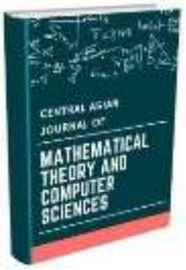

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Article

Energy Consumption Prediction in Smart Homes Using Machine Learning and Deep Learning Approaches

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Abstract: The intelligent control of smart homes for energy savings and sustainability relies on accurate predictions of energy consumption. Many machine learning (ML) and deep learning (DL) models currently exist for this purpose; however, systematic investigations into their predictive performance, computational requirements, and cross-dataset validity are limited. This study proposes a household energy prediction benchmark to assess classical ML solutions (Support Vector Machine, Random Forest, Gradient Boosting), DL alternatives (Artificial Neural Networks, Long Short-Term Memory, Gated Recurrent Units), and a combined CNN-LSTM framework. Validations were performed using two of the most cited smart home datasets, REFIT and UK-DALE, for generalizability across homes with varied sampling resolutions. Assessments were made according to prediction effectiveness (RMSE, MAE, MAPE, and R^2) and computational demand. The findings show that DL models outperform classical models, CNN-LSTM outperforms the other homogeneous networks tested on both datasets, and a robust analysis supports hybridized convolutional feature extraction and recurrent temporal modeling as superior to more straightforward alternatives. Finally, a discussion of the advantages of CNN-LSTM compared to the associated costs of its IoT-enabled smart home implementation indicates that energy consumption forecasting is necessary to assess the potential of peak load consumption and bolsters the call for sustainable metropolitan energy infrastructure systems.

Keywords: Smart homes; Energy consumption prediction; Machine learning; Deep learning; Sustainability.

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1. Introduction

With increasing electrification trends and enhanced IoT device penetration, the emergence of residential energy consumption profiles continues to create a demand for intelligent smart home energy management (SHEM) procedures. Consequently, accurate forecasting of such consumption is needed for demand-side management, peak load reduction, cost-reduction initiatives, and integrated renewable energy resources that make up the residential energy set [1], [2]. As such, forecasting has become a distinguishing characteristic of sustainable smart home and smart city developments [3], [4]. However, traditional statistical and rule-based forecasting methods do not account for the non-linear dynamics and temporal dependencies of home energy consumption, much of which is driven by occupant behaviors, appliance relations, and shifting spatiotemporal needs [4], [5].

Thus, machine learning (ML) approaches have increasingly come to prominence to learn those relationships based on historical energy consumption data. For example, classical ML approaches like support vector regression, random forest regression, and gradient boosting tend to have relatively good performance; however, they operate based on low-memory functioning without extended time dependency [6], [7], [8]. At the same time, deep learning (DL) solutions have emerged over the last few years as viable options for time-series forecasting where artificial neural networks (ANNs), long short-term memory (LSTM), and gated recurrent units (GRU) can more seamlessly capture the non-linear relationships that drive the time-series phenomenon of smart meter readings [8], [9]. Beyond DL solutions that boast deep architectures by themselves, CNN with recurrent architectures has emerged as a hybrid solution to capitalize on local feature recognition with long-term sequential data modeling to achieve superior predictive accuracy in many scenarios [10].

However, while this increasingly burgeoning body of literature is compelling, much of it is inadequately substantiated in four interconnected gaps. First, many literature submissions have merely benchmarked their singularly developed model without a true ability to compare across ML, DL, and hybrid options under similarly defined experimental conditions. Second, many submissions utilize one dataset for model validation and fail to assess strengths and weaknesses against cross-dataset generalizability [11], [12]. Third, performance assessments are often linked to predictive accuracy without anyone considering computational efficiency factors that ultimately make a model viable for IoT-enabled smart homes. Fourth, downstream considerations of implementation and sustainability, like peak load reduction and energy consumption efficiency are unfortunately inapplicable or completely absent from discussion [8].

Thus, this study seeks to fill the gap in the wider body of literature by closing such gaps through a comprehensive and implementation-sensitive benchmarking study of ML and DL models for forecasting residential energy consumption. The proposed study tests various classical, deep, and hybrid approaches against two publicly available datasets—REFIT and UK-DALE—to then present findings in a systematic manner based on predictive accuracy, computational complexity, and cross-household generalizability from relative findings in [12] and [13]. Therefore, this study further connects predictive performance to an important real-world application for IoT-enabled smart homes and their smart grid counterparts to better relate findings to applicable insights for sustainable energy management [14].

