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Research Paper

Smart buildings: Federated learning-driven secure, transparent and smart energy management system using XAI

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ABSTRACT

In modern smart grids and decentralized systems, smart buildings face several key energy management challenges, including data privacy concerns, the need for accurate real-time decisions, the complexity of managing Distributed Energy Resources (DERs), and the lack of transparency in Artificial Intelligence (AI) systems, which erodes user trust. Traditional energy management systems rely on centralized data gathering and processing, where energy data from various sources is accumulated and processed in one location. While centralization aids in decision-making regarding energy distribution, it also raises concerns about data privacy, cybersecurity, and the opaque nature of AI decisions, all of which undermine user confidence. To address these issues, Federated Learning (FL) and Explainable Artificial Intelligence (XAI) offer promising solutions. FL decentralizes model training, enhancing data privacy and security, while XAI provides clear explanations of AI decisions, fostering user trust. When combined, FL and XAI create a secure, transparent, and interpretable framework for managing energy in smart buildings. This paper proposes an FL-driven XAI model that aims to improve data privacy, accelerate real-time decision-making, enhance efficiency, and increase transparency, thereby building user trust. The proposed model demonstrates superior performance in simulations compared to previously published approaches.

1. Introduction

The enormous development and changes of the Internet of Things (IoT) affected various aspects of urban development including, space and urban planning (Lau et al., 2017), smart transport systems (Heidari et al., 2023; Heidari et al., 2023), weather monitoring (Pradhan et al., 2017), prognosis of health (Cook et al., 2018), and energy forecasting (Qi and Hossain, 2024; Abdel-Basset et al., 2021; Norozpour and Darbandi, 2020). In particular, industrial and commercial sectors are using technologies based on the IoT to raise the efficiency of performing equipment maintenance. The integration of historical IoT sensor data with Machine Learning (ML)/Deep Learning (DL) models allows for the prediction of the internal status or operating and ambient conditions of equipment in the future. Following the prediction outcome, management staff can take the initiative in programming the maintenance task of equipment to minimize downtime expenses.

The energy consumption and carbon emissions related to buildings are excessively high. In 2020, buildings around the world consumed

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36 % of total energy and produced 37 % of total carbon emissions; these two data points are now on the agenda and should fall by 50 % and 45 % respectively by 2030 toward a low-carbon transition (Dean et al., 2016). There has been an uptick in interest in smart buildings in recent years due to the deployment of advanced technologies, such as smart meters, ML, and big data analysis (Kylili and Fokaides, 2015), which facilitate a sustainable, economical, and comfortable use of energy for users. For the above functions to succeed, developing an autonomous building EMS that delivers the best performance in terms of energy consumption, energy expenditure, carbon emission, and user comfort is vital and urgent, thanks to intelligent building energy system scheduling (Mariano-Hernández et al., 2021).

Smart buildings are strong proponents of data gathered by IoT sensors to contribute to diverse positive outcomes, such as saving costs, improving safety and maintenance efficacy, and the preventing of downtime for building equipment. In easy terms, IoT means a network consisting of sensors and other kinds of devices that send and receive data (Mosenia and Jha, 2016), enabling a range of network components to cooperate and share their resources to perform a specific task. IoT helps build interoperable networks in smart buildings by linking different types of sensors and other devices, providing actionable insights through the collection and analysis of substantial amounts of real-time data.

The use of IoT in smart buildings is transforming the way of life by harnessing intelligent devices to oversee and control vital equipment in the buildings while increasing energy and operational efficiency (Khamesi et al., 2020; Ma et al., 2016). In an environment characterized by intelligence, a prime objective is to supply tools to assist building managers and users in making economically viable choices about the use of, say, electrical energy. Commercial buildings account for over 50 % of the global electrical energy consumption, and approximately 45 % of that energy is the result of Heating, Ventilation and Air Conditioning (HVAC) systems (D'Oca et al., 2018).

In the meantime, the information collected through IoT from public spaces may contain hidden details that could be misused to track certain staff if it gets into unauthorized hands. In order to defend against potential privacy threats, it is advisable to implement encryption when collecting and blending data from multiple sources of the IoT. The adoption of these safeguards would create substantial computational overhead since the full dataset from each data source would require encryption before transmission and decryption before learning the models. Also, the enhanced data volume from encryption can cause latency to increase, particularly given the restrictions on internet bandwidth. To address the above challenges, one of the best state-of-the-art approaches is to adopt the FL paradigm. By supporting data-driven decision-making and optimizing resource allocation, AI and ML have transformed the energy management sector. These classical centralized ML approaches, however, can introduce dangers in the area of data privacy and security. In order to meet these challenges, FL has come forward as a decentralized method that permits training of models across distributed networks without putting sensitive data at risk (Ghazal et al., 2024).

A distributed ML paradigm known as FL performs well with multi-source data and respects privacy. Under the FL framework, local data sources operate to train their own local models separately from each other. Until then, the criteria of these local models will be traded and collected across all local data sources to form a global model that includes the wisdom from all local models. Each community data source modifies the settings of its local model based on the global model. This process gets repeated often to enable the sharing of knowledge and better privacy protections among all local data sources via model parameter exchange, bypassing the demand for actual local data combination. The swap of model parameters instead of bulky local data results in a substantial decrease in transmitted data. This has supported the practicality of executing encryption while data is in transit to lower the privacy risk. Therefore, FL can handle alterations in multi-source data as well as attacks against privacy. Though researchers have gradually begun using FL in studies of IoT (Zhang et al., 2022; Nguyen et al., 2021), smart healthcare (Elayan et al., 2021) and smart cities (Pandya et al., 2023).

