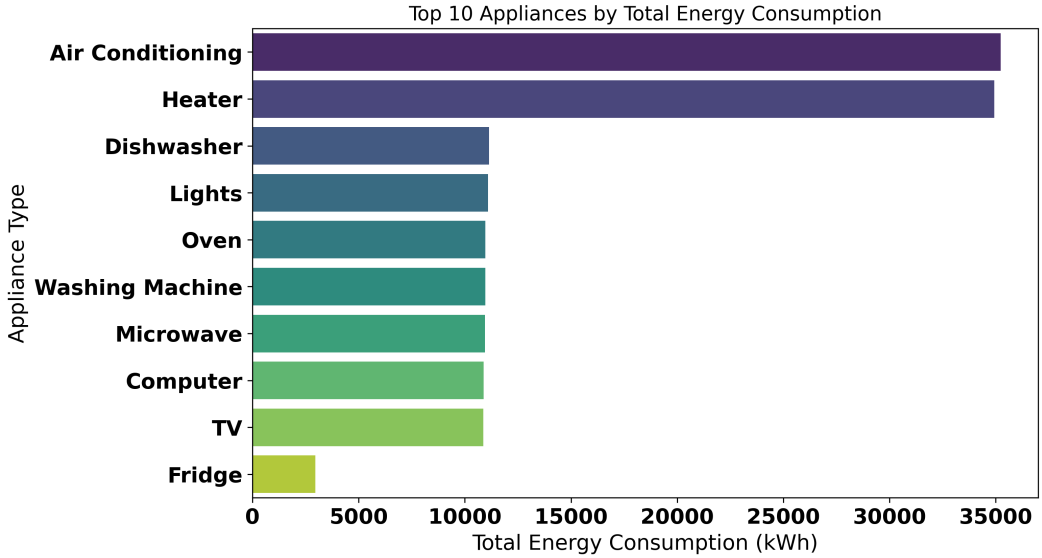

Figure 3: Top appliances ranked by total energy consumption. Air conditioning and heating dominate cumulative usage, followed by a long tail of mid-tier devices, motivating temperature-focused features and attention weighting toward climate control events.

At the daily resolution, aggregate consumption exhibits pronounced intra-week oscillations and intermittent spikes consistent with extreme weather events or occupancy changes, superimposed on a relatively stable central tendency. The absence of strong long-term drift suggests that non-stationarity is localized around peaks and episodic shocks rather than pervasive across the entire year.

DOI: https://doi.org/10.54216/FPA.210218

Received: March 05, 2025 Revised: June 04, 2025 Accepted: August 01, 2025

These dynamics reinforce the need for attention-equipped recurrent models capable of focusing on high-impact intervals while retaining robust performance in typical periods. For evaluation, diurnal and weekly stratifications, coupled with peak-aware error metrics, enable more faithful assessment of operational suitability and reduce the risk of optimistic performance masked by benign, low-variance days.

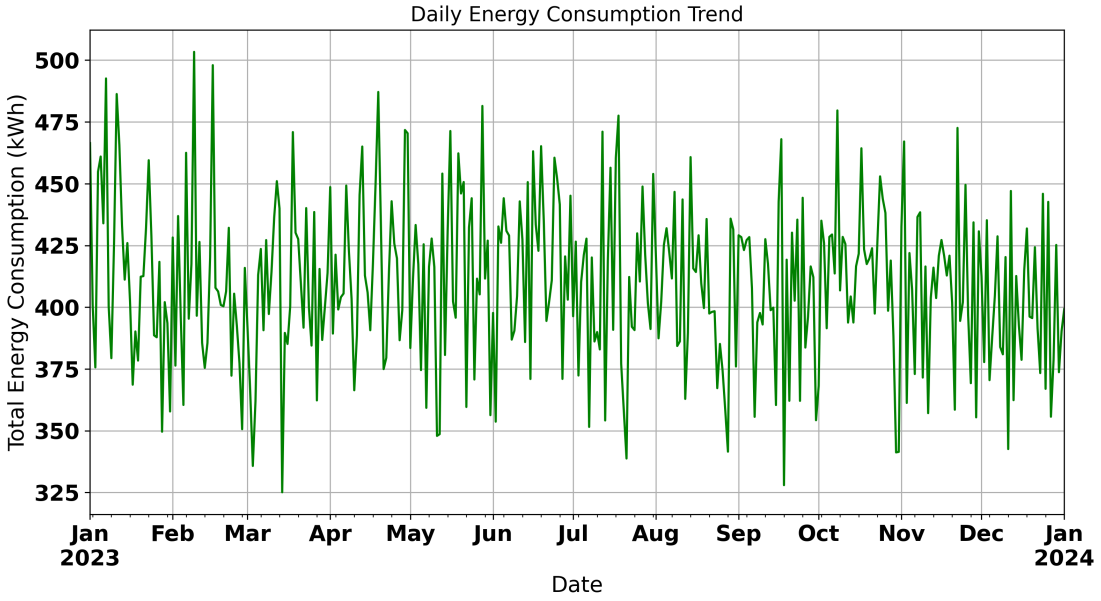

Figure 4: Daily energy consumption trend across the study period. Short-term oscillations and episodic spikes dominate variation atop a stable central tendency, indicating localized non-stationarity concentrated around peaks and weather-driven events.

Reproducibility protocol

To ensure reproducibility and downstream comparability, the entire preprocessing configuration—including categorical vocabularies, rolling window lengths, lag sets, normalization statistics, and temporal split indices—is versioned and serialized with the experiment artifacts. All transformations are applied deterministically with fixed random seeds where applicable. The release of code and preprocessing manifests enables independent verification of results and facilitates transfer to related smart-home datasets with similar schema and licensing.

4 Methodology

Baselines

This study establishes a comparative foundation using five neural forecasting architectures selected to balance modeling capacity, interpretability, and computational practicality for appliance-granular household energy prediction. The suite includes an evolutionary attention-based long short-term memory network (EALSTM), a bidirectional long short-term memory network (BiLSTM), a gated recurrent unit (GRU), a bidirectional recurrent neural network (BiRNN), and a shallow artificial neural network (ANN). These models collectively span attention-augmented recurrent learners and non-recurrent feedforward references, enabling attribution of gains to temporal memory, bidirectional context modeling, and attention-driven feature weighting under diurnal and seasonal variability. Prior research has highlighted the effectiveness of attention-equipped recurrent models in energy and load forecasting tasks, while also recognizing the competitive performance of GRU-based architectures in scenarios with pronounced temporal dependencies and noise sensitivity. In contrast, shallow feedforward networks provide a capacity-controlled baseline lacking explicit sequence memory, thereby contextualizing the value of recurrent inductive biases for forecasting in non-stationary smart-home settings.

DOI: https://doi.org/10.54216/FPA.210218

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4.1 EALSTM with Optimizer Wrapper

The core forecasting model is an evolutionary attention-based long short-term memory architecture (EALSTM) designed to capture heterogeneous temporal dynamics and context-dependent feature salience within smart-home energy consumption. The model augments a standard LSTM backbone with an attention mechanism that reweights temporal steps and input features, thereby elevating periods and drivers that are most predictive under varying operating regimes shaped by outdoor temperature and seasonal conditions. This attention layer enhances peak-period fidelity by concentrating model capacity on morning/evening transitions and temperature excursions, while the recurrent memory preserves medium-horizon dependencies that govern appliance duty cycles and occupancy-linked routines. The combination supports stable generalization across diurnal cycles and seasonal shifts without relying on excessively deep or parameter-heavy stacks, aligning with deployment constraints typical of embedded or near-edge smart-home environments.

