# Evaluation of Ensemble and Hybrid Models for Predicting Household Energy Consumption: A Comparative Study of Machine Learning Approaches

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**ABSTRACT**
Accurately predicting household energy consumption is critical for efficient energy management, particularly as global energy demands rise. This study explores the predictive performance of various machine learning models, including linear regression, Ridge regression, Lasso regression, Random Forest, Gradient Boosting, XGBoost, CatBoost, and a hybrid model combining Long Short-Term Memory (LSTM) networks with Random Forest regression. The models were evaluated on a dataset consisting of minute-level energy readings over a 350-day period. Key performance metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination ($R^2$) were used to assess model accuracy. The results demonstrate that ensemble models, particularly Random Forest and CatBoost, outperformed traditional regression models in terms of error minimization. CatBoost achieved the lowest MSE among all models, highlighting its effectiveness in handling non-linearities and categorical data. However, none of the models achieved a positive ($R^2$) score, indicating their limitations in fully explaining the variance within the dataset. The hybrid LSTM + Random Forest model, despite its expected strength in capturing temporal dependencies, performed worse than simpler models, suggesting issues with feature extraction and model integration.These findings suggest that while ensemble methods are well-suited for energy consumption prediction, more advanced modeling techniques or enhanced feature engineering are needed to improve performance. Future research could explore deeper neural networks or time-series models such as ARIMA to better capture the temporal patterns in household energy consumption.


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## 1. INTRODUCTION

The growing global demand for energy, coupled with concerns about environmental sustainability, has made energy consumption a critical area of research [1]–[3]. Residential energy usage, in particular, accounts for a significant share of total energy demand, especially in urban areas [4]. As energy consumption continues to rise, managing this demand effectively has become essential for achieving broader energy efficiency goals [5]. In recent years, the deployment of smart meters and home energy management systems has enabled the collection of detailed, real-time energy consumption data [6]. This has opened new possibilities for analyzing usage patterns and developing predictive models that can help optimize energy use in households [7]. Predictive models that accurately forecast household energy consumption can assist in managing electricity grids more effectively, reducing energy waste, and promoting sustainable living practices [8]. However, forecasting energy consumption is inherently complex due to the wide range of factors that influence it, including weather conditions, solar energy generation, and the usage patterns of individual household appliances [9]. Therefore, it is crucial to develop models that can capture both long-term consumption trends and short-term fluctuations, allowing for more reliable and actionable predictions [10].

Energy consumption forecasting has a long history, with earlier methods relying on statistical models such as Autoregressive Integrated Moving Average (ARIMA) models [11]. While effective for modeling linear relationships, these traditional approaches often struggle with the non-linear and complex interactions that characterize modern energy systems [12]. In response, machine learning models have emerged as a promising alternative, with a particular emphasis on deep learning techniques like Long Short Term Memory (LSTM) networks [13]. LSTM networks have proven to be especially effective in time series forecasting due to their ability to learn long-term dependencies and avoid the vanishing gradient problem, which hinders other types of RNNs. For instance, [14] demonstrated the efficacy of LSTM models in predicting short-term load in residential buildings, outperforming traditional statistical models. Similarly, [15] used LSTM networks to forecast energy consumption in commercial buildings, achieving higher accuracy compared to conventional methods. Despite these successes, LSTM models have limitations, particularly when it comes to handling highly variable or noisy data. Ensemble methods like Random Forests, on the other hand, excel at mitigating overfitting and improving model robustness. [16] proposed a hybrid model combining LSTM with Random Forest for energy forecasting, which significantly improved predictive performance compared to standalone models. This suggests that hybrid approaches, which integrate deep learning with traditional machine learning techniques, could offer more accurate and generalizable models for energy consumption forecasting.

As the global population continues to urbanize, the demand for energy is expected to increase significantly [17]. This rise in energy consumption poses several challenges, including strain on energy infrastructure, increased operational costs, and the environmental impact of higher carbon emissions. To address these issues, it is critical to improve energy efficiency, particularly in the residential sector where energy demand is diverse and unpredictable [18]. Accurate energy consumption forecasts can play a vital role in optimizing energy distribution, reducing operational inefficiencies, and enabling demand-response strategies [19]. With the increasing deployment of smart meters in households, there is a growing need for real-time predictive models that can help homeowners and utilities make informed decisions about energy use [20]. Predictive models that fail to accurately capture energy consumption patterns can lead to misallocation of resources, increased energy costs, and unnecessary stress on the energy grid [21]. Therefore, developing accurate and reliable forecasting models for household energy consumption is of utmost importance in achieving sustainability goals.