The integration of XAI becomes crucial after implementing FL for EMS, in order to boost the interpretability and transparency of ML models. FL's ability to efficiently train models across dispersed energy networks while guarding data privacy comes at the cost of models that are often complex and hard to comprehend. This lack of interpretability might impede energy management professionals' willingness to adopt and have trust in these models. Combining XAI with FL enables the explanations of predictions and decisions executed by these elaborate models to be easily comprehensible for people. XAI provides information which makes it easy for stakeholders to understand the 'why' for any result or output from the operational models. This fosters higher confidence in the results obtained from the model and helps outperformance in decision-making by providing consumable insights. When the FL is implemented with the XAI, the foundation for effective, easy-to-understand but highly reliable and up-to-date AI in energy management is formed.

2. Contribution of the proposed methodology

This paper introduces important advancements to overcome the challenges of privacy and transparency in smart building EMS. By leveraging distributed computation and XAI, the proposed model addresses security and user trust concerns. The use of FL and ML techniques provides a balanced approach to secure, decentralized data processing and decision-making transparency.

- **Federated learning:**
  The proposed model utilizes distributed computation for data processing in FL to reduce the vulnerabilities of centralized systems. This enhances data privacy and minimizes the risks of cyber threats, making EMS more secure.
- **Explainable AI (XAI):**

By integrating ML techniques with XAI, the proposed model improves the transparency of the decision-making process. This empowers users to understand the reasoning behind the model's actions, increasing trust and acceptance of EMS decisions.

3. Related work

Numerous papers developed methods for analyzing and predicting energy consumption. The concept of predictive energy analysis plays an essential role in optimizing energy efficiency; it assists the building EMS in making further assessments.

This work Azuatalam et al. (2020) have focused on the issue of improving HVAC systems in commercial buildings for incorporating DR. The objective was to obtain an optimal comfort level for the building occupants while achieving an ostensibly efficient consumption of energy along with an effective DR response. Earlier methods which were based on Reinforcement Learning (RL), probabilistically failed because those models did not account for real building imperfection. This study proposed a new RL architecture enhancing energy efficiency, and thermal comfort, and incorporating DR in its complete form. The RL controller adjusted up to 22 % weekly energy savings and decreased the overall electricity usage by 50 % during DR events without overly compromising comfort. However, it had limitations such as high computational complexity and the inability to generalize from one building and climate to another.

This study Nutakki and Mandava (2023) have also discussed the historical development of optimization techniques for Home EMS (HEMS) in a smart grid where optimization started from mathematical heuristics and advanced towards metaheuristics and AI. Whereas conventional methods were adequate, they failed to incorporate the non-linear constraints and multi-variant problems, which invoked the genetic Meta-heuristic algorithms. However, the following also has the same problem such as; The problem of premature convergence and long optimization time. The study focuses on AI efficiency by optimizing decision-making and pattern recognition by ML and DL. It also indicates that, in future work on Deep RL (DRL), some aspects of HEMS can be enhanced even further.

The study, GK (2020) have introduced a Multi-output Adaptive Neuro-Fuzzy Inference System (MANFIS) tailored for smart home energy management within smart grids. This innovative approach was designed to optimize energy management, focusing on reducing electricity costs and mitigating reverse power flow. The system utilized daily input data, including variables such as temperature, wind speed, solar radiation, and the power usage of both controllable and uncontrollable appliances. By effectively managing the balance between energy production and consumption, the system demonstrated a notable decrease in electricity costs and overall power consumption.

Big data and ML techniques serve to explore different methods for timely savings in smart homes discussed in Machorro-Cano et al. (2020). The research uses the J48 ML algorithm, through the WEKA API, to investigate and learn from user behavior patterns tied to energy consumption. This analysis permits categorizing homes according to their energy consumption. As well, recommendations generated for user preferences utilize the RuleML and Apache Mahout frameworks. This approach demonstrates its effectiveness via a case study that stresses a major decrease in energy consumption.

In Alilou et al. (2021), an innovative strategy for energy management is advanced to address the issues around wind power forecasting uncertainties. This study aspect to minimize electricity costs by finding the best way to schedule the devices in smart homes. To accomplish this, a dragonfly algorithm with multiple objectives is in use, maximizing both technical and economic factors. Post deriving the best Pareto front, an analytical hierarchy process is used to identify the most efficient operational schedule for smart homes. Testing of the proposed method in a sample smart grid reveals that this energy management strategy dramatically increases the performance of the entire grid.

In Atef et al. (2022) have presented a fuzzy logic strategy for optimizing household appliance scheduling while taking both electricity rates and consumption load into consideration. The approach employs a predictive model together with a DR framework to project daily electrical demand. Implementing an LSTM-optimized predictive model enables the system to aggregate data and send it to a DR fuzzy logic controller in an efficient manner. Compared to other baseline models, the LSTM model illustrates improved performance, leading to a considerable drop in electricity costs.

In Jogunola et al. (2022) have introduced DL approaches to predict the energy demands of both residential and commercial buildings. A hybrid framework consisting of a CNN, an autoencoder, and Bidirectional Long Short-Term Memory (BiLSTM) networks is part of the proposed architectural design. The experimental study confirms that the approach improves computation speed, additionally offering strong predictive reliability, which makes it a sound solution for energy consumption forecasting.

A study conducted in Chou et al. (2022) have addressed energy consumption forecasting via advanced decomposition algorithms. Empirical mode decomposition and wavelet transformation in conjunction with LSTM networks are used in the study. The study includes twenty different buildings, distributed across various locations and purposes. Results indicate that the LSTM model in conjunction with empirical mode decomposition achieves superior performance compared to other techniques, showing the greatest accuracy in the prediction of energy consumption.

Mothukuri et al. (2021) have performed a study that points out essential areas of data privacy and security related to FL, revealing multiple topics that need further research. Li et al. investigated the application of FL through an industrial engineering lens as well as a computer science framework (Li et al., 2020; Li et al., 2020). The study examined multiple aspects, including asynchronous training, gradient aggregation, returned model verification, blockchain-based FL, and federated training for unsupervised ML, all of which they identified as important research areas within FL. Moreover, the authors covered prominent challenges and research areas that need attention in forthcoming studies to refine both of these fields.