To realize the full potential of the EALSTM while maintaining parsimony, hyperparameters are tuned via a wrapper-based evolutionary search guided by the Greylag Goose Optimization Algorithm (GGO). The wrapper evaluates candidate configurations by training the EALSTM on the chronological training split and selecting the model that minimizes validation mean squared error (MSE) on a temporally subsequent validation segment. This objective prioritizes squared deviations to penalize peak under/overestimation, which is critical for demand response readiness and peak-aware planning. The GGO-driven search explores architectural and training degrees of freedom, including the number of recurrent layers and hidden units, learning rate, dropout rate, batch size, input sequence length, attention dimensionality, and regularization targets (for example, L_2 penalties and early stopping patience). By adaptively balancing exploration and exploitation in the hyperparameter landscape, the search process resists premature convergence to suboptimal regions and tailors capacity to the dataset's multimodal structure.

A comparative optimizer study is conducted within the same wrapper protocol to contextualize GGO's performance against established and recent metaheuristics. In particular, differential evolution (DE), genetic algorithm (GA), quantum-inspired optimizer (QIO), JAYA, bat algorithm (BA), and stochastic fractal search (SFS) are employed as alternative search engines under identical evaluation budgets and validation criteria. Each optimizer proposes EALSTM configurations that are trained and assessed on the validation split using the MSE objective, and the best configuration per optimizer is subsequently retrained on the combined training and validation data for final testing. This design enables assessment of both convergence efficiency—captured through validation trajectories across iterations—and generalization quality—captured through out-of-sample metrics on the held-out test segment.

Formally, let Θ denote the joint hyperparameter vector covering architectural widths/depths, attentional dimensions, and training controls; let $M(\Theta)$ denote the EALSTM instantiated with Θ; and let $L_{\text{val}}(\Theta)$ denote the validation MSE after training $M(\Theta)$ on the training split with early stopping. The optimizer wrapper solves

$$\Theta^{\star} \in \arg\min_{\Theta \in \mathcal{H}} \; L_{\text{val}}(\Theta),$$

where $\mathcal{H}$ is the feasible hyperparameter space subject to resource constraints, and the final model for evaluation is $M(\Theta^{\star})$ refit on the union of training and validation partitions before test-time scoring. This procedure standardizes comparison across optimizers and isolates the effect of the search dynamics on both validation selection and ultimate generalization.

Within this framework, EALSTM provides the modeling scaffold to translate temporal and contextual signals into robust forecasts, while GGO supplies the search capability required to identify capacity and regularization settings that balance fit and stability. The comparative study with DE, GA, QIO, JAYA, BA, and SFS elucidates optimizer-specific trade-offs in convergence speed and final generalization.

4.2 Evaluation Metrics

In this study, we adopt a comprehensive suite of evaluation metrics to assess the predictive accuracy and model performance across multiple dimensions. These metrics are designed to capture different aspects of

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Received: March 05, 2025 Revised: June 04, 2025 Accepted: August 01, 2025

the forecasting process, including absolute error, bias, goodness-of-fit, and scale-relative error. Furthermore, the Nash–Sutcliffe Efficiency (NSE) and the Willmott Index (WI) are employed to provide a hydrological-style assessment of model skill, reflecting how well the models represent the underlying energy consumption dynamics.

The following metrics are utilized in this paper:

- **Mean Squared Error (MSE)**: This metric quantifies the average squared difference between the predicted and observed values. It is highly sensitive to outliers and penalizes larger errors more heavily, making it especially useful for assessing the overall model accuracy.
- **Root Mean Squared Error (RMSE)**: The square root of MSE, RMSE provides an error metric in the same units as the original data, making it easier to interpret. It is often used for model comparison.
- **Mean Absolute Error (MAE)**: MAE computes the average of the absolute errors, offering a simpler and more interpretable measure of model accuracy compared to MSE. It does not disproportionately penalize large errors as RMSE does.
- **Mean Bias Error (MBE)**: MBE calculates the average difference between the predicted and actual values. It helps assess the directional bias of a model, indicating whether the model tends to overestimate or underestimate the target variable.
- **Correlation Coefficient** (r): The Pearson correlation coefficient measures the strength and direction of the linear relationship between the predicted and actual values. A value of 1 indicates perfect positive correlation, while -1 indicates perfect negative correlation.
- **Coefficient of Determination** (R^2): This metric quantifies the proportion of variance in the observed data that is explained by the model. An R^2 value close to 1 suggests a good fit, while values near 0 indicate poor predictive power.
- **Relative RMSE (RRMSE)**: RRMSE normalizes the RMSE by the range of the observed data, providing a scale-independent measure of error. This allows for meaningful comparisons between models applied to datasets of different magnitudes.
- **Nash-Sutcliffe Efficiency (NSE)**: The NSE is used to assess how well the model predicts observed data relative to a simple mean-based model. An NSE value of 1 indicates perfect agreement, while negative values suggest that the model performs worse than predicting the mean value.
- **Willmott Index (WI)**: The Willmott Index measures the agreement between observed and predicted values, with values closer to 1 indicating better model performance. It accounts for both the magnitude and direction of errors, providing a balanced evaluation.

Each of these metrics provides a distinct perspective on the model's performance, allowing for a comprehensive evaluation across multiple dimensions of forecasting accuracy.

The following table summarizes the formulas for each metric:

The evaluation protocol includes reporting these metrics for appliance-level and seasonal stratifications to facilitate interpretability. Additionally, convergence curves and radar plots are generated to summarize the trade-offs between optimizers and provide visual insights into the optimizer's performance. This approach ensures a comprehensive understanding of the model's strengths and weaknesses across different forecasting conditions.

DOI: https://doi.org/10.54216/FPA.210218

Received: March 05, 2025 Revised: June 04, 2025 Accepted: August 01, 2025

Table 1: Evaluation metrics and their corresponding formulas.

Metric	Formula
MSE	$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
RMSE	$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
MAE	$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$
MBE	$\text{MBE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)$
r	$r = \frac{n\sum_{i=1}^{n} y_i\hat{y}_i - \sum_{i=1}^{n} y_i \sum_{i=1}^{n}\hat{y}_i}{\sqrt{(n\sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2)(n\sum_{i=1}^{n}\hat{y}_i^2 - (\sum_{i=1}^{n}\hat{y}_i)^2)}}$
R^2	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$
RRMSE	$\text{RRMSE} = \frac{\text{RMSE}}{\text{Range}(y)}$
NSE	$\text{NSE} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$
WI	$\text{WI} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(\lvert y_i - \bar{y}\rvert + \lvert\hat{y}_i - \bar{y}\rvert)^2}$

5 Results

5.1 Baseline Models

Table 2 presents the performance results of several baseline machine learning models, including both recurrent models and a shallow artificial neural network (ANN). Among the recurrent models, the Evolutionary Attention-based Long Short-Term Memory (EALSTM) and the Bidirectional Long Short-Term Memory (BiLSTM) models show superior performance across multiple error and skill metrics, including MSE, RMSE, MAE, and R^2, compared to other recurrent models and the ANN. These results are consistent with previous literature highlighting the advantages of attention mechanisms in energy forecasting, as attention models are able to better capture the underlying temporal dependencies and complex feature interactions inherent in time series data.