The current state of research in energy consumption forecasting has evolved significantly with the rise of machine learning and deep learning techniques [13]. Traditional statistical methods, such as ARIMA and exponential smoothing, have been largely supplanted by machine learning models that can handle the complex and non-linear relationships present in energy data [22]. Among these, LSTM networks have emerged as one of the leading methods for time series forecasting, due to their ability to capture both long-term trends and short-term variations in energy consumption [23]. However, LSTM models alone may struggle with certain types of data, particularly when the data is highly variable or affected by external factors such as weather conditions [24]. In such cases, combining LSTM with more robust machine learning models like Random Forest can help improve the model's accuracy and generalizability [25]. Hybrid models that integrate deep learning and ensemble techniques have shown significant promise in recent studies, offering improved predictive performance over standalone models [26]. Despite these advancements, there remains a gap in the application of hybrid models to household-level energy consumption forecasting. While LSTM and Random Forest models have been used in commercial and industrial settings, their application in residential energy forecasting is still relatively unexplored [27]. This study aims to address this gap by developing and testing a hybrid LSTM-Random Forest model specifically for household energy consumption prediction.

The goal of this research is to develop a hybrid machine learning model that can accurately forecast household energy consumption using a combination of LSTM and Random Forest techniques. LSTM networks will be used to extract temporal features from the time series data, while Random Forest will be used to make predictions based on these features. By leveraging the strengths of both models, we aim to improve the accuracy of short-term and long-term energy consumption forecasts. This study uses real-world energy consumption data collected over a period of 350 days, with 1-minute resolution data for various household appliances such as dishwashers, furnaces, and refrigerators and can be downloaded from [28]. The model's performance is evaluated using standard metrics like mean absolute error (MAE), root mean squared error (RMSE), and R-squared ($R^2$) score. Our goal is to minimize prediction errors and develop a model that generalizes well across different household usage patterns.

The remainder of this article is organized as follows. The Methodology section outlines the dataset and the preprocessing steps involved in preparing the data for modeling. It also describes the architecture of the LSTM-Random Forest hybrid model and the evaluation metrics used to assess its performance. The Results and Discussion section presents the outcomes of the model's predictions and provides an analysis of the factors influencing household energy consumption. Finally, the Conclusion summarizes the key findings of the study and discusses the implications of this research for future work in energy forecasting.

## 2. MATERIAL AND METHOD

This research adopts a structured methodological approach to predict household energy consumption using a hybrid model that integrates Long Short-Term Memory (LSTM) networks and Random Forest Regression. The methodology encompasses data acquisition, preprocessing, model development, feature extraction, and model evaluation. Each step is rigorously explained with mathematical formulations to enhance clarity and precision.

### 2.1. Data Acquisition

The dataset utilized in this research was collected from a smart meter installed in a residential household over a span of 350 consecutive days, with minute-level readings. The dataset includes various energy consumption metrics such as overall house energy consumption, specific appliance-level consumption, and energy generated from renewable sources. Let $(D = \{d_1, d_2, \ldots, d_N\})$ represent the dataset, where each observation $(d_i)$ consists of multiple features such as $d_i = \{\text{time,use [kW],gen [kW],House overall [kW]}, \ldots\}$. The primary target variable is the "House overall [kW]" value, denoted as $(y_i)$, representing the total energy consumed by the household at time $( i )$. The dataset is resampled to daily intervals, computing the daily energy consumption by averaging the minute-level readings $y_{\text{daily}} = \frac{1}{1440}\sum_{i=1}^{1440} y_i$ where 1440 represents the total number of minutes in a day. Furthermore, the data is normalized using Min-Max scaling to ensure consistency during model training. The normalization for each data point $(y_i)$. Next, time series sequences are created for the LSTM model, where each sequence represents the previous $( T )$ days of energy consumption $X_i = [y_{i-T}, y_{i-T+1}, \ldots, y_{i-1}]$. The corresponding output value is $y_i = y_i'$. The preprocessing steps employed in this study aimed to prepare the dataset for optimal performance of the machine learning models by ensuring consistency, accuracy, and relevance. Initially, missing values in the dataset were imputed using linear interpolation, which is particularly suitable for time-series data as it estimates missing values based on the continuity of data points. This approach ensures that the temporal structure of the data remains intact.