Li et al. (2021) have introduced a comprehensive taxonomy for FL, categorizing FL systems into six distinct aspects: flavors of data distribution, ML algorithms, privacy implementations, network design, the size of the federation, along the reasons for FL. They analyzed principal design considerations, gave examples, and detailed opportunities for future studies. Likewise, Li et al. (2020), Li et al. (2020) have provided a brief introduction to FL, discussing its issues and providing an overview of the related works. They highlighted several key areas for future research, particularly addressing four main challenges in Federated Learning: improving communication efficiency, managing system heterogeneity, handling statistical inconsistencies, and ensuring privacy.

4. Limitations of the previously published approaches

Smart building energy management faces two major challenges: data privacy and transparency of decision-making. Centralized systems gather data from remote and dispersed distributed energy resources thus posing privacy and security challenges. These systems are prone to cyber threats, including hacking, making them vulnerable to data breaches (GK, 2020, Machorro-Cano et al., 2020). Further, due to the nature of such systems, they are called 'black boxes,' which makes their suggested actions quite opaque, and therefore, decreases the user's trust (Alilou et al., 2021; Atef et al., 2022). Both issues are critical as energy grids transform, and there is more sensitivity to the personal data being collected. The balance of privacy and transparency is now important since the generation of secure energy solutions is imperative (Liu et al., 2020). The EMS often face challenges, such as:

- **Data privacy and security:**
  Centralized EMS in smart buildings face significant data privacy and security risks due to the collection of data from various energy sources (GK, 2020; Machorro-Cano et al., 2020).
- **Transparency (Opaque decision-making):**

Centralized EMS are often labelled as 'black boxes' due to their opaque decision-making processes, which erodes user trust by preventing them from understanding or verifying the system's actions (Alilou et al., 2021; Atef et al., 2022; Liu et al., 2020) (Table 1).

5. Proposed methodology

In the evolving landscape of smart energy management, data privacy and transparency in decision making are critical challenges due to the growing reliance on AI and centralized systems. As energy systems increasingly rely on AI-driven, centralized technologies, concerns about privacy breaches and the lack of transparency in "black box" AI models erode user trust and hinder adoption. Addressing privacy and transparency is crucial for ensuring secure, efficient, and widely accepted sustainable energy management solutions. In this paper, FL is proposed to enhance data privacy by decentralizing data processing, ensuring sensitive information remains local and reducing the risk of breaches. Simultaneously, XAI is integrated to enhance transparency, providing clear and interpretable insights into AI-driven decisions, thereby fostering greater user trust and system adoption.

To address synchronization between local devices and cloud-based AI, the proposed periodic aggregation approach involves regularly uploading local models from each smart home to the cloud. This ensures the learning from every local model is fed into the global model while at

Table 1
Comprehensive overview of various energy management models.

Reference	Model	Learning Manner	Outcome	Limitations	Privacy	Predictive Model	FL	XAI
(GK, 2020)	MANFIS	Centralized	Reduce electricity costs	Renewable energy fluctuations may vary performance	×	√	×	×
(Machorro-Cano et al., 2020)	Big Data and ML	Centralized	Reduces energy consumption	May face compatibility issues	×	√	×	×
(Alilou et al., 2021)	Multi-objective dragonfly algorithm	Centralized	Improve smart grid performance	Increase in wait time	×	√	×	×
(Atef et al., 2022)	Fuzzy Logic and ML	Centralized	Reduction in electricity cost, optimal scheduling	Inaccuracy in results due to assumptions	×	√	×	×
(Jogunola et al., 2022)	CNN, Bi-LSTM, Auto Encoders	Centralized	Improve load distribution, performance, computation time	Trial and Error experiments for selecting optimal hyperparameter values, insufficient data	×	√	×	×
(Chou et al., 2022)	Wavelet Transformation, LSTM	Centralized	Efficient forecasting for real case electricity consumption	Specific forecasting framework, training latkes longer and more memory	×	√	×	×
(Selim et al., 2021)	LR, LDA, KNN, CART, NB, and SVM	Centralized	Successfully detected anomalies	Limited to a specific dataset, lacking adaptability to evolving real-time threats in IIoT	×	√	×	×
(Nguyen et al., 2019)	DL	Centralized	Effectively detects network anomalies	Performance may vary with different datasets	×	√	×	×
(Liu et al., 2020)	CNN and LSTM	Federated	Improve generality in IIoT systems	Limited to the performance on four datasets	√	√	√	×
(Al-Abassi et al., 2020)	DNN and DT	Centralized	Improve the accuracy and reduce false positives	limited to datasets and performance may vary depending on the complexity of evolving data	×	√	×	√
(Saleem et al., 2024)	SVM	Centralized	Enhance data security, transparency, and decision-making	Performance and scalability depend on data quality computational overhead	√	√	×	√
(Hwang and Lee, 2021)	Bi-LSTM	Centralized	Improve accuracy for quick action	Different datasets may face challenges	×	√	×	√

the same time protecting data privacy. In the next iteration, the cloud-based global model aggregates the updates likewise and synchronizes with all local clients to ensure that the system remains up-to-date with the latest information from every local device. The synchronization mechanism is the key factor in enhancing the model's performance and respecting the confidentiality of each user. Fig. 1 shows the abstract view of the local proposed model.

Fig. 1, illustrates the local model flow for the proposed model to predict energy management in smart homes. The model initializes with the collection of input dataset Kaggle (Offmann, 2024) from various smart energy devices within a home. Table 2 shows the features of the dataset.

This collected information about energy control and usage is fed into the preprocessing layer. The preprocessing layer is responsible for cleaning and normalizing using techniques like moving average, normalization, etc. After preprocessing, the data is split into training (70 %) and testing (30 %) datasets. The training dataset is then used to apply multiple ML models as the local clients. These models are trained until the desired learning rate is achieved. If the learning rate is met, the trained patterns are stored in the local server's cloud data storage. If the learning rate is not met, the model is retrained using the local client data.