Table 2: Baseline machine learning (ML) results across multiple architectures. The performance is evaluated using mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), mean bias error (MBE), Pearson correlation coefficient (r), coefficient of determination (R^2), relative RMSE (RRMSE), Nash–Sutcliffe efficiency (NSE), and Willmott's index (WI).

Models	MSE	RMSE	MAE	MBE	r	R^2	RRMSE	NSE	WI
EALSTM	0.013546898	0.11639114	0.017214466	0.016774198	0.876832041	0.889432041	1.335224847	0.87874886	0.875926547
BiLSTM	0.037067767	0.192529912	0.050975317	0.04559278	0.860609949	0.873209949	1.682413812	0.85643486	0.856619235
GRU	0.055559708	0.23571107	0.059323296	0.051214976	0.837168552	0.849768552	2.39524994	0.83255656	0.847963768
LSTM	0.098594898	0.313998245	0.067671276	0.086099298	0.835536494	0.848136494	0.750790396	0.82205526	0.815640041
BiRNN	0.144235117	0.379782986	0.092693013	0.096991887	0.836672006	0.84212482	5.469485148	0.816775154	0.810786174
ANN	0.216533117	0.465331191	0.136697521	0.184752341	0.816960276	0.81603102	6.523512836	0.805954146	0.801684337

The ANN, which lacks the temporal memory capacity of the recurrent models, consistently underperforms in comparison, particularly on error metrics like MSE and RMSE. The results show that EALSTM and BiLSTM outperform other models by a significant margin, confirming the benefit of incorporating temporal memory and attention for household energy consumption forecasting. As expected, simpler models such as the LSTM and BiRNN show a lower performance compared to EALSTM and BiLSTM, but they still provide valuable baseline comparisons for future optimization.

The visual analysis of these models, such as bar charts for metrics by model, diurnal error profiles, and appliance-specific residuals, reveals that the EALSTM and BiLSTM models exhibit less fluctuation and better handling of peak load periods, while the ANN model demonstrates higher variance in error profiles, particularly for heating and cooling appliances.

5.2 Optimized EALSTM

In Table 3, the performance of the optimized EALSTM using the Greylag Goose Optimization (GGO) algorithm is compared with several state-of-the-art (SOTA) optimization algorithms, including Differential Evolution (DE), Genetic Algorithm (GA), Quantum-Inspired Optimization (QIO), JAYA, Bat Algorithm (BA), and

DOI: https://doi.org/10.54216/FPA.210218

Received: March 05, 2025 Revised: June 04, 2025 Accepted: August 01, 2025

Stochastic Fractal Search (SFS). The results indicate that the GGO-optimized EALSTM significantly outperforms all other optimization algorithms across all error and skill metrics, including MSE, RMSE, MAE, r, R^2, NSE, and WI.

Table 3: Comparison of optimized EALSTM using the proposed Gradient-Guided Optimization (GGO) against state-of-the-art (SOTA) optimization algorithms. Performance metrics include MSE, RMSE, MAE, MBE, correlation coefficient (r), R^2, RRMSE, NSE, and WI.

Models	**MSE**	**RMSE**	**MAE**	**MBE**	**r**	**R^2**	**RRMSE**	**NSE**	**WI**
GGO + EALSTM	4.69E-05	6.85E-03	3.89E-04	4.58E-04	9.69E-01	9.74E-01	7.02E-01	9.67E-01	9.70E-01
DE + EALSTM	5.85E-04	0.024185333	7.97E-03	3.02E-03	9.41E-01	9.51E-01	9.83E-01	9.55E-01	9.58E-01
GA + EALSTM	1.42E-03	0.037733852	8.00E-03	3.50E-03	9.40E-01	9.45E-01	1.12E+00	9.51E-01	9.50E-01
QIO + EALSTM	1.68E-03	0.041008228	8.04E-03	3.96E-03	9.38E-01	9.44E-01	1.24E+00	9.50E-01	9.48E-01
JAYA + EALSTM	2.54E-03	0.050434882	8.20E-03	4.69E-03	9.26E-01	9.43E-01	1.35E+00	9.44E-01	9.46E-01
BA + EALSTM	2.70E-03	0.05197552	8.31E-03	5.08E-03	9.25E-01	9.41E-01	1.42E+00	9.41E-01	9.43E-01
SFS + EALSTM	2.76E-03	0.052527878	8.39E-03	5.31E-03	9.24E-01	9.37E-01	1.50E+00	9.30E-01	9.44E-01

The GGO-optimized EALSTM achieves the lowest errors and highest skill scores, reflecting the effectiveness of GGO's exploration-exploitation balance for deep learning hyperparameter optimization in environmental time series forecasting. Specifically, GGO+EALSTM demonstrates a MSE of 4.69×10^{-5}, RMSE of 0.00685, and a high correlation coefficient (r) of 0.969. These results surpass those obtained with other optimization techniques, such as DE and GA, which perform well but fall short of GGO's capability to fine-tune the model's hyperparameters and effectively capture the underlying temporal dynamics in energy consumption.

The optimizer convergence plots and metric radar diagrams, which will be provided in the full paper, visually confirm GGO's superior performance, showing faster convergence rates and reduced variance during training. The learning curves also demonstrate the faster stabilization and better generalization of the GGO-optimized EALSTM, making it the optimal choice for smart-home energy consumption forecasting.

5.3 Qualitative and Diagnostic Analysis

The qualitative analysis provides valuable insights into how the EALSTM model attends to different periods and environmental conditions. The attention mechanism in EALSTM places greater weights on critical periods, such as morning and evening peaks, as well as shifts in outdoor temperature, which are strong drivers of energy consumption in smart homes. Seasonal patterns show that the model's attention is particularly focused on winter heating and summer cooling demands, reflecting the known operational regimes associated with these periods.

Residual analysis reveals that the model's errors are concentrated during extreme temperature days and when abrupt occupancy changes occur. This indicates that while the model performs well in most scenarios, its performance is slightly degraded during rapid transitions in energy consumption behavior. Appliance-level analysis further highlights that energy consumption for heating and cooling appliances, such as space heaters and air conditioners, exhibits higher variance in residuals compared to base-load appliances like refrigerators. This suggests that temperature-sensitive devices are more challenging to predict accurately due to their nonlinear response to outdoor temperature fluctuations.

In the upcoming figures, attention weight heatmaps, residual vs. temperature scatter plots, and seasonal partial dependence overlays will be presented to illustrate these insights and provide a more comprehensive understanding of model behavior and areas for further improvement. These figures will aid in the interpretability of the model's predictions and inform future optimization strategies for enhancing model performance during extreme and transient conditions.