### 2.2. LSTM and Random Forest Model Design

The selection of models and meta-model combinations was guided by the need to balance temporal feature extraction and robust regression capabilities. Preliminary experiments highlighted the individual strengths of LSTM and Random Forest models. LSTM excelled at capturing sequential patterns and long-term dependencies, while Random Forest demonstrated robustness against overfitting and adaptability to complex interactions. The hybrid model combining LSTM with Random Forest was chosen to leverage these complementary strengths. LSTM served as the feature extractor, summarizing temporal dynamics into fixed-size vectors, which were then used as inputs for Random Forest. While initial standalone experiments with LSTM and Random Forest produced moderate performance, their combination showed promise in improving predictive accuracy. Figure 2 showcases a comparison of model performances during the preliminary experimentation phase, reinforcing the rationale for the hybrid approach.

The LSTM model captures temporal dependencies through its memory cell structure. At each time step $( t )$, the LSTM cell processes the input $(x_t)$ and the previous hidden state $(h_{t-1})$. The forget gate is computed as $f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$. The input gate and candidate cell state are calculated as $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$ and $\widetilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$. Then, the final cell state $(C_t)$ and hidden state $(h_t)$ are updated as $C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t$ and $h_t = o_t * \tanh(C_t)$. The LSTM model is trained using the Mean Squared Error (MSE) loss function as computed as $\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \widehat{y}_i)^2$. Once the LSTM model is trained, the hidden state $( h_T )$ is extracted as a feature vector representing the energy consumption patterns over the previous $( T )$ days $H = \{ h_T^i \}_{\{i=1\}}^{\{N\}}$. On the other hand, the Random Forest model predicts the next day's energy consumption by averaging the predictions from multiple decision trees $\widehat{y}_i = \frac{1}{M}\sum_{m=1}^{M} f_m\left(h_T^i\right)$ where $( M )$ is the number of decision trees. Each tree minimizes the Mean Squared Error (MSE) $\mathcal{L}_{\text{te}}(f_m) = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - f_m\left(h_T^i\right)\right)^2$. Finally, the hybrid model is evaluated using Mean Squared Error (MSE), Mean

Absolute Error (MAE), and the coefficient of determination ($R^2$) as computed as $\text{MSE} = \frac{1}{N_{\text{test}}}\sum_{i=1}^{N_{\text{test}}}(y_i - \widehat{y_i})^2$, $\text{MAE} = \frac{1}{N_{\text{test}}}\sum_{i=1}^{N_{\text{test}}}|y_i - \widehat{y_i}|$, $R^2 = 1 - \frac{\sum_{i=1}^{N_{\text{test}}}(y_i-\widehat{y_i})^2}{\sum_{i=1}^{N_{\text{test}}}(y_i-\bar{y})^2}$.

Furthermore, hyperparameter optimization played a crucial role in enhancing model performance. A grid search strategy was employed for the ensemble models, exploring ranges of critical hyperparameters such as the number of trees, learning rates, and maximum depth. For instance, the Random Forest model was optimized by varying the number of trees between 50 and 500 and testing maximum depths ranging from 10 to 50. For gradient-boosting models like XGBoost and CatBoost, Bayesian optimization was preferred over grid search due to its efficiency in high-dimensional spaces. The optimization targeted learning rates (0.01–0.1), maximum depths (3–12), and the number of boosting rounds (50–300). The hybrid LSTM-Random Forest model underwent a two-step tuning process: first, the LSTM's architecture was optimized (hidden layers: 1–3, neurons: 32–128, and dropout rates: 0.2–0.5), followed by tuning the Random Forest parameters based on the extracted features.