Once the local models are trained, the models are sent to the global cloud where the aggregation takes place. This allows the global model to

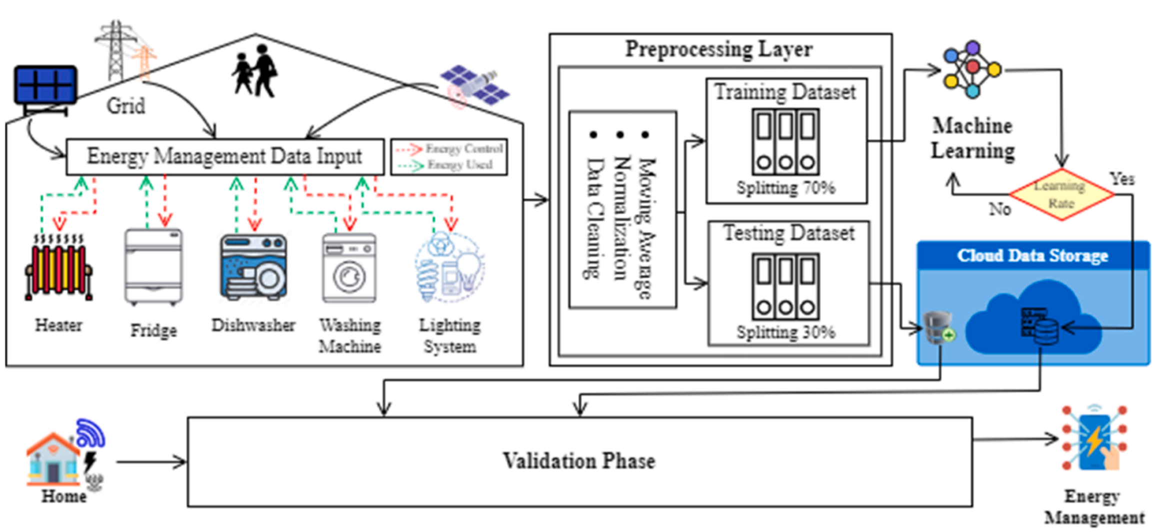

Fig. 1. Proposed model (Local server).

Table 2
Dataset features description Kaggle (Offmann, 2024).

Features	Description
Time	Time
use [kW]	Total energy consumption
gen [kW]	Total energy generated through solar or other power generation resources
House overall [kW]	Overall house energy consumption
Dishwasher [kW]	Energy consumption of a specific appliance
Furnace 1 [kW]	Energy consumption of a specific appliance
Furnace 2 [kW]	Energy consumption of a specific appliance
Home office [kW]	Energy consumption of a specific appliance
Fridge [kW]	Energy consumption of a specific appliance
Wine cellar [kW]	Energy consumption of a specific appliance

receive inputs from all the local models and adjust its decision-making accordingly. Subsequently, the cloud system synchronizes with all local clients in each round of the model update.After this, the validation phase begins, where the testing dataset is used. The trained local model stored on the local client-server is then imported, and it is checked whether the system has successfully detected energy management at the local level in the smart home. Table 2 shows the pseudocode of the proposed model (local server) (Fig. 2 and Table 3).

Fig. 3 illustrates the concept of FL being applied to a dataset Kaggle (Offmann, 2024) of energy management, where local client models from multiple homes are collaboratively used to build a global model on the cloud. The process begins with each home (e.g., Home 1, Home 2, Home 3, and so on) using Internet of Energy Things (IoET) to collect local data through the Data Acquisition Layer. After the data is collected, it is passed through the Preprocessing Layer where it is cleaned and

Table 3
Pseudocode of the proposed model (local server).

Sr. No.	Steps
1	Start
2	Split local data to mini-batches of size S
3	Initialization layer weights m_{ij} & u_{jk}), Error (E)= 0, and the number of epochs $\epsilon = 0$
4	For each training pattern p, do:
5	a. Perform the feedforward phase: Calculate Δ_j using the equation: $\Delta_j = f'(net_j) \times \sum_k w_{jk}\Delta_k$ (Eq. 1) Calculate Δ_j using the equation: $\Delta_k = f'(net_k) \times (target_k - output_k)$ (Eq. 2)
6	b. Calculate the output of errors for signals & hidden layer signals.
7	c. Then update u_{jk} and m_{ij} (error backpropagation) using the equations: $\Delta u_{jk} = \eta \Delta_k y_j$ (Eq. 3) $\Delta m_{ij} = \eta \Delta_j x_i$ (Eq. 4)
8	Increment the epoch count: $\epsilon = \epsilon + 1$
9	Test the ending conditions: if no ending conditions are satisfied, go to step 4.
10	Return optimum local trained model weights m_{ij} and u_{jk} to the server
11	Stop