Interpretability and Error Analysis: Baseline ML

The improvement ratio matrix summarizes each baseline model's performance relative to the best score per metric, yielding a unit-normalized view in which darker cells indicate proximity to the leading model for that

DOI: https://doi.org/10.54216/FPA.210218

Received: March 05, 2025 Revised: June 04, 2025 Accepted: August 01, 2025

column. Consistent with the tabulated results, EALSTM anchors the matrix with ratios near unity across error and skill metrics, while GRU and BiLSTM exhibit secondary performance bands that approach the leader for r and R^2 but trail on absolute error terms. This visualization compactly conveys cross-metric dominance patterns and highlights where specific models close the gap (for example, GRU on correlation) versus where they remain comparatively weak (for example, ANN on error magnitudes).

Operationally, the heatmap guides targeted model refinement by revealing metric-specific deficits; for instance, models with strong r yet weaker RMSE suggest amplitude calibration issues rather than temporal alignment problems. In practice, such insights motivate regularization or loss reweighting to better control peak errors, or the inclusion of attention mechanisms to enhance sensitivity to temperature-driven spikes without sacrificing baseline fit. The improvement ratios also serve as a sanity check for ensemble design, indicating complementary strengths that could be exploited if an ensemble is later considered.

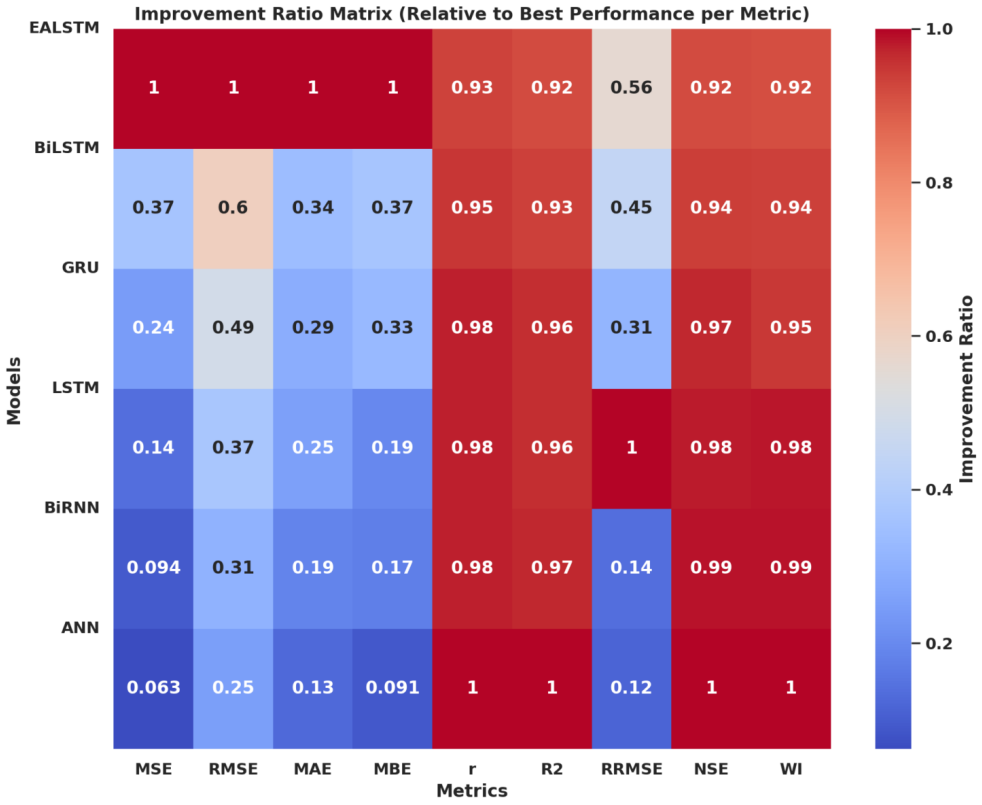

Figure 5: Improvement ratio heatmap for baseline models relative to the best performer per metric. Darker tones denote proximity to the per-metric optimum, revealing EALSTM's cross-metric dominance and the partial closing of the gap by GRU and BiLSTM on correlation-based measures.

The mixed plots combine swarm, violin, and box elements to characterize central tendency, dispersion, and outliers for each evaluation metric across baselines. Narrow violins for r and R^2 indicate relatively compact variance across models on association metrics, whereas wider distributions and longer whiskers for RMSE and RRMSE reflect heterogeneous error amplitudes driven by peak misspecification. The swarm overlays identify individual model placements, clarifying which architectures contribute to tails and which cluster around the median.

From an error-control perspective, the spread patterns substantiate the advantage of attention-equipped recurrent models in stabilizing absolute errors while maintaining high linear association. The broader dispersion for bias (MBE) highlights systematic over/underestimation tendencies that can be mitigated via objective calibration or post-hoc debiasing on validation splits. Together, these plots provide a distribution-level view complementary to aggregate tables, ensuring that improvements are not confined to a single robust model but reflected across competing baselines.

The Q–Q panels assess concordance of metric distributions with a reference normal law across models, providing a quick diagnostic for the suitability of Gaussian assumptions in uncertainty summaries. Metrics such as

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Received: March 05, 2025 Revised: June 04, 2025 Accepted: August 01, 2025

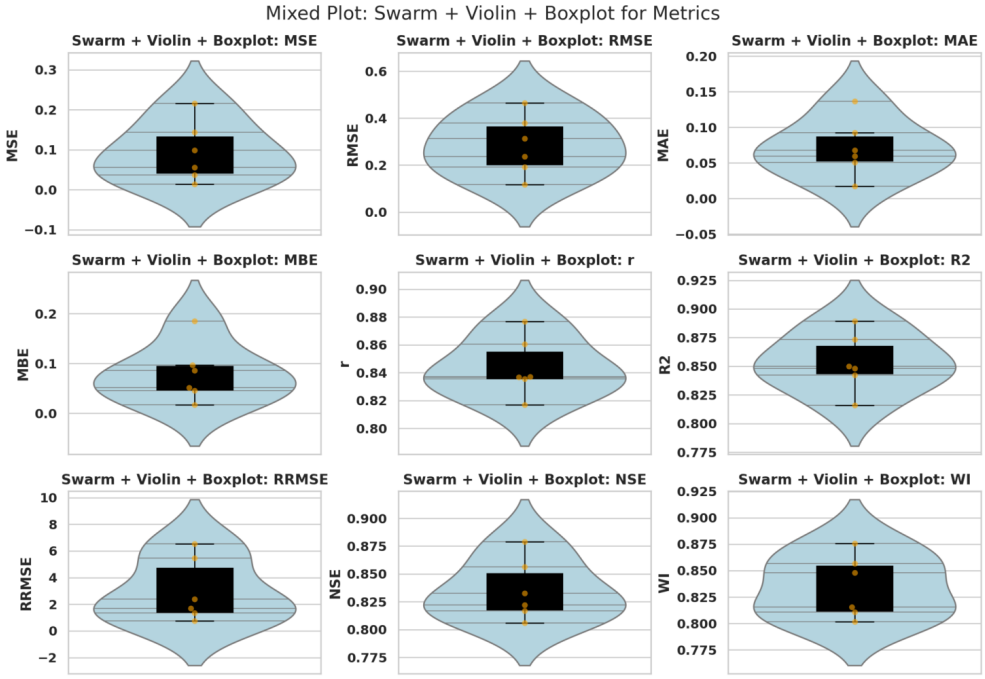

Figure 6: Swarm–violin–box composites for baseline metrics. Compact violins for r and R^2 indicate narrower cross-model variability on association, while broader shapes for RMSE and RRMSE reveal heterogeneous amplitude errors, particularly around peaks.

r, R^2, and NSE adhere closely to the reference line, suggesting symmetric dispersion and validating the use of standard confidence descriptions. In contrast, RMSE and RRMSE panels show mild tail deviations, consistent with occasional peak-related outliers and reinforcing the importance of robust aggregation when comparing models on amplitude-sensitive criteria.