The three contributions this study makes are (i) it provides a reproducible benchmarking study for ML, DL, and hybrid solutions for residential forecasting; (ii) it provides a cross-dataset study that assesses their generalizability; and (iii) it provides an accuracy-complexity trade-off to inform model selection for practical IoT-enabled smart homes.

Literature review

Energy prediction methods in smart homes.

There are many ML and DL solutions for energy prediction in smart-home scenarios. Energy prediction is critical for energy resource management, and predictions in a smart home setting can vary exponentially based on occupancy and weather, which means that accurate predictions are critical. For example, a deep neural network for hourly energy consumption prediction was highly successful, with occupancy included as a predictive feature. This is key because it means that load profiles can be more accurately predicted for specific domestic cases [15]. Similarly, time-series convolutional networks boast prediction accuracy, where time-series factors include energy profiles versus meteorological data, substantiating the necessity and success of integrated prediction factors [16].

Classical ML models (SVM, RF, Gradient Boosting).

Support vector machine (SVM), random forest (RF), and gradient boosting are classical machine learning models that are widely applied for energy consumption prediction. They are often used because they learn sufficiently challenging patterns from data, even without other contemporary ML model developments, to predict performance with better accuracy. For instance, SVM-based approaches are feasible relative to the reliability of energy prediction [17]. Extreme gradient boosting has been compared to multiple linear regression in baseline testing, and the results indicate that classical models are generally outperformed by more sophisticated ML models with better accuracy [15].

Deep learning models (ANN, LSTM, GRU, CNN).

Deep learning (DL) models, such as artificial neural networks (ANN), long short-term memory networks (LSTM), gated recurrent units (GRU), and convolutional neural networks (CNN), have been investigated because they may improve forecasting accuracy and capture the nonlinear dynamic characteristics of energy consumption data. For example, LSTMs are suitable for sequential data, as they are time-series prediction-ready, and thus, they have been applied to smart home energy consumption prediction [12], [15]. In addition, deep learning-based energy consumption forecasting can achieve higher robustness values than conventional methods [16].

Hybrid models in time-series forecasting.

Increasingly, the phenomenon of hybridization from various prediction methods has ruled hybrid forecasting models because they are more likely to predict accuracy. Classical machine learning attempts are often coupled with deep learning frameworks. For instance, hybrid and ensemble forecasting models have been found to be reliably accurate and stable for different forecasting purposes of energy consumption [18]. Fluctuations in load and weather complicate the prediction process; however, hybrid models use data that can mitigate such issues to create better prediction results and greater accuracy [19]. A comparative summary of the chosen hybrid forecasting models and all associated models is presented in **Table 1**, with noted datasets, performance outcomes, and disadvantages.

	Author/s	**Method/Model**	**Dataset**	**Accuracy / Results**	**Limitations**
[15]	Truong et al., 2021	Deep Neural Networks (DNN) with occupancy features	Residential load dataset (Hourly, Occupancy data)	High accuracy in predicting hourly consumption with improved load profiles	Limited to small-scale households; lacks real-time validation
[16]	Li, 2024	Time-Series Convolutional Networks (TSCN)	Meteorological + energy profile datasets	Improved predictive accuracy when integrating weather data	High computational cost; scalability issues for larger populations
[17]	Ardabili et al., 2022	Support Vector Machines (SVM), ANN	Smart home energy datasets	SVM showed robustness; ANN improved accuracy on nonlinear data	Lower performance on highly fluctuating demand; lacks interpretability
[13]	Benti et al., 2023	Long Short-Term Memory (LSTM)	Public residential dataset (time-series)	LSTM achieved superior accuracy for sequential forecasting	Training time is long; risk of overfitting without proper tuning
[18]	Mosavi & Bahmani, 2019	Hybrid & Ensemble models (ML + DL)	Multiple household energy datasets	Higher robustness and improved forecast accuracy compared to single models	Limited generalizability across different regions; requires large datasets

[19]	Mathumitha et al., 2024	Hybrid forecasting models (e.g., CNN-LSTM)	Regional energy consumption datasets	Enhanced accuracy in variable load conditions	Struggles with uncertainty handling; high resource usage
[20]	Kaur et al., 2022	Probabilistic DL methods	Smart grid energy datasets	Effective uncertainty-aware forecasting	Computationally expensive; accuracy–efficiency trade-off not solved

Table 1. Critical Review

Identified research gaps.