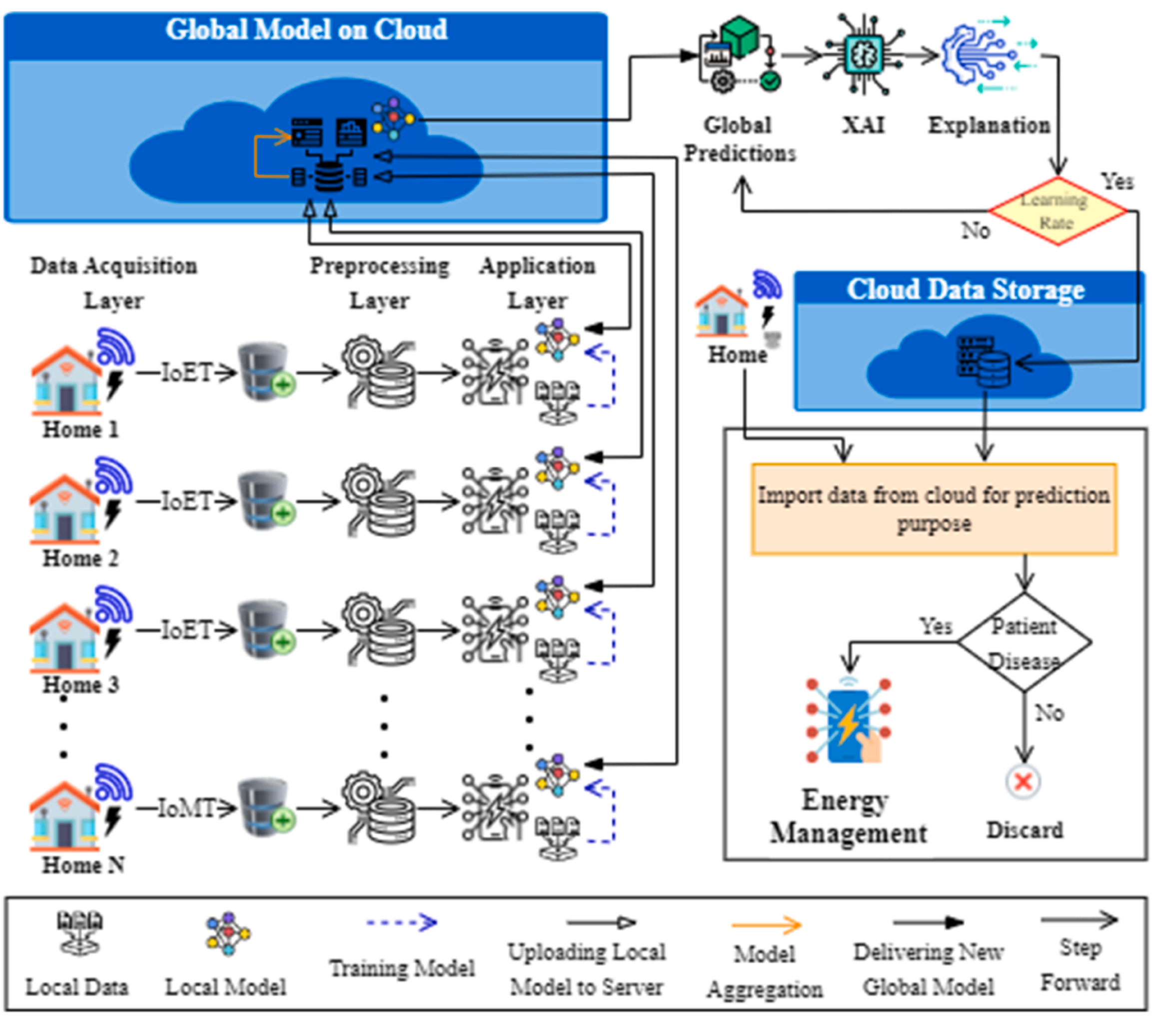

Fig. 2. Proposed FL model for energy management with XAI integration.

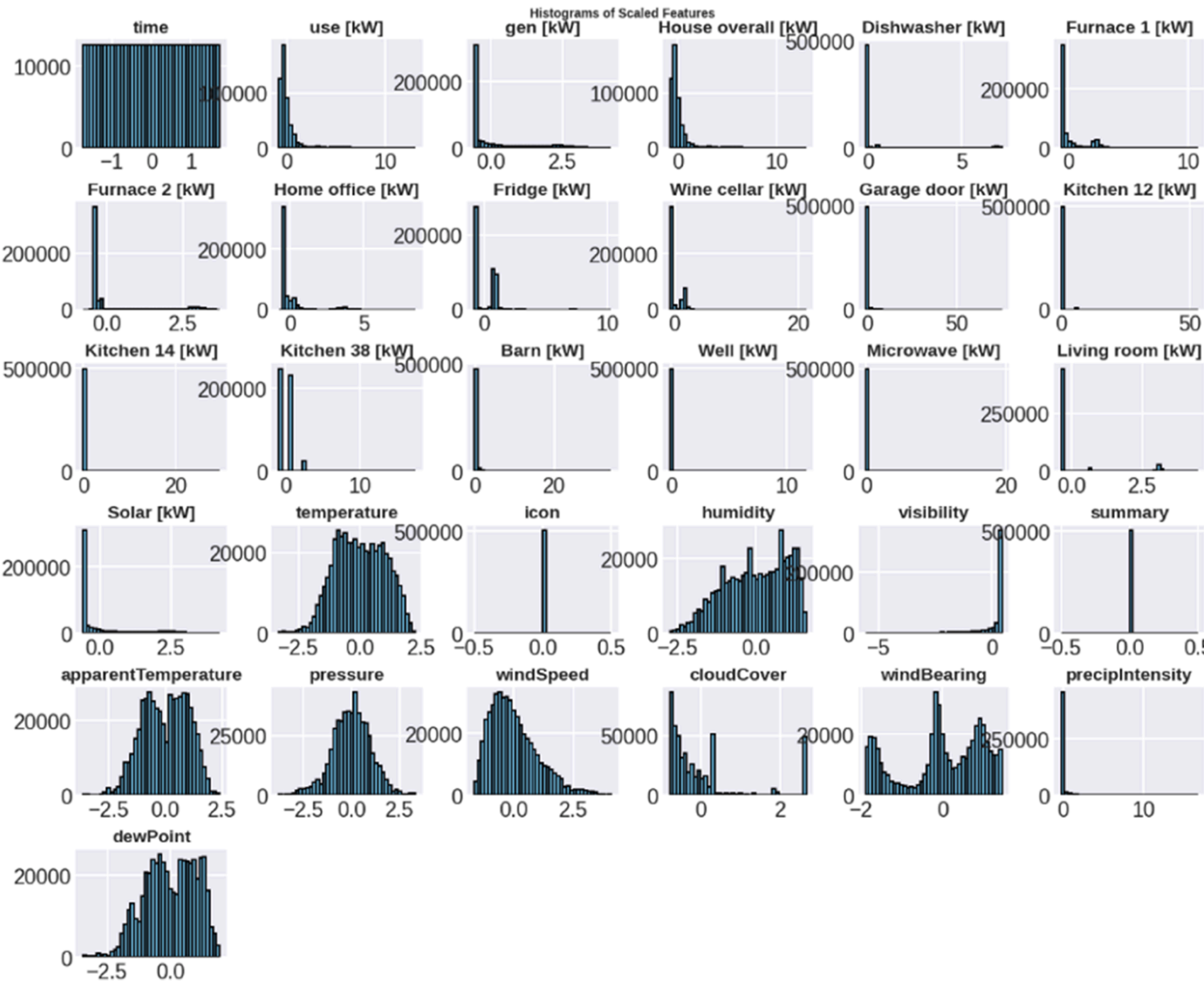

Fig. 3. Histograms of scaled energy usage and environmental features.