## 3. RESULTS AND ANALYSIS

### 3.1 Result Discussion

This section presents a detailed analysis of the performance of several regression models for predicting household energy consumption. The models assessed include linear regression, Ridge regression, Lasso regression, Random Forest, Gradient Boosting, XGBoost, CatBoost, and a hybrid model that combines Long Short-Term Memory (LSTM) networks with Random Forest regression. The evaluation is based on key metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination ($R^2$) as presented in the figure 1-3 respectively. The linear regression model performed poorly, as indicated by a high MSE of 0.2022 and a substantial MAE of 0.2950. The negative $R^2$ value of -2.9206 suggests that the model is not able to capture the variability in the dataset, performing worse than a simple mean-based prediction. This result highlights the limitations of linear models when dealing with complex and non-linear datasets like energy consumption data, where temporal dependencies and other non-linear factors likely play a significant role. The poor performance underscores the linearity assumption's inadequacy in this context, making linear regression unsuitable for this prediction task.

Ridge regression, which incorporates L2-norm regularization to reduce overfitting, showed a noticeable improvement in performance compared to the standard linear regression model. The MSE dropped to 0.0765, and the MAE decreased to 0.1921, but the $R^2$ value remained negative at -0.4843. This suggests that, while regularization helps to reduce the prediction error, the model still fails to explain the underlying patterns in the data effectively. The improvement over linear regression can be attributed to the regularization term penalizing large coefficients, which mitigates some of the overfitting. However, the results still indicate that Ridge regression, despite its improvements, cannot adequately model the non-linear relationships present in the dataset. Lasso regression, which applies L1-norm regularization, resulted in a further reduction in MSE to 0.0633, although the MAE increased slightly to 0.2114. The $R^2$ score of -0.2269 indicates that the model still underperforms in terms of explaining the variance in the data. The key advantage of Lasso over Ridge regression is its ability to perform feature selection by shrinking some coefficients to zero, thereby simplifying the model. However, even with this simplification, the negative $R^2$ score highlights the model's struggle to capture the complex non-linearities in the dataset. This suggests that, while regularization methods like Ridge and Lasso can mitigate overfitting, they are not sufficient for this type of data, where non-linear and temporal dependencies are prevalent. MSE Comparison of Machine Learning Models can view figure 1.

The Random Forest model exhibited a significant improvement in predictive performance compared to the linear and regularized regression models. With an MSE of 0.0600 and an MAE of 0.1682, the Random Forest model benefits from its ability to capture non-linear relationships by constructing multiple decision trees and averaging their predictions. Although the $R^2$ score remained negative at -0.1645, the improvement in MSE and MAE demonstrates that Random Forest is better suited to this dataset than linear methods. The ensemble nature of the Random Forest model, which reduces variance by aggregating the outputs of several decision trees, allows it to model more complex interactions between features. However, the negative $R^2$ still indicates that the model's performance is suboptimal, possibly due to the inherent noise in the data or the limitations of decision trees in capturing long-term temporal dependencies.