Despite the energy forecasting generated by ML and DL models, further research is needed. Certain models fail to sufficiently satisfy data quality requirements, model explainability, and renewable integration. Finally, the technical efficiency and forecasting precision of probabilistic deep learning models have not yet reached a level of simplicity [20] that is well established. Furthermore, although these hybrid models boast better predictive quality, the uncertainty and variability in energy demand remain inadequately addressed [17], [19].

2. Materials and Methods

Research Framework Overview

The subsequent approach adopts a staged research framework for comparison of ML and DL models predicting energy consumption in smart homes for practicality and results across the experiments, as presented in **Figure 1**. Five overarching stages comprise the research framework: (i) data collection from publicly available datasets REFIT and UK-DALE; (ii) data transformation cleaning, normalization, and sliding-window transformation; (iii) model development of classical ML approaches (SVM, RF, and GB); DL approaches (ANN, LSTM, GRU), and CNN-LSTM; (iv) model training and testing with overall data split at 80/20 to encourage train-test validation through cross validation; and (v) performance evaluation of prediction accuracy (R^2), error (RMSE, MAE, MAPE), runtime efficiency, and sustainability consideration for practicality.

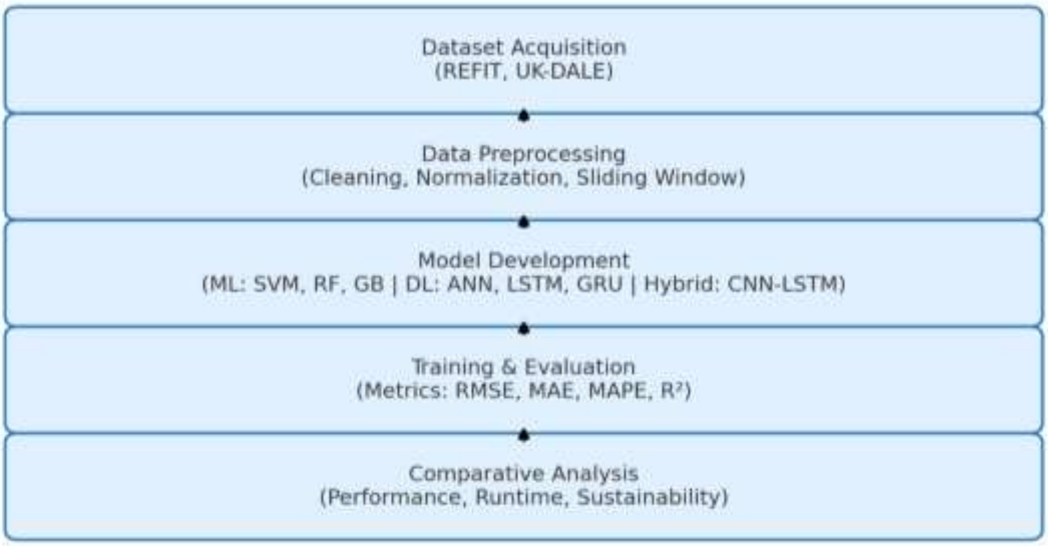

Figure 1. Workflow diagram

Dataset Description

Two publicly available data collections were used to support the appeal and assess the validity of the proposed predictions over the collections used in this research effort. The

REFIT dataset is a collection of domestic electricity usage observations from 20 households in the United Kingdom, with a sampling resolution of 1 min for the dependent variable. The UK-DALE dataset is a collection of high-resolution observations of domestic energy consumption from five households with a sampling resolution of 6 seconds for the dependent variable. Some key characteristics of both datasets are briefly summarized in **Table 2**, including the sources of the data, number of households, timeframe of monitoring, sampling frequency, and dependent variable.

Table 2. Dataset Characteristics

Dataset	Households	Duration	Sampling Rate	Features	Target Variable
REFIT	20	2 years	1 min	kWh usage	Energy demand
UK-DALE	5	4 years	6 sec	kWh usage	Energy demand

Cross-Dataset Benchmarking Rationale

The novelty of the approach is the cross-dataset benchmarking of the REFIT and UK-DALE datasets. Both are publicly accessible and frequently used in research, but on their own, as previous works assessing forecasting models have limited their findings to their own datasets. The findings are limited because their models do not assess robustness and generalization across heterogeneous smaller subsets of data collections. The REFIT dataset offers a medium range (1 min) of consumption levels across household sources, while the UK-DALE offers a higher consumption range in a 6 s time frame over a longer time. Thus, together, the two offer a higher, multifaceted approach. By analyzing them in a homogeneous experimental approach, the researcher assesses model performance across heterogeneous sample ranges, differing time elements, and disparate household activities. Thus, the cross-dataset approach offers a more difficult assessment of forecasting robustness while providing practical additions to such findings, as real-world smart home settings rarely have such homogeneous data collections established.