prepared. Once pre-processed, the data is used in the application layer to apply local ML models at each home. These local models are then uploaded to the Global Cloud for further processing.

To ensure that the local and global models remain synchronized, the aggregation occurs periodically. This process ensures that updates from the local models are integrated to form a cohesive global model. Each model is tested for performance and if the required learning rate is achieved, the newly developed model replaces it in every local client.

In the Global Cloud, the local client models from different homes are aggregated to form a Global Model. The aggregation process identifies the best-performing model based on local contributions, which is then sent back to all local clients for future iterations of energy management. The pseudocode of the proposed model (global server) is shown in Table 4. The Global Model predictions are passed through an XAI to generate explanations for the decisions made by the global model, enhancing the interpretability.

The global model predictions are passed through a post-hoc explanation framework such as Local Interpretable Model-agnostic Explanations (LIME) or SHapley Additive exPlanations (SHAP). These techniques provide both local and global explanations, respectively, by enhancing the interpretability of complex machine learning models.

LIME provides local explanations by constructing surrogate models to approximate the behavior of the original model around a specific instance. The goal is to minimize the difference between the predictions

Table 4
Pseudocode of the proposed model (global server).

Server Side	
Sr. No.	Steps
1	Start
2	Initialize w_0 & v_0
3	for each cycle k from I to K do
4	Sk (Random set of clients from n)
5	a. for each client $n \in Sk$ (parallel execution): $[w_n, v_n] \leftarrow$ Client Training$(n$, w_k, $v_k)$ end for
6	end for
7	$w_k^{(t+1)} = \frac{1}{\sum_{n=1}^{N} S_n} \sum_{n=1}^{N} S_n w_k^{(t)}$ (Average aggregation of weights)
8	$v_k^{(t+1)} = \frac{1}{\sum_{n=1}^{N} S_n} \sum_{n=1}^{N} S_n v_k^{(t)}$ (Average aggregation of values)
9	end for
10	Stop

of the original model f and the interpretable surrogate model g. This is achieved through the following loss function:

$$\gamma(x) = arg_{g\in G}\min(L(f, g, \pi_x) + \Omega(g)) \quad \text{(Eq. 1)}$$

Where $L(f, g, \pi_x)$ quantifies the discrepancy between the original and surrogate models, and $\Omega(g)$ represents the regularization term to ensure the simplicity of the surrogate model.

SHAP, on the other hand, provides global explanations by calculating the Shapley values, which quantify the contribution of each feature to the model's decision. The Shapley value for the feature x_j is given by:

$$\phi_j(x) = \sum_{s \subseteq \{x_1, x_2, \ldots, x_m\} \{x_j\}} \frac{|s|!(m - |s| - 1)!}{m!} \left(val\left(s \cup \{x_j\}\right) - val(s)\right) \quad \text{(Eq. 2)}$$

Where $\phi_j(x)$ represents the Shapley value for a feature $\boldsymbol{x_j}$, and $val\left(s \cup \{x_j\}\right) - val(s)$ quantifies the incremental value of adding a feature x_j to the subset s.

Additionally, to understand the global impact of features, this proposed model uses the concept of partial dependence, which assesses the effect of a single feature on the predictions while averaging the remaining features. The following partial dependence function captures this:

$$\widehat{f}(x_s) = \frac{1}{n} \sum_{i=1}^{n} f(x_s, x_i^c)) \quad \text{(Eq. 3)}$$

Where $\widehat{f}(x_s)$ is the average prediction over n instances, and x_s represents the feature of interest, while x_i^c represents the complementary features.

These techniques—LIME for local explanations, SHAP for global explanations, and partial dependence for feature-level insights—help ensure that the decision-making process of our machine-learning models is transparent and easily understandable by users and stakeholders.

The global model's performance is checked to see if it meets the required learning rate. If the learning rate is achieved, the model (with its explainable patterns) is stored on the global cloud server. If the learning rate is not met, the global model is retrained.

Finally, during the Validation Phase, the Global Model is imported and tested on the local testing datasets from the smart homes. The global model is then validated to check whether the energy management is found or not. If found the energy management message is displayed else the process is discarded.

6. Simulation results

This paper addresses the critical challenges of data privacy and transparency in AI-driven EMS for ensuring secure, efficient, and reliable operations. To tackle these issues, the proposed model integrates FL and XAI, offering a solution designed to enhance privacy protection and decision-making transparency. This approach was applied to a dataset (Offmann, 2024), with 70 % allocated for training and 30 % reserved for testing, to rigorously assess the model's effectiveness in managing energy while safeguarding privacy and providing clear, interpretable outcomes. The following simulation results illustrate the model's success in addressing these challenges, leading to optimized energy management in smart systems.

Fig. 3 shows histograms for various scaled energy usage features and environmental variables. Each plot displays the distribution of data for a specific variable, such as energy consumption (e.g., "use [kW]," "Furnace 1 [kW]," "Fridge [kW]") or environmental factors (e.g., "temperature," "humidity," "windSpeed"). Most of the energy usage variables appear to be highly skewed with low values, indicating that the majority of the data points fall within a narrow range of energy consumption. On the other hand, environmental factors like temperature, pressure, and wind speed show more normal or uniform distributions, indicating a broader variation in these measurements. This helps in understanding how energy is distributed and consumed across various appliances and environmental conditions.