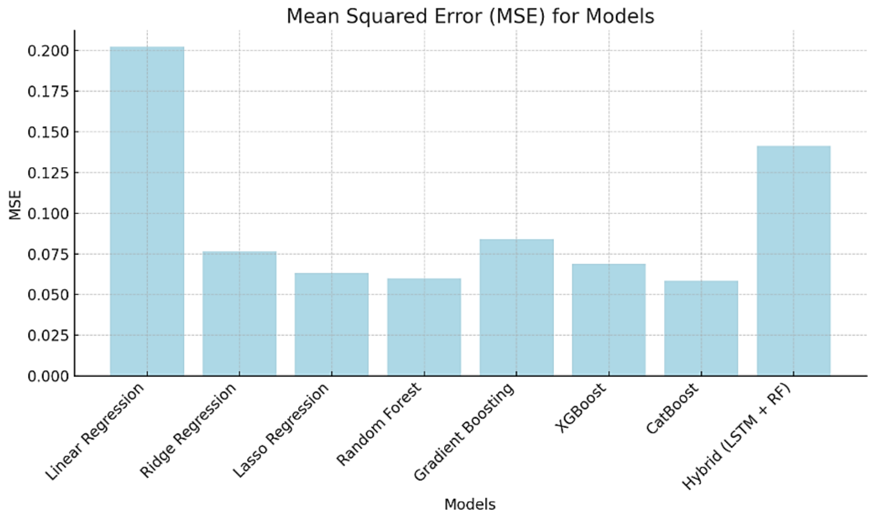


**Figure 1.** MSE Comparison of Machine Learning Models

The Gradient Boosting model did not perform as well as Random Forest, yielding an MSE of 0.0841 and an MAE of 0.1885. The $R^2$ score of -0.6304 indicates that Gradient Boosting struggles more to generalize to the data compared to Random Forest. Gradient Boosting builds trees sequentially, with each new tree attempting to correct the errors of the previous one. However, the model may have overfitted to the training data, as evidenced by the relatively poor performance on the test set. One possible explanation for this is the sensitivity of Gradient Boosting to hyperparameters, such as the learning rate and the number of trees, which may not have been optimally tuned in this case. Additionally, Gradient Boosting can struggle with noisy data, which might explain its higher error rates compared to Random Forest. XGBoost, an optimized version of Gradient Boosting, showed an improvement over its predecessor with an MSE of 0.0690 and an MAE of 0.1805. However, the $R^2$ score remained negative at -0.3384, indicating that while XGBoost performs better than Gradient Boosting, it still fails to capture the complexity of the data fully. XGBoost's enhancements, such as its use of regularization to prevent overfitting and its ability to handle missing data, contribute to its improved performance. However, the negative $R^2$ suggests that more advanced feature engineering or temporal modeling techniques may be necessary to further enhance the model's predictive accuracy. Despite XGBoost's popularity for regression tasks, its performance in this case highlights the challenges posed by the specific nature of this dataset, which likely contains intricate temporal patterns that the model is not fully able to capture. MAE Comparison of Machine Learning Models and R^2 Comparison of Machine Learning Models can view figure 2 and figure 3.