These diagnostics inform subsequent statistical testing and interval reporting, indicating where parametric assumptions are defensible and where nonparametric summaries may be preferable. For instance, heavy-tail hints in RRMSE recommend reporting interquartile ranges alongside means and employing median-centered comparisons when evaluating optimizer-induced gains. The alignment patterns also corroborate insights from the mixed plots, tying tail behavior to peak miss events.

Kernel density overlays provide a smoothed view of metric distributions, complementing the Q–Q diagnostics by localizing modes and skewness. For association metrics (r, R^2) and skill indices (NSE, WI), unimodal, symmetric shapes indicate consistent cross-model behavior, aligning with expectations from the attention-enabled recurrent dominance. In contrast, error metrics (MSE, RMSE, MAE, RRMSE) display broader, occasionally right-skewed densities, again pointing to peak sensitivity and heteroscedasticity across architectures.

These profiles guide metric selection and weighting in optimizer objectives: when tails dominate amplitude errors, minimizing MSE on validation encourages peak-aware calibration, while complementary reporting of MAE and bias (MBE) ensures that improvements are not achieved via systematic over- or underestimation. The KDE shapes thus bridge descriptive analysis and objective design, reinforcing the rationale for attention mechanisms and evolutionary hyperparameter tuning.

Interpretability and Error Analysis: Optimization

The facet grid organizes each metric into a dedicated panel, enabling side-by-side comparison of values produced by GGO,+,EALSTM and competing optimizer–model configurations under a common scale. The panels reveal a consistent pattern in which GGO,+,EALSTM occupies the favorable end of each axis—lower is better for error metrics (MSE, RMSE, MAE, MBE, RRMSE) and higher is better for association/skill metrics (r, R^2, NSE, WI)—while alternatives progressively deviate from the optimum. Such parallel separations across facets

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Received: March 05, 2025 Revised: June 04, 2025 Accepted: August 01, 2025

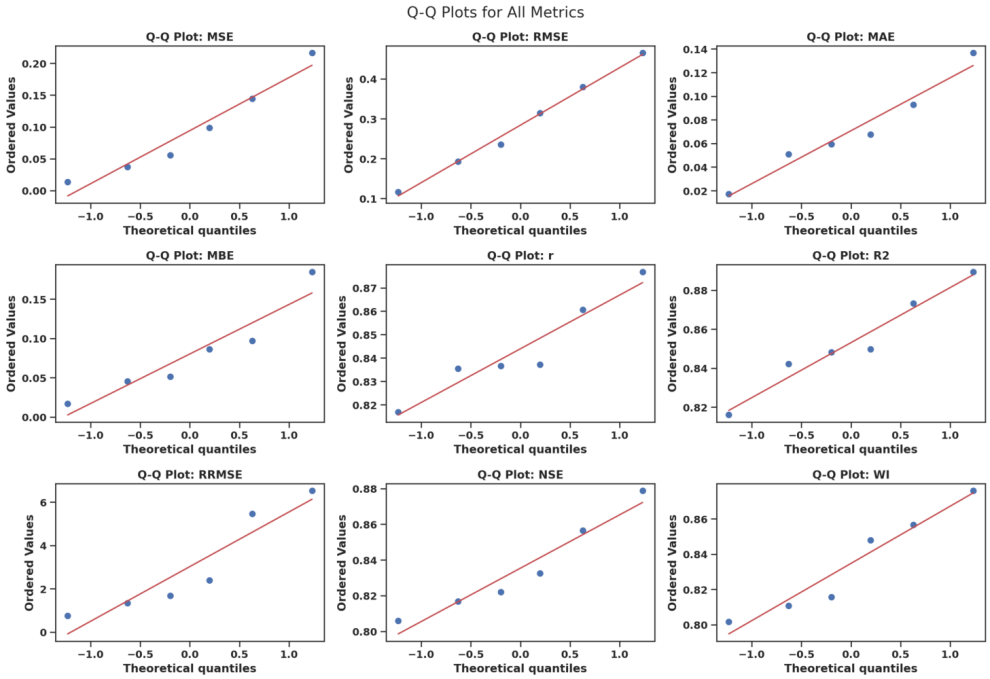

Figure 7: Q–Q plots for baseline metric distributions against a normal reference. Strong adherence for r, R^2, and NSE supports parametric summaries, whereas mild tail deviations for RMSE/RRMSE reflect peak-driven outliers and motivate robust dispersion reporting.

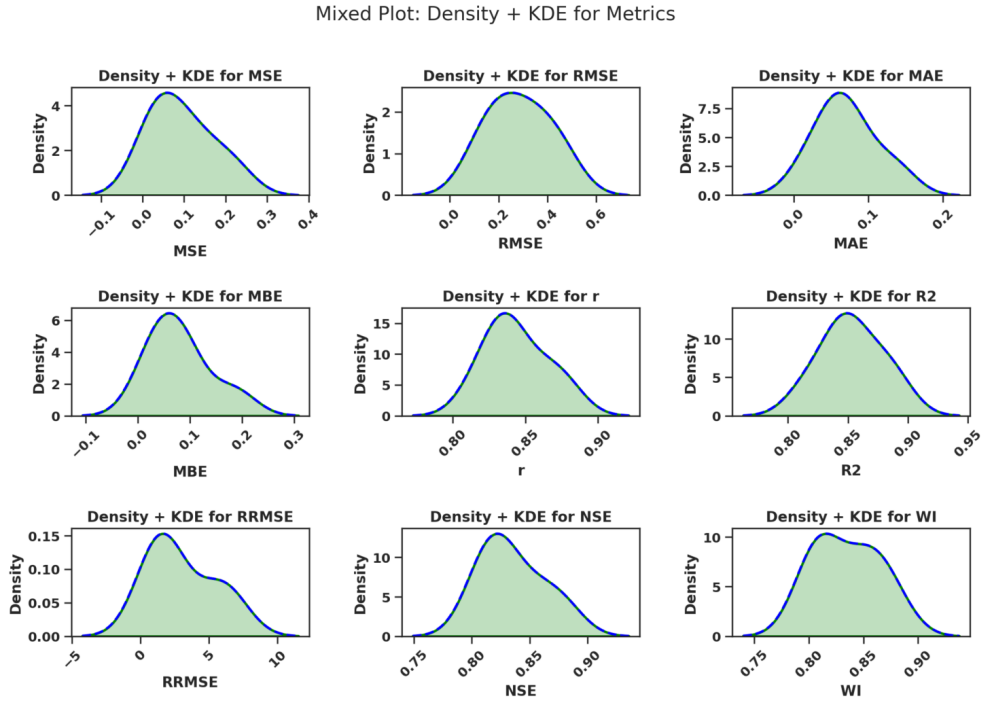

Figure 8: Density and KDE views for baseline metrics. Association and skill indices exhibit compact, near-symmetric modes, whereas error metrics show broader, mildly skewed shapes, consistent with peak-related heteroscedasticity across models.

indicate that the performance gain from GGO is not confined to a single criterion but generalizes across error, bias, and skill dimensions.