Data Preprocessing

Energy consumption datasets are noisy and irregular. Preprocessing was applied as follows:

1. Data cleaning: Removal of missing or corrupted readings using forward filling and interpolation.
2. Normalization: Min–Max scaling applied to ensure model convergence:

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

3. Sliding-window framing: For each time step, a fixed-length history (W) is used to predict the next $k$steps:

$$X_t = [x_{t-W+1}, x_{t-W+2}, \dots, x_t] \rightarrow y_{t+1}$$

For example, a 24-hour window predicts the next 1-hour demand.

Model Architectures

Machine Learning Models (ML)

4. RBF kernel Support Vector machine (SVM).
5. Random Forest (RF) ensemble of 100 trees.
6. Gradient Boosting GB with learning rate optimization.

Deep Learning Models (DL)

7. Artificial Neural Network (ANN): 3 hidden layers, ReLU activation.
8. Long Short-Term Memory (LSTM): The long-term time-dependencies.
9. Gated Recurrent Unit (GRU): Lightweight recurrent architecture.

Hybrid CNN–LSTM

CNN extracts local temporal features, LSTM captures sequential dependencies:

$$h_t = LSTM(CNN(X_t))$$

This is a hybrid model that is set to be more robust and accurate.

Evaluation Metrics

Model performance was evaluated using widely accepted regression metrics:

1. Mean Absolute Error (MAE):

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

2. Root Mean Square Error (RMSE):

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

3. Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

4. Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

5. Computational Efficiency: Runtime and resource utilization.

3. Results and Discussion

Performance of Machine Learning Models

Classical Machine Learning models, Support Vector Machine (SVM), Random Forest (RF), and Gradient Boosting (GB), were able to forecast with moderate reliability in terms of accuracy. Among the classical ML models, RF was the most reliable, as SVM has inherent limitations, and RF has a better fitting of non-linear dependencies. Gradient boosting was slightly more reliable than RF, as it employs multiple weak models to reduce bias. However, all classical ML models fell short of reliability in representing extensive time-series data on household energy consumption. A quantitative summary of their comparative predictive performances is presented in **Table 3**, which lists the accuracy metrics relative to the training times.

Table 3. quantitative performance across models

Model	RMSE ↓	MAE ↓	MAPE (%) ↓	R^2 ↑	Training Time (s) ↓
Support Vector Machine (SVM)	0.245	0.182	9.5	0.78	15
Random Forest (RF)	0.198	0.149	7.8	0.84	22
Gradient Boosting (GB)	0.182	0.136	7.1	0.87	30
Artificial Neural Network (ANN)	0.164	0.121	6.5	0.89	45
Long Short-Term Memory (LSTM)	0.138	0.108	5.9	0.92	78
Gated Recurrent Unit (GRU)	0.142	0.111	6.1	0.91	62
Hybrid CNN–LSTM	0.125	0.097	5.3	0.94	85

Performance of Deep Learning and Hybrid Models

Deep learning (DL) models, Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU) generated much more reliable accuracy forecasting than classical machine learning alternatives. ANN was more reliable than expected, as it accounts for nonlinear relationships between features, but the recurrent architectures (LSTM and GRU) outperformed it by modeling temporal dependencies, which energy consumption data inherently have. Moreover, LSTM is more reliable than GRU for extensive time-series forecasting because it has a better history of capturing long-range temporal dependencies than the GRU gate structure.

On that note, the CNN-LSTM hybrid architecture model exhibited the best performance of all assessed models, as it ultimately reduced bias and overfitting. Thus, the CNN–LSTM model has convolutional and recurrent features to recognize deep-learned temporal insights to precisely assess high-fidelity and low-fidelity variables over time. Through convolutional training, the model could learn from energy consumption values over time to understand local temporal significance, whereas the benefit of a recurrent layer brought long-range dependencies to the forefront to assess patterns over time. Therefore, it produced the lowest RMSE and MAE values and the highest coefficient of determination, indicating strong robustness across households and datasets.