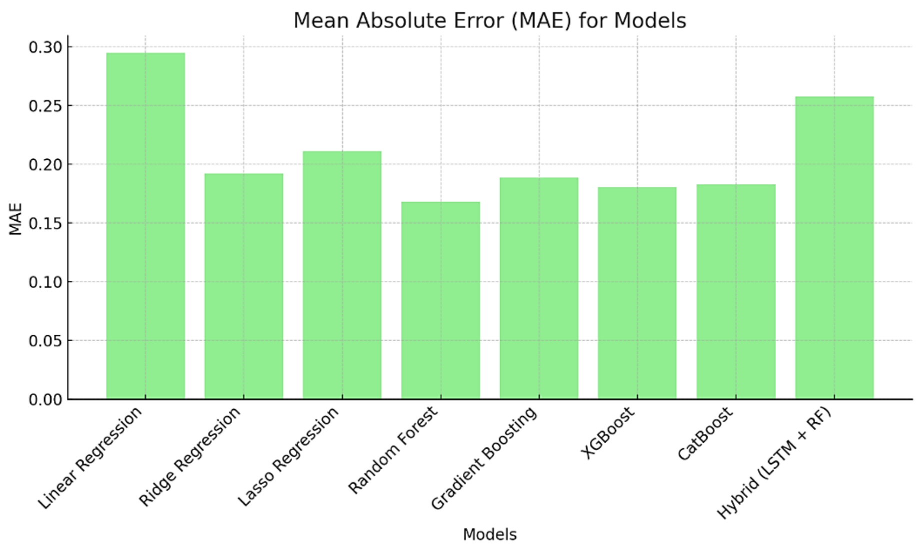


**Figure 2.** MAE Comparison of Machine Learning Models

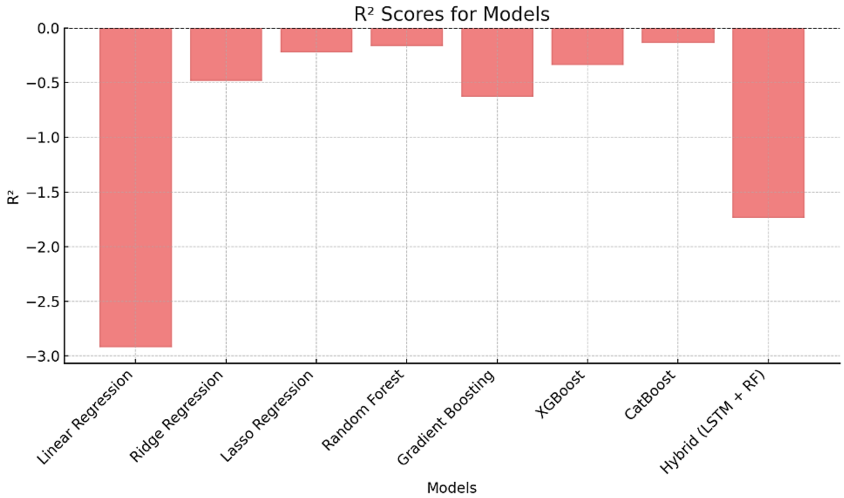


**Figure 3.** $R^2$ Comparison of Machine Learning Models

CatBoost, another gradient-boosting algorithm optimized for categorical features, outperformed both Gradient Boosting and XGBoost in terms of MSE, achieving a value of 0.0586. The MAE for CatBoost was 0.1830, slightly higher than that of Random Forest, but the model's overall performance is superior in terms of error minimization. The $R^2$ score of -0.1371, while still negative, is the least negative among the ensemble models, indicating that CatBoost captures more variance in the data than the other models. CatBoost's ability to efficiently handle categorical variables and its use of ordered boosting, which reduces overfitting, likely contributed to its superior performance. However, the fact that the $R^2$ score is still negative suggests that there are limitations to what boosting methods can achieve with this dataset. The failure to achieve a positive $R^2$ value indicates that even the most advanced boosting models struggle to fully explain the data's complexity, likely due to the presence of long-term dependencies that are not easily captured by these models.

The hybrid model, combining LSTM and Random Forest, performed worse than expected. The MSE of 0.1412 and MAE of 0.2578 indicate that the hybrid approach did not improve prediction accuracy compared to the simpler models. The highly negative $R^2$ score of -1.7391 suggests that the hybrid model failed to capture the patterns in the data effectively. LSTM is designed to capture temporal dependencies in sequential data, which should have been advantageous for this time-series task. However, in this case, the feature extraction from LSTM may not have been sufficiently informative or may have introduced noise that negatively impacted the performance of the Random Forest model. The combination of these two models, which are both powerful individually, may not have been synergistic due to improper tuning or issues in the feature extraction process. Additionally, the high complexity of the hybrid model could have led to overfitting, especially if the LSTM component failed to generalize well to unseen data.

**Table 1.** The Performance of Machine Learning Models

| Model | MSE | MAE | $R^2$ |
|---|---|---|---|
| Linear Regression | 0.20216862012614534 | 0.2950177504247536 | -2.920.555 |
| Ridge Regression | 0.07654014595541446 | 0.1920687323023098 | -0.4843048 |
| Lasso Regression | 0.06326449564539213 | 0.21140984433244656 | -0.226856 |
| Random Forest | 0.06004752773825827 | 0.16816828258703692 | -0.164471 |
| Gradient Boosting | 0.08407317596929552 | 0.18846674316965906 | -0.630389 |
| XGBoost | 0.06901520425444 | 0.18047730509070126 | -0.338377 |
| CatBoost | 0.05863519998110511 | 0.18302092656941996 | -0.137083 |
| Hybrid (LSTM + Random Forest) | 0.14124454723586197 | 0.25783152016106997 | -1.739.085 |

### 3.2 Practical Implication

The findings of this study have significant practical applications in various domains, particularly in energy management and sustainability. One of the primary implementations is the integration of the predictive models into smart home systems. By embedding the Random Forest and CatBoost models into smart thermostats and energy monitors, households can optimize energy consumption, reduce utility costs, and minimize environmental impacts. For instance, these systems can predict peak usage periods and automatically adjust appliance schedules to avoid high energy costs during peak times. Such automation not only improves energy efficiency but also enhances user convenience. Utility companies can benefit from the predictive capabilities of these models by incorporating them into demand response programs. The ability to forecast household energy consumption enables utilities to incentivize off-peak energy use, thereby balancing grid loads and reducing the risk of outages. This approach aligns with broader efforts to transition toward more efficient and resilient energy systems. Additionally, the hybrid LSTM and Random Forest model, despite its current limitations, can be employed in real-time monitoring systems to analyze temporal energy usage patterns. This application can identify anomalies or unusual consumption spikes, which may indicate malfunctioning appliances or inefficiencies, allowing homeowners to take corrective actions promptly.