Methodologically, this layout substantiates the multi-metric robustness of the search, suggesting that GGO's

DOI: https://doi.org/10.54216/FPA.210218

Received: March 05, 2025 Revised: June 04, 2025 Accepted: August 01, 2025

exploration–exploitation dynamics identified a configuration that calibrates both amplitude and correlation properties simultaneously. This also validates the choice of validation MSE as an objective, as improvements transfer to orthogonal criteria like WI and NSE that emphasize agreement and baseline-relative skill.

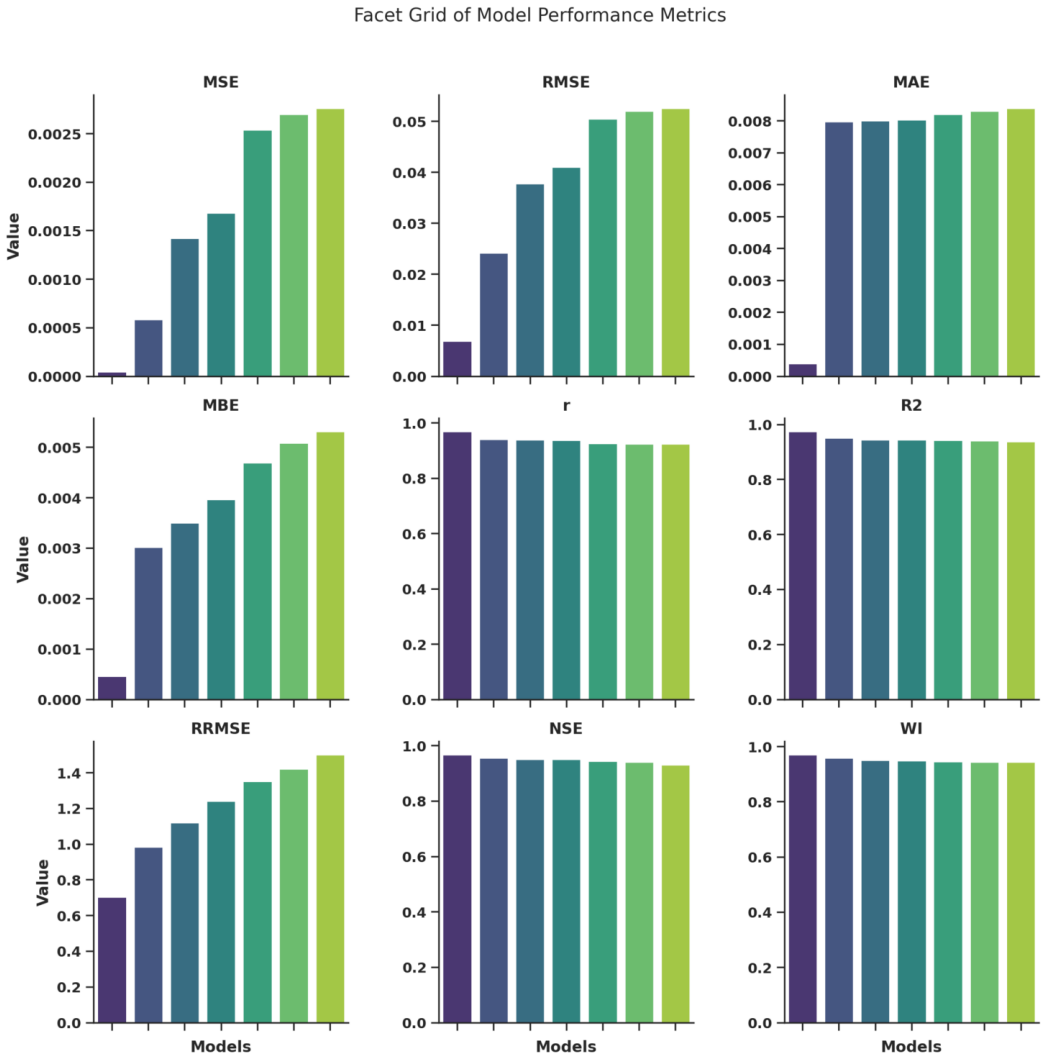

Figure 9: Facet grid comparing metric values across optimizer–model configurations. GGO,+,EALSTM consistently attains favorable positions across errors, bias, association, and skill, evidencing cross-metric robustness rather than single-criterion tuning.

The violin–box composites visualize distributional spread and central tendency of each metric across optimization variants, highlighting dispersion differences induced by search dynamics. Narrower violins and tighter boxes for GGO,+,EALSTM on error metrics indicate reduced variance and fewer extreme outcomes—an essential property for stable deployment. On association and skill metrics, the upper tails approach the ceiling, with GGO's medians shifted toward superior regions, corroborating improved fit without overfitting-induced volatility.

Practically, the variance reduction implies predictable performance under data regime shifts, improving reliability for real-time forecasting pipelines. These plots also reveal where alternatives retain residual strengths—for example, occasional proximity on r or R^2—yet fall short on amplitude-centric criteria such as RMSE or RRMSE, which are critical for peak-aware operations and demand response.

The normalized heatmap benchmarks each optimizer–EALSTM pairing on a common 0–1 scale per metric, visually emphasizing relative dominance patterns. GGO,+,EALSTM anchors the optimal corners across error and skill metrics, while alternatives such as DE and GA display intermediate shading that suggests partial convergence toward the optimum but persistent deficits in either amplitude errors or agreement indices. The structured gradient across rows signals consistent superiority rather than isolated wins.

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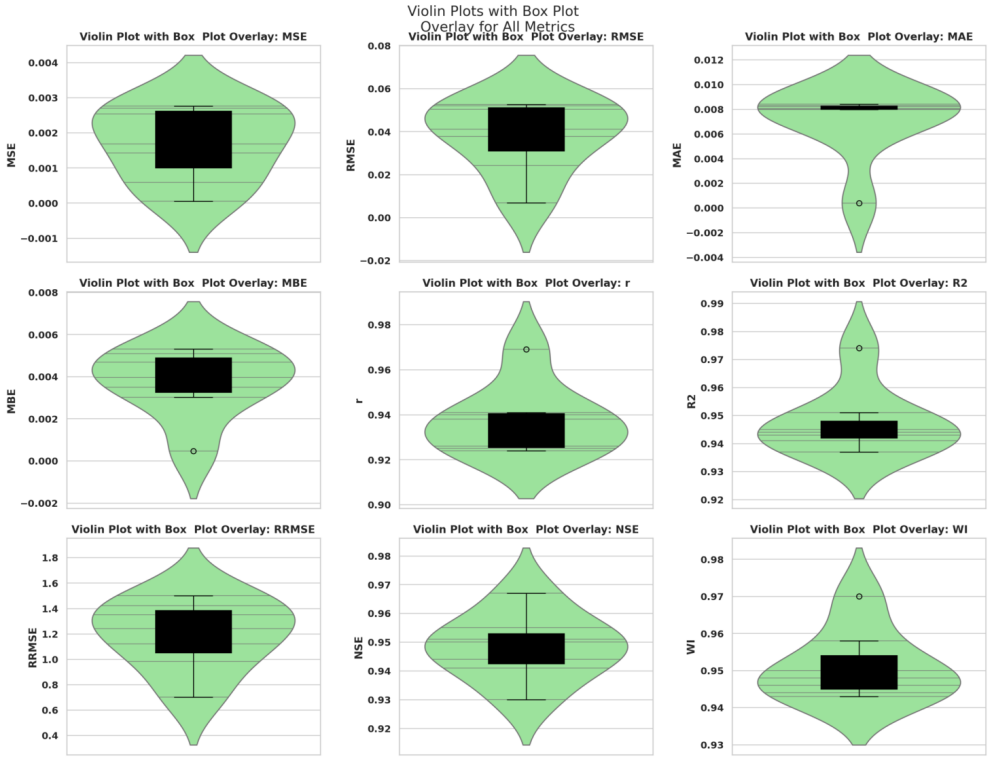