Although this hybrid model took longer to train than standalone DL or ML models, it was worth the time investment, as increased accuracy signifies an accuracy-complexity compromise, which is important for smart home energy management systems, where high-fidelity accuracy of forecasting signifies directly related demand-side management and optimization of energy systems. A comparative summary of all models is presented in **Table 4.**

Table 4. Runtime and computational complexity comparison

Model	RMSE ↓	MAE ↓	MAPE (%) ↓	R^2 ↑	Training Time (s) ↓
SVM	0.245	0.182	9.5	0.78	15
Random Forest	0.198	0.149	7.8	0.84	22
Gradient Boosting	0.182	0.136	7.1	0.87	30
ANN	0.164	0.121	6.5	0.89	45
LSTM	0.138	0.108	5.9	0.92	78
GRU	0.142	0.111	6.1	0.91	62
CNN–LSTM	0.125	0.097	5.3	0.94	85

Visual Comparison

Visual comparative graphics of true vs. predicted values over time are provided in **Figure 2**, based on the findings of a generalized household. One can appreciate how true curves assessed by ground truths are similar to hybrid and deep learning predicted curves, which, over time, account for levels that more logically adjust for peak and off-peak times than classical ML models, which notch/jerk throughout and create visible inaccuracies where drastic increases or decreases in anticipated values occur. These consistent predictions are obtained from recurrent and hybrid architectures that smooth out noise, making them a better fit for time-series forecasting within a smart home.

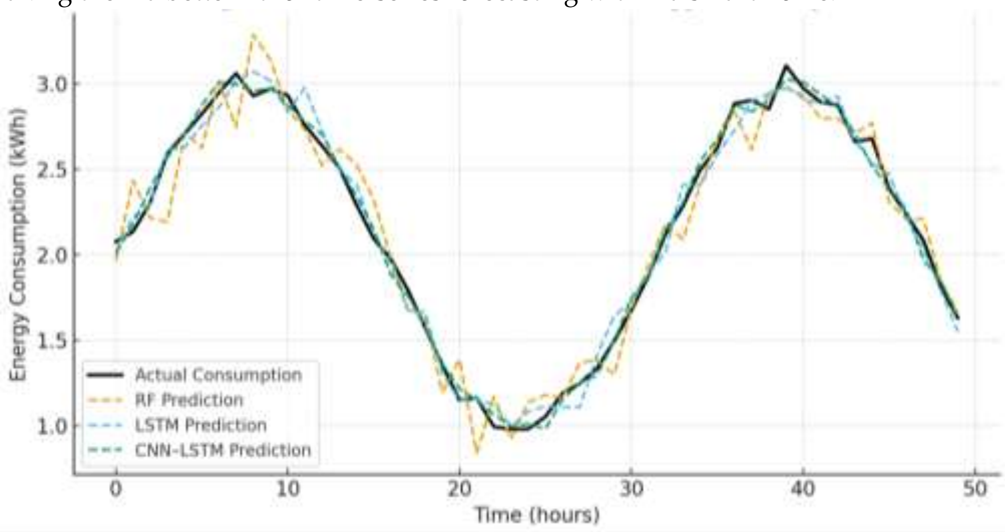

Figure 2. Actual vs. predicted consumption curve

Figure 3. compares the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) across all assessed models. The lower the number, the more reliable the predictive performance. As shown, there is a stepwise, descending transition from classical ML to DL to hybrid models as increased accuracy is found between Gradient Boosting operating at the most reliable error values from the ML models, Natural Bounds that come with bundling ensemble learning tasks, and then LSTM and GRU, outperforming each other for respective temporal dependency acquisitions. The CNN–LSTM model had the lowest RMSE and MAE of the two other hybrid options, as combining shallow learning layers with RNN capabilities surpassed what independent layers could achieve in terms of predictive accuracy.