Fig. 4 represents a correlation heatmap of scaled features, showing the relationships between various energy usage metrics (e.g., "gen [kW]," "Dishwasher [kW]") and environmental factors (e.g., "temperature," "humidity"). The color gradient from blue to red indicates the correlation strength, with red signifying strong positive correlations (closer to +1) and blue indicating strong negative correlations (closer to −1). The diagonal values are self-correlations (always 1). This heatmap visually identifies which features are closely related, aiding in understanding the interplay between energy usage and external conditions, and guiding better energy management strategies.

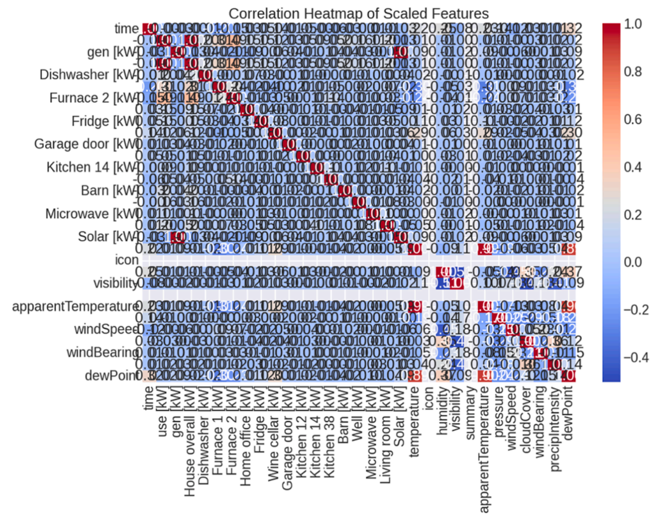

Fig. 4. Correlation heatmap of scaled energy usage and environmental features.

Fig. 5 demonstrates the performance of a Random Forest model in predicting energy consumption for smart home energy management, comparing actual and predicted values for both training (left) and testing (right) datasets. The dashed black line represents the perfect prediction, while the red line shows the model's fit, with the shaded red area indicating the confidence interval. In the training data, the predicted values closely match the actual values, showing a strong fit. In testing data, the prediction is slightly less accurate but still reasonable for the model to be used for predicting energy usage in smart homes to ensure efficiency and effective energy consumption.

In the context of smart home energy management, the residual distribution is depicted in Fig. 6 (on the left side for training data and the right side for testing data). Most residuals lie at the 0 level (represented by the red line), meaning that the actual energy values are close to the values that have been predicted by the model. In the same way in the training data, the residuals are uniformly spread around the zero which indicates a satisfactory fit of the model. In the testing data, there is much more variance meaning higher variability as compared to training data and slightly less accurate results when trying to predict unknown energy consumption. This analysis is significant in enhancing the energy control of smart homes by reducing prediction errors to offer enhanced optimization.

The performance of the Random Forest model in terms of predicting energy consumption for smart home energy management is presented in Fig. 7 and Actual Values v/s RF Regression Line, Training Dataset (left) and Testing Dataset (right). The regression line almost matches the actual values of the training data, meaning that it has had a good fit on the data set, and thus a great confidence is placed on the predictions since the band of standard deviation is quite narrow. For testing data, as in the figure above while the regression line tries to capture the actual values, the shaded area represents larger variability, hence higher uncertainty, in predicting the values for unseen data. In general, the model is suitable for managing energy consumption in smart homes as the model shows excellent results when trained on datasets and provides reasonable accuracy on testing sets, thus allowing minimizing energy waste.

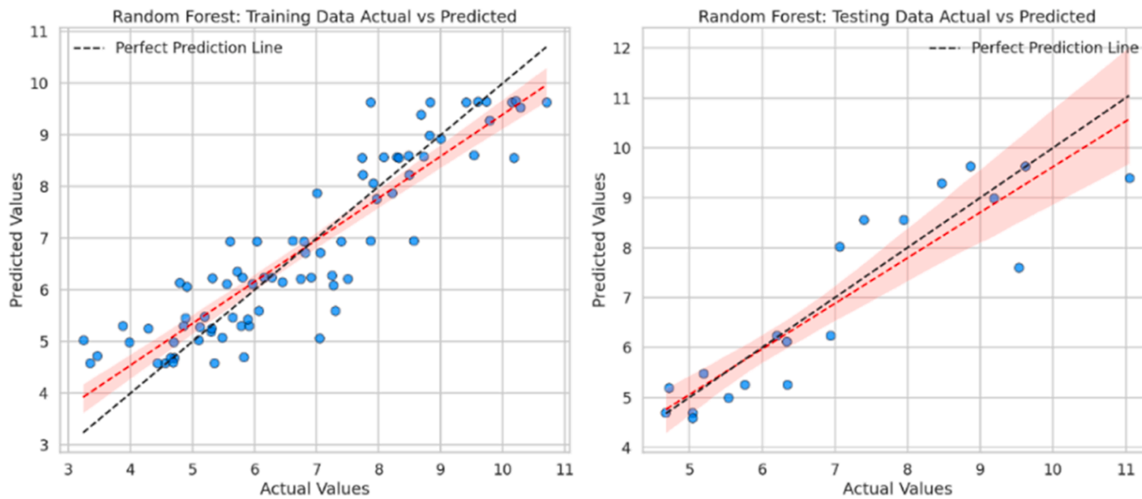

Fig. 5. Random forest model performance on training and testing data (actual vs predicted values).