The study also has potential applications in renewable energy management. Predictive insights from the models can assist in aligning energy demand with renewable energy generation, such as solar or wind power. For example, the system could forecast high-demand periods and ensure that energy storage systems or renewable sources are optimally utilized during these times, enhancing the overall efficiency of energy distribution. Furthermore, policymakers and planners can leverage these models to develop strategies that promote energy efficiency at the household level. Insights into model performance and limitations provide a strong foundation for investing in advanced energy infrastructure, such as smart grids and distributed energy resources. Beyond residential applications, the scalability of these models makes them suitable for larger-scale energy management in commercial and industrial settings. With retraining and data customization, these algorithms can optimize energy use in businesses, helping reduce operational costs and support corporate sustainability initiatives. Moreover, the research findings can serve as an educational resource, raising public awareness about the importance of energy efficiency and sustainability. Universities and training programs can integrate this work into their curriculum to teach students about the practical applications of machine learning in addressing global challenges.

## 4. CONCLUSION

This study aimed to evaluate various regression models for predicting household energy consumption using a dataset containing minute-level energy readings. The models tested included traditional linear regression, regularized regression (Ridge and Lasso), ensemble methods (Random Forest, Gradient Boosting, XGBoost, and CatBoost), and a hybrid model that combined LSTM networks with Random Forest regression. The performance of these models was assessed using Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination ($R^2$). The results indicate that ensemble methods, particularly Random Forest and CatBoost, outperformed traditional linear models and regularized regression models. The Random Forest model exhibited a strong capacity to capture non-linear patterns in the data, while CatBoost, which is specifically designed for handling categorical data, achieved the lowest MSE among all models. However, despite the improvements offered by these methods, none of the models achieved a positive ($R^2$) score, which suggests that the models were unable to fully explain the variance in the dataset.

The hybrid model, combining LSTM and Random Forest, was expected to leverage LSTM's strength in capturing long-term temporal dependencies and Random Forest's robust regression capabilities. However, the hybrid approach underperformed, yielding higher MSE and MAE values than most models. This outcome suggests that either the feature extraction from LSTM was suboptimal or that the combination of these two models did not lead to the expected synergistic effects. In conclusion, while ensemble methods such as Random Forest and CatBoost demonstrated the best overall performance, none of the models could fully capture the complexity of the energy consumption data, as evidenced by the negative ($R^2$) values. This suggests that future research should explore more sophisticated techniques, such as advanced feature engineering, autoregressive models (e.g., ARIMA), or deeper neural network architectures, to better handle the temporal and non-linear nature of the dataset. Improvements in model tuning, feature extraction, and preprocessing are also essential to achieving higher predictive accuracy and better performance in explaining the variance in household energy consumption.

## REFERENCES

[1] A. Q. Al-Shetwi, “Sustainable development of renewable energy integrated power sector: Trends, environmental impacts, and recent challenges,” Sci. Total Environ., vol. 822, p. 153645, 2022.
[2] C. Magazzino, P. Toma, G. Fusco, D. Valente, and I. Petrosillo, “Renewable energy consumption, environmental degradation and economic growth: the greener the richer?,” Ecol. Indic., vol. 139, p. 108912, 2022.
[3] D. Kirikkaleli and T. S. Adebayo, “Do renewable energy consumption and financial development matter for environmental sustainability? New global evidence,” Sustain. Dev., vol. 29, no. 4, pp. 583–594, 2021.
[4] S. Wang, S. Sun, E. Zhao, and S. Wang, “Urban and rural differences with regional assessment of household energy consumption in China,” Energy, vol. 232, p. 121091, 2021.
[5] C. W. Gellings, The smart grid: enabling energy efficiency and demand response. River Publishers, 2020.
[6] D. B. Avancini, J. J. P. C. Rodrigues, R. A. L. Rabêlo, A. K. Das, S. Kozlov, and P. Solic, “A new IoT-based smart energy meter for smart grids,” Int. J. Energy Res., vol. 45, no. 1, pp. 189–202, 2021.
[7] A. A. A. Gassar and S. H. Cha, “Energy prediction techniques for large-scale buildings towards a sustainable built environment: A review,” Energy Build., vol. 224, p. 110238, 2020.
[8] R. Liaqat, I. A. Sajjad, M. Waseem, and H. H. Alhelou, “Appliance level energy characterization of residential

electricity demand: prospects, challenges and recommendations," Ieee Access, vol. 9, pp. 148676–148697, 2021.

[9] D. Yang et al., "A review of solar forecasting, its dependence on atmospheric sciences and implications for grid integration: Towards carbon neutrality," Renew. Sustain. Energy Rev., vol. 161, p. 112348, 2022.