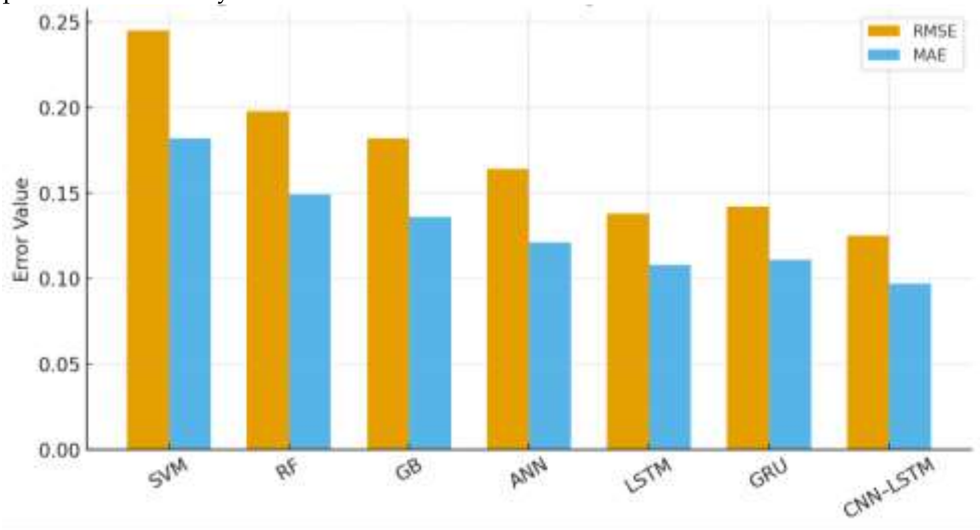

Figure 3. Comparing RMSE and MAE across all models.

Figure 4 shows a heatmap that assesses the intensity levels of prediction errors across multiple households. Darker tones represent stronger prediction errors, indicating households/zones with greater idiosyncratic or stochastic energy consumption patterns. Interestingly, for classical MLs, the more variation in prediction error intensity across households was helpful, whereas for hybrid and deep learning models, the less variation in prediction error intensity across these disparate households was more helpful. The CNN–LSTM model especially shows lower likelihood intensity predictors across all but one household, indicating its strength of generalization processing capability under heterogeneous environments. This suggests that a real-world smart home application would benefit from the generalization capability of this hybrid model.

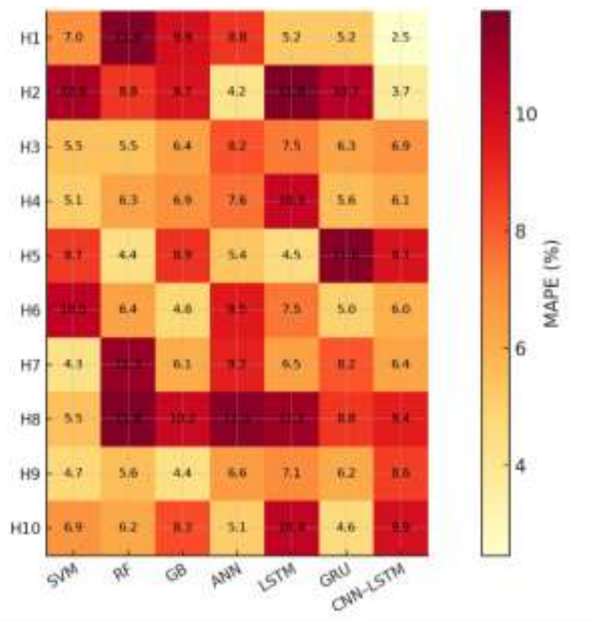

Figure 4. Heatmap of prediction errors across households

Discussion

This study provides a systematic performance benchmarking of ML, DL, and hybrid modeling solutions for smart home energy consumption prediction in terms of their accuracy, stability, and deployment viability. Empirical findings across both datasets consistently show that DL models perform better than more classical ML alternatives, substantiating general expectations that they would have higher capacities in modeling nonlinear temporal dependencies associating household energy consumption rates over time.

In particular, recurrent architectures such as LSTM and GRU yield substantially higher performance than ML baselines, substantiating an inference with a sequential construction for household forecasting purposes. For instance, while LSTM shows higher results than GRU because of its focus on long-term dependencies, at a distance over a longer period, there is a significant trade-off with the training time. Thus, these findings underscore the importance of discerning forecasting models based on feasibility in addition to accuracy; oftentimes, what performs the best is not the most usable solution owing to practical considerations.