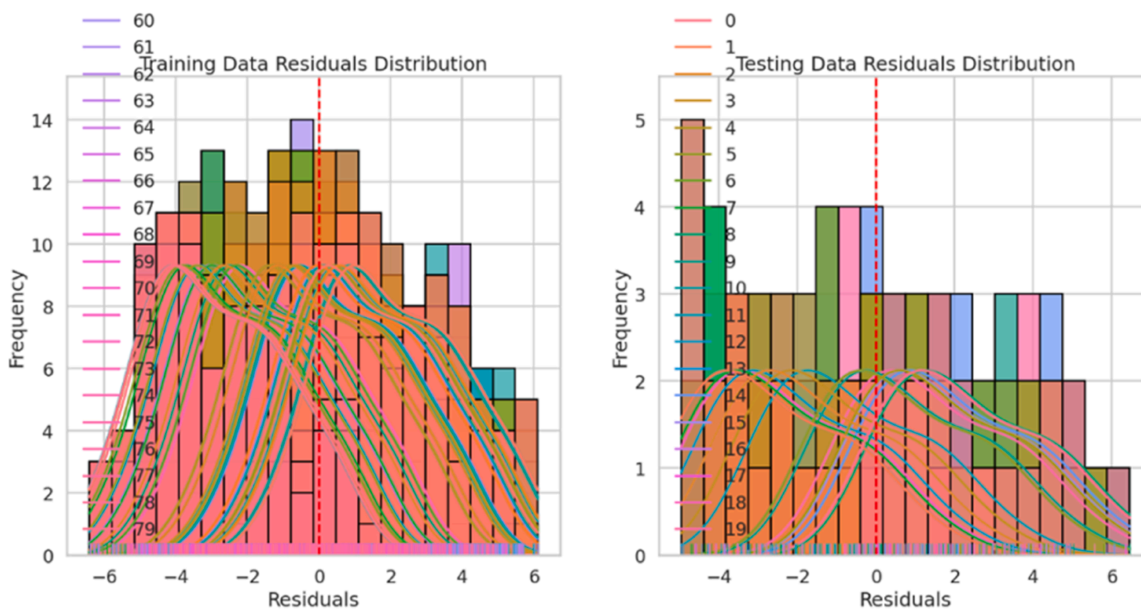

Fig. 6. Residuals distribution for training and testing data using random forest.

In Fig. 8, the left part represents a plot of the training dataset in Gradient Boosting for smart home energy management; This part gives the actual and predicted amount of energy consumed. Observing the training data, it can be seen that the model predicts a similar trend to those observed in the actual data, further establishing the fact that the model learns energy consumption pattern of the smart home correctly. On the testing data there are more scatter points, which means the accuracy of the model is slightly less on unseen data, yet it follows the overall trend. This proves how the model can predict the energy consumption—significant for enhancing the efficiency of smart homes.

The residual plots are shown in Fig. 9 for training (left) and testing (right) datasets in the area of smart home energy management. Residual plots for the training set-up reveal that the residuals have average values of 0, indicating that the model developed estimates energy consumption precisely though with some discrepancies. Similar to the testing data, they exhibit residuals around the zero line but with higher variability, which indicates that the model is not very accurate in predicting new energy consumption profiles. In general, this model is accurate and can be used for energy optimization in smart homes because it minimises errors in the prediction of energy requirements.

The predicted regression line and the actual values of energy consumption for the Gradient Boosting model of smart home energy management are shown in Fig. 10 in the training data set (on the left) and in the testing data set (on the right with the corresponding orange points). The shaded area is for the 1 standard deviation which displays confidence of the model. For the training data, the model captures very accurately the actual energy consumption with minimal error bars, and for the testing data, prediction is equally good but with slightly higher variability. Altogether, the proposed model is helpful for the forecast of energy usage, which is crucial for the efficient regulation of smart homes energy consumption.

An XGBoost model is used for smart home energy consumption prediction and the model performance is displayed in Fig. 11. The plot of the training data (left) displays a good fit between predicted and actual values as most of the points are closely grouped in a region close to the line of perfect prediction, which reveals high model accuracy in training for patterns of energy consumption. The testing data plot (right) also shows that the amount of variability is fairly small, which indicates that while it extrapolates well to new observations, there is a slight increase in error. It especially captures energy usage well, which is pivotal while

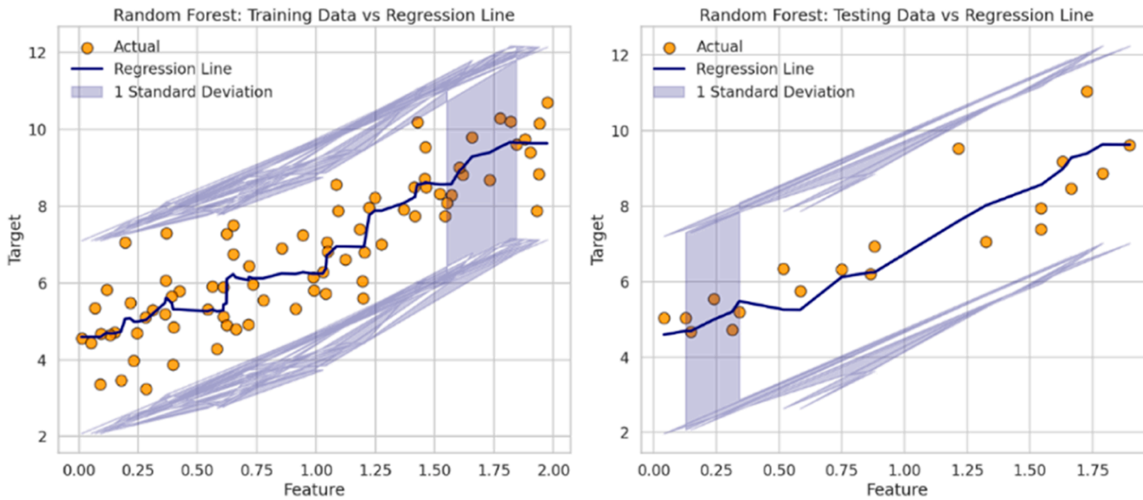

Fig. 7. Random forest model performance on training and testing data with regression line and standard deviation.