[10] H. Hampton and A. Foley, "A review of current analytical methods, modelling tools and development frameworks applicable for future retail electricity market design," Energy, vol. 260, p. 124861, 2022.

[11] F. Kaytez, "A hybrid approach based on autoregressive integrated moving average and least-square support vector machine for long-term forecasting of net electricity consumption," Energy, vol. 197, p. 117200, 2020.

[12] S. Razavi et al., "The future of sensitivity analysis: an essential discipline for systems modeling and policy support," Environ. Model. \& Softw., vol. 137, p. 104954, 2021.

[13] M. M. Forootan, I. Larki, R. Zahedi, and A. Ahmadi, "Machine learning and deep learning in energy systems: A review," Sustainability, vol. 14, no. 8, p. 4832, 2022.

[14] D. G. da Silva and A. A. de Moura Meneses, "Comparing Long Short-Term Memory (LSTM) and bidirectional LSTM deep neural networks for power consumption prediction," Energy Reports, vol. 10, pp. 3315–3334, 2023.

[15] N. Jin et al., "Highly accurate energy consumption forecasting model based on parallel LSTM neural networks," Adv. Eng. Informatics, vol. 51, p. 101442, 2022.

[16] M. Alizamir et al., "Improving the accuracy of daily solar radiation prediction by climatic data using an efficient hybrid deep learning model: Long short-term memory (LSTM) network coupled with wavelet transform," Eng. Appl. Artif. Intell., vol. 123, p. 106199, 2023.

[17] E. Rehman and S. Rehman, "Modeling the nexus between carbon emissions, urbanization, population growth, energy consumption, and economic development in Asia: Evidence from grey relational analysis," Energy Reports, vol. 8, pp. 5430–5442, 2022.

[18] L.-G. Giraudet, "Energy efficiency as a credence good: A review of informational barriers to energy savings in the building sector," Energy Econ., vol. 87, p. 104698, 2020.

[19] M. Y. Erten and N. \.Inanç, "Forecasting Electricity Consumption for Accurate Energy Management in Commercial Buildings With Deep Learning Models to Facilitate Demand Response Programs," Electr. Power Components Syst., vol. 52, no. 9, pp. 1636–1651, 2024.

[20] L. Ardito, "Behavioural Modelling for Sustainability in Smart Homes," in Proceedings of the 19th International Conference on Availability, Reliability and Security, 2024, pp. 1–11.

[21] G. T. S. Ho, S.-K. Choy, P. H. Tong, and V. Tang, "A forecasting analytics model for assessing forecast error in e-fulfilment performance," Ind. Manag. \& Data Syst., vol. 122, no. 11, pp. 2583–2608, 2022.

[22] T. Ahmad and H. Chen, "A review on machine learning forecasting growth trends and their real-time applications in different energy systems," Sustain. Cities Soc., vol. 54, p. 102010, 2020.

[23] D. Durand, J. Aguilar, and M. D. R-Moreno, "An analysis of the energy consumption forecasting problem in smart buildings using LSTM," Sustainability, vol. 14, no. 20, p. 13358, 2022.

[24] T. Lees et al., "Benchmarking Data-Driven Rainfall-Runoff Models in Great Britain: A comparison of LSTM-based models with four lumped conceptual models," Hydrol. Earth Syst. Sci., vol. 25, no. 10, 2021.

[25] M. Zolfaghari and M. R. Golabi, "Modeling and predicting the electricity production in hydropower using conjunction of wavelet transform, long short-term memory and random forest models," Renew. Energy, vol. 170, pp. 1367–1381, 2021.

[26] D. K. Roy, S. K. Biswas, M. P. Haque, C. R. Paul, T. H. Munmun, and B. Datta, "Multiscale groundwater level forecasts with multi-model ensemble approaches: Combining machine learning models using decision theories and Bayesian model averaging," Groundw. Sustain. Dev., p. 101347, 2024.

[27] S. Aslam, H. Herodotou, S. M. Mohsin, N. Javaid, N. Ashraf, and S. Aslam, "A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids," Renew. Sustain. Energy Rev., vol. 144, p. 110992, 2021.

[28] T. V. Singh, "Smart Home Dataset with Weather Information." 2021.

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