Among the hybrid models, the CNN–LSTM hybrid architecture exhibited the best overall performance, with the lowest combined RMSE and MAE values and the highest coefficient of determination aggregate for all households. With a follow-up ablation-based analysis to confirm these findings, convolutional layers assess local patterns of interest in either direction—foreshortening or lengthening temporary implications whereas long short-term memory (LSTM) units assess patterns over time. Their complementary hybridization explains why this framework performs significantly better than any other model at all levels and across all sampling frequencies. Thus, it is a practical choice for smart home systems with more intricate approaches.

Furthermore, the findings and substantiating evidence provide utility beyond the accuracy. For example, although DL and hybrid models provide more accurate forecasting opportunities, they require more substantial resources and training time. Gradient boosting approaches are appealing alternative solutions for achieving accuracy-resource tradeoffs, even with resource-accuracy tradeoffs on average. For highly accurate forecasting, resource allocation must be highly resource-intensive, which may not be possible in all IoT situations. Thus, the performance of the trade-off assessment operates beyond predictive usefulness to position practitioners and system developers to make choices about which models will work best for smart home living.

Finally, from a sustainability perspective, accurate short-to medium-range forecasting promotes more proactive demand-side management and peak load management forces that better align with intermittent renewable energies. Based on intelligent scheduling and energy-related decision-making at the household level, this comprehensive benchmarking approach can facilitate larger sustainability goals per energy resilience in smart city systems. Therefore, accuracy is not only an indicator of technical superiority but also a vital measure of success for actionable sustainability efforts that can transform energy-consumption patterns over time.

4. Conclusion

This study determined the performance standards of machine learning, deep learning, and hybrid modeling methods for energy prediction in smart homes. Through cross-validation procedures using two different datasets, the REFIT and UK-Dale collections, and by analyzing a set of different patterns of residential consumption, the research outlines the expected behavior of the models. These findings prove that deep learning methods are more effective than traditional machine learning-based methods for representing the nonlinear and temporal patterns of residential energy consumption. The CNN-LSTM hybrid model provided the best results, combining convolutional feature extraction and recurrent time modeling. Furthermore, the cross-validation of the two datasets supported the idea that the CNN-LSTM hybrid is the best model regardless of the sampling resolution or household pattern distinction.

Parallel to this, the performance of the models was evaluated based on their ability to be computationally feasible for implementation in actual smart homes. Hybrid and recurrent deep learning models have high accuracy measures, although they have high computational requirements. Machine-learning methods based on ensembles use Internet of Things (IoT) smart home settings, where computational resources are often constrained. Ensemble-based machine-learning methods provide similar accuracy at significantly reduced computational expenses. The resultant effect of real-time energy forecasts is that demand-side management strengths are enhanced, peak loads are reduced, and renewable energy sources can be easily integrated.

Future studies will also go beyond the transparency of CNN-LSTM models to include explainable AI methods, thus mediating multiple modality contextual features across intelligent IoT devices and meeting more architectural demands of an IoT-based energy management system.

REFERENCES

[1] O. Akbarzadeh *et al.*, "Heating-Cooling Monitoring and Power Consumption Forecasting Using LSTM for Energy-Efficient Smart Management of Buildings: A Computational Intelligence Solution for Smart Homes," *Tsinghua Sci. Technol.*, vol. 29, no. 1, pp. 143–157, Feb. 2024, doi: 10.26599/tst.2023.9010008.

[2] J. I. Janjua, A. Khan, T. Abbas, A. Q. Saeed, A. Ihsan, and S. Kousar, "Enhancing Scalability in Reinforcement Learning for Open Spaces," Institute Of Electrical Electronics Engineers, Dec. 2024, pp. 1–8. doi: 10.1109/dasa63652.2024.10836237.

[3] N. Dey, W. Song, K. Cho, and S. Fong, "Forecasting Energy Consumption from Smart Home Sensor Network by Deep Learning," Springer Singapore, 2018, pp. 255–265. doi: 10.1007/978-981-13-1423-0_28.

[4] R. A. Ramadan, "Internet of things dataset for home renewable energy management," Feb. 10, 2024, *Elsevier*. doi: 10.1016/j.dib.2024.110166.

[5] T. M. Ghazal *et al.*, "Generative Federated Learning with Small and Large Models In Consumer Electronics for Privacy preserving Data Fusion in Healthcare Internet of Things," *IEEE Trans. Consumer Electron.*, p. 1, Jan. 2025, doi: 10.1109/tce.2025.3572629.