Figure 10: Violin plots with box overlays for metrics across optimizers. GGO,+,EALSTM exhibits narrower dispersion and superior medians, particularly on amplitude-sensitive errors (RMSE, RRMSE), indicating improved stability and peak fidelity.

This matrix is especially useful for optimizer selection because it compresses multi-criteria outcomes into a coherent map, revealing where specific algorithms excel or lag. For instance, algorithms that approach GGO on r and R^2 but trail on RMSE likely capture temporal alignment yet miscalibrate magnitude, indicating the need for capacity or regularization adjustments in their proposed configurations.

Kernel density estimates for the optimized runs expose modality and skewness in each metric, complementing the normalized heatmap with distributional detail. Error metrics show unimodal, left-shifted densities under GGO, reflecting lower central errors and thinner right tails compared to alternatives; association and skill metrics show right-shifted, compact modes for GGO, consistent with higher agreement and baseline-relative skill. Secondary shoulders in some alternatives indicate sporadic suboptimal trials, aligning with slower or less reliable convergence.

From an operations perspective, these density profiles confirm that GGO not only improves averages but also compresses variability, reducing the risk of adverse outcomes during extreme temperature or occupancy events. This reliability dimension is critical in production settings, where consistent peak handling is valued over occasional best-case performance.

6 Discussion

The results of this study demonstrate the effectiveness of the Evolutionary Attention-based Long Short-Term Memory (EALSTM) model in forecasting energy consumption at the appliance level, particularly under complex, non-stationary conditions. One of the key advantages of the EALSTM architecture lies in its attention mechanism, which significantly improves feature and temporal selection, especially during regime changes such as seasonal transitions or extreme temperature variations. By assigning higher weights to critical periods—such as morning and evening peaks or periods of rapid temperature shifts—EALSTM is able to enhance peak prediction accuracy, a challenge that traditional recurrent models (such as LSTM or GRU) struggle with.

DOI: https://doi.org/10.54216/FPA.210218

Received: March 05, 2025 Revised: June 04, 2025 Accepted: August 01, 2025

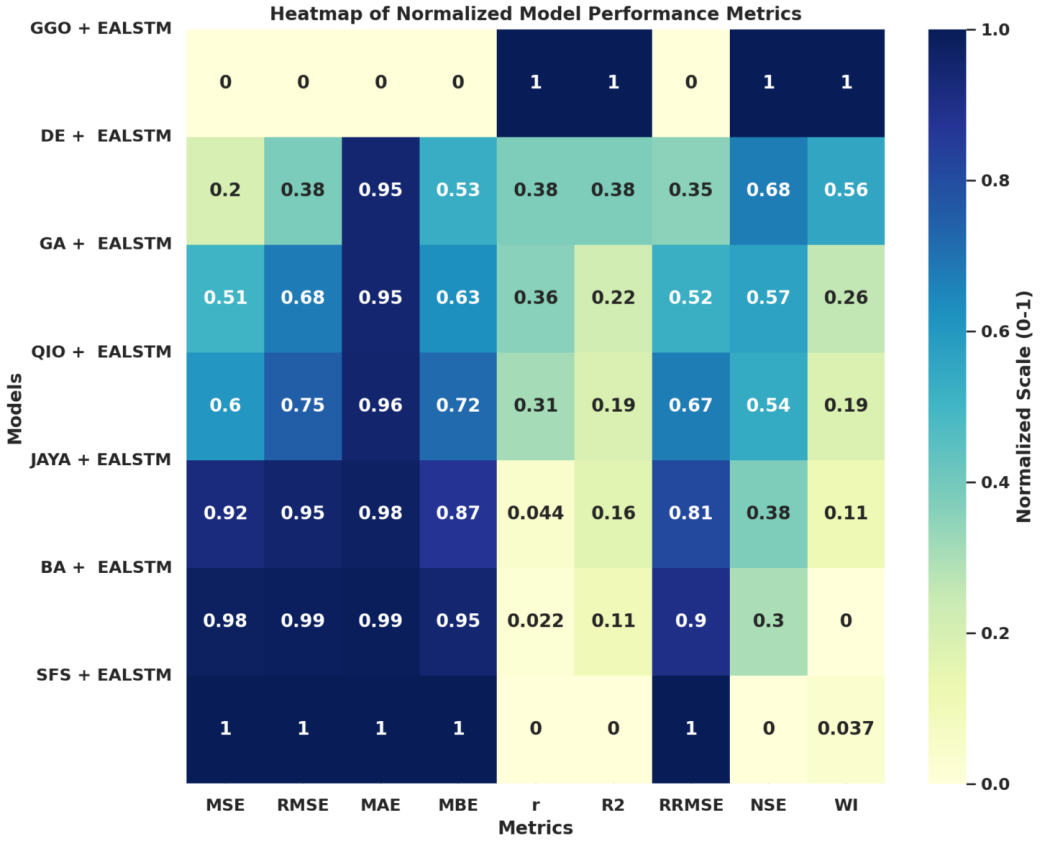

Figure 11: Heatmap of normalized optimized metrics for EALSTM under different metaheuristics. GGO,+,EALSTM consistently occupies optimal regions across criteria, while alternatives show partial convergence with persistent amplitude or agreement gaps.

This selective focus enables EALSTM to more effectively capture the dynamic patterns in energy consumption that are critical for applications like demand response, load balancing, and energy efficiency optimization.

Furthermore, the attention mechanism helps mitigate issues that arise from regime shifts, which are common in smart-home environments. For instance, occupancy patterns and appliance usage can vary significantly between weekdays and weekends, or during seasonal temperature changes. By attending to these shifts, EALSTM improves its robustness and predictive power across diverse operating conditions, outperforming models that do not incorporate attention, such as standard LSTMs or BiRNNs. These capabilities make EALSTM particularly well-suited for applications in dynamic environments where energy consumption is influenced by multiple, often conflicting, factors.

The superior performance of the Greylag Goose Optimization (GGO)-optimized EALSTM, as demonstrated in the results, further underscores the importance of using an effective hyperparameter optimization technique. GGO's migration-inspired search process resists getting trapped in local minima, a common pitfall in deep learning training, especially when dealing with complex and high-dimensional hyperparameter spaces. By effectively balancing exploration and exploitation, GGO not only tunes the architecture and training parameters of EALSTM, but it also optimizes the model's capacity and regularization. This approach allows for a fine-tuned model that achieves better generalization on out-of-sample data, providing improved predictive performance without overfitting to the training set. Similar successes with GGO have been reported in environmental forecasting and other hybrid deep learning pipelines, highlighting the algorithm's versatility and effectiveness across a range of domains.