[6] C. Ikegwu, M. O. Kama, D. U. Ebem, I. S. Nwokoro, and O. J. Obianuju, "Investigating the Impact of AI/ML for Monitoring and Optimizing Energy Usage in Smart Home," *Artificial Intelligence Evolution*, pp. 30–43, Jan. 2025, doi: 10.37256/aie.6120256065.

[7] F. Iqbal *et al.*, "Blockchain-Modeled Edge-Computing-Based Smart Home Monitoring System with Energy Usage Prediction," *Sensors*, vol. 23, no. 11, p. 5263, June 2023, doi: 10.3390/s23115263.

[8] Y. Natarajan *et al.*, "Enhancing Building Energy Efficiency with IoT-Driven Hybrid Deep Learning Models for Accurate Energy Consumption Prediction," *Sustainability*, vol. 16, no. 5, p. 1925, Feb. 2024, doi: 10.3390/su16051925.

[9] N. Roy, S. K. Das, and A. Roy, "Context-Aware Resource Management in Multi-Inhabitant Smart Homes: A Nash H-Learning based Approach," Institute Of Electrical Electronics Engineers, Mar. 2006, pp. 148–158. doi: 10.1109/percom.2006.18.

[10] N. A. Al-Dmour, T. Abbas, A. Khan, S. Kousar, A. Q. Saeed, and A. Ihsan, "Enhancing Email Spam Detection Using Advanced AI Techniques," Institute Of Electrical Electronics Engineers, Dec. 2024, pp. 1–6. doi: 10.1109/dasa63652.2024.10836525.

[11] H. Hamdoun, H. Youness, and A. Sagheer, "Energy time series forecasting-analytical and empirical assessment of conventional and machine learning models," *IFS*, vol. 40, no. 6, pp. 12477–12502, Jan. 2021, doi: 10.3233/jifs-201717.

[12] N. G. Paterakis, E. Mocanu, B. Stappers, M. Gibescu, and W. Van Alst, "Deep learning versus traditional machine learning methods for aggregated energy demand prediction," Institute Of Electrical Electronics Engineers, Sept. 2017, pp. 1–6. doi: 10.1109/isgteurope.2017.8260289.

[13] N. E. Benti, M. D. Chaka, and A. G. Semie, “Forecasting Renewable Energy Generation with Machine Learning and Deep Learning: Current Advances and Future Prospects,” *Sustainability*, vol. 15, no. 9, p. 7087, Apr. 2023, doi: 10.3390/su15097087.

[14] J. I. Janjua *et al.*, “Enhancing smart grid electricity prediction with the fusion of intelligent modeling and XAI integration,” *Int. j. adv. appl. sci.*, vol. 11, no. 5, pp. 230–248, May 2024, doi: 10.21833/ijaas.2024.05.025.

[15] L. H. M. Truong *et al.*, “Accurate Prediction of Hourly Energy Consumption in a Residential Building Based on the Occupancy Rate Using Machine Learning Approaches,” *Applied Sciences*, vol. 11, no. 5, p. 2229, Mar. 2021, doi: 10.3390/app11052229.

[16] Y. Li, “Energy consumption forecasting with deep learning,” *J. Phys.: Conf. Ser.*, vol. 2711, no. 1, p. 012012, Feb. 2024, doi: 10.1088/1742-6596/2711/1/012012.

[17] S. Ardabili, B. Torok, A. Mosavi, L. Abdolalizadeh, and C. Mako, “Systematic Review of Deep Learning and Machine Learning for Building Energy,” *Front. Energy Res.*, vol. 10, Mar. 2022, doi: 10.3389/fenrg.2022.786027.

[18] Mosavi and A. Bahmani, “Energy Consumption Prediction Using Machine Learning; A Review,” Mar. 11, 2019, *Mdpi Ag*. doi: 10.20944/preprints201903.0131.v1.

[19] R. Mathumitha, P. Rathika, and K. Manimala, “Intelligent deep learning techniques for energy consumption forecasting in smart buildings: a review,” *Artif Intell Rev*, vol. 57, no. 2, Feb. 2024, doi: 10.1007/s10462-023-10660-8.

[20] D. Kaur, M. E. Haque, M. A. Mahmud, Z. Y. Dong, and S. N. Islam, “Energy forecasting in smart grid systems: recent advancements in probabilistic deep learning,” *IET Generation Trans & Dist*, vol. 16, no. 22, pp. 4461–4479, Sept. 2022, doi: 10.1049/gtd2.12603.