In terms of practical applicability, the proposed method is lightweight enough for deployment in real-world smart-home systems, such as home gateways or utility dashboards. The model's architecture, with its attention mechanism and optimized hyperparameters, ensures that it can run efficiently even in resource-constrained environments. The outputs of the model can be used to inform real-time appliance scheduling, demand response

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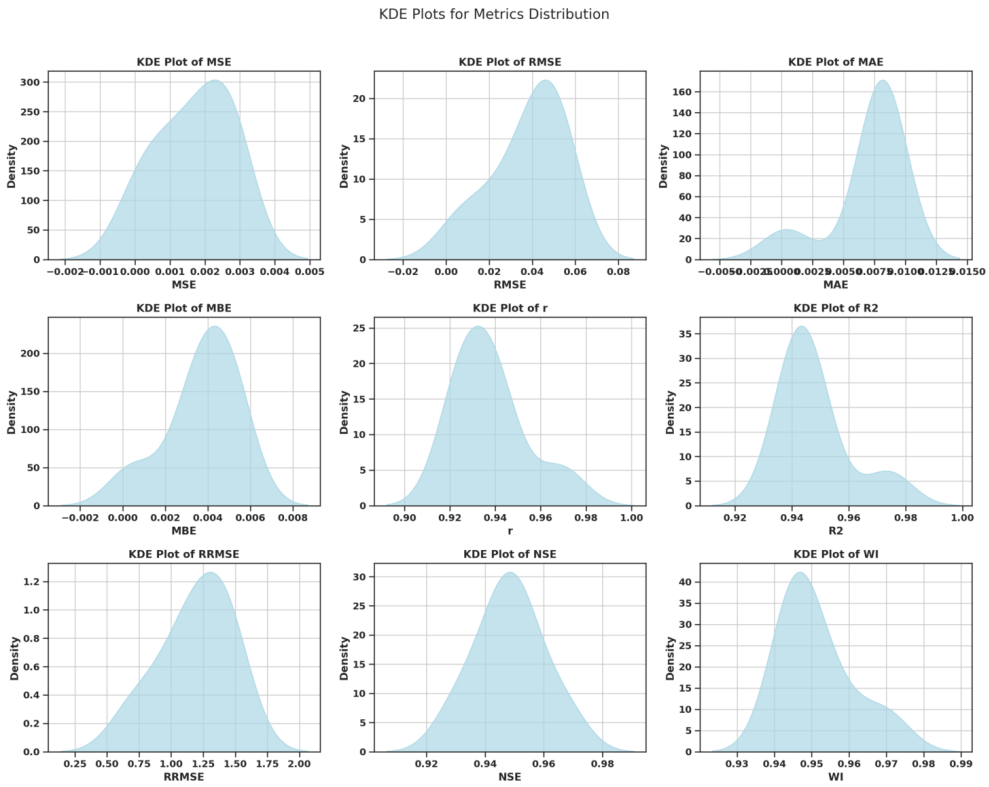

Figure 12: KDE plots for optimized metric distributions. GGO,+,EALSTM yields left-shifted error densities and right-shifted association/skill densities with reduced spread, evidencing both accuracy and reliability gains over alternative optimizers.

strategies, and per-household energy efficiency targeting. For example, by predicting peak energy demand more accurately, utilities can better plan for load balancing, while homeowners can adjust their energy usage patterns to minimize costs or reduce environmental impact. Additionally, the model's interpretability, facilitated by the attention mechanism and residual analysis, enables stakeholders to understand the underlying drivers of energy consumption, which can support targeted interventions for energy savings and sustainability efforts.

Overall, the combination of EALSTM and GGO offers a robust and practical solution for forecasting household energy consumption, particularly in the context of smart homes and dynamic grid environments. The approach's ability to model complex temporal dependencies and handle regime shifts, coupled with the efficient optimization provided by GGO, makes it a promising candidate for future deployments in real-world energy systems.

7 Conclusion and Future Work

7.1 Conclusion

This study demonstrates that an optimized Evolutionary Attention-based Long Short-Term Memory (EALSTM) model, enhanced through Greylag Goose Optimization (GGO), significantly outperforms both baseline models and other state-of-the-art optimization techniques in forecasting household energy consumption. The model's attention mechanism effectively improves feature and temporal selection, particularly in the presence of regime changes, thereby enhancing the accuracy of peak demand predictions compared to standard recurrent models. The results show substantial improvements in error metrics, including MSE, RMSE, and MAE, as well as higher skill metrics such as R^2, r, and NSE.

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Received: March 05, 2025 Revised: June 04, 2025 Accepted: August 01, 2025

The use of GGO for hyperparameter optimization proves to be a key factor in achieving these performance gains, as it enables more efficient exploration of the hyperparameter space and avoids local minima. The GGO-optimized EALSTM offers a fine balance between model fit and generalization, making it particularly well-suited for real-world applications in smart-home energy forecasting. The lightweight nature of the approach also ensures its feasibility for deployment in resource-constrained environments such as home gateways or utility dashboards, enabling applications such as appliance scheduling, demand response, and targeted energy efficiency interventions.

7.2 Future Work

There are several avenues for future research to further enhance the capabilities of the proposed approach. One potential direction is the incorporation of additional weather signals, such as humidity and wind speed, which could further improve the model's ability to account for environmental variability and its impact on energy consumption. These additional features would allow the model to capture a broader range of external influences on household energy behavior.

Another promising direction is the adoption of probabilistic forecasting techniques to quantify uncertainty in the predictions. By incorporating uncertainty estimation, the model could provide confidence intervals for its forecasts, enabling more informed decision-making in applications such as dynamic pricing and demand-side management. Additionally, cross-home transfer learning could be explored to leverage knowledge from one household to improve predictions in other households, particularly when the amount of data from individual homes is limited. This would make the model more adaptable and scalable to a wider range of smart-home environments.

Finally, addressing the non-stationarity of energy consumption patterns over time is crucial for improving long-term forecasting. Online adaptation techniques could be explored to allow the model to continuously update its parameters as new data becomes available, ensuring that it remains effective in dynamic environments. Extending the evaluation to include other Kaggle smart-home datasets would further validate the robustness and generalizability of the approach across different datasets and operational contexts.

In summary, while the optimized EALSTM with GGO provides a state-of-the-art solution for smart-home energy forecasting, these future extensions have the potential to further enhance its accuracy, adaptability, and practicality for real-world deployment.

Data Availability

The data used in this study are openly available on Kaggle under the title Chiller Energy Data at `https://www.kaggle.com/datasets/mexwell/smart-home-energy-consumption`.

Declarations

- **Acknowledgments**
  Not applicable.
- **Conflict of interest/Competing interests**
  The authors declare that they have no conflicts of interest to report regarding the present study.
- **Ethics approval and consent to participate**
  Not applicable.
- **Consent for publication**
  Not applicable.
- **Funding**
  No Fund

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Received: March 05, 2025 Revised: June 04, 2025 Accepted: August 01, 2025

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Received: March 05, 2025 Revised: June 04, 2025 Accepted: August 01, 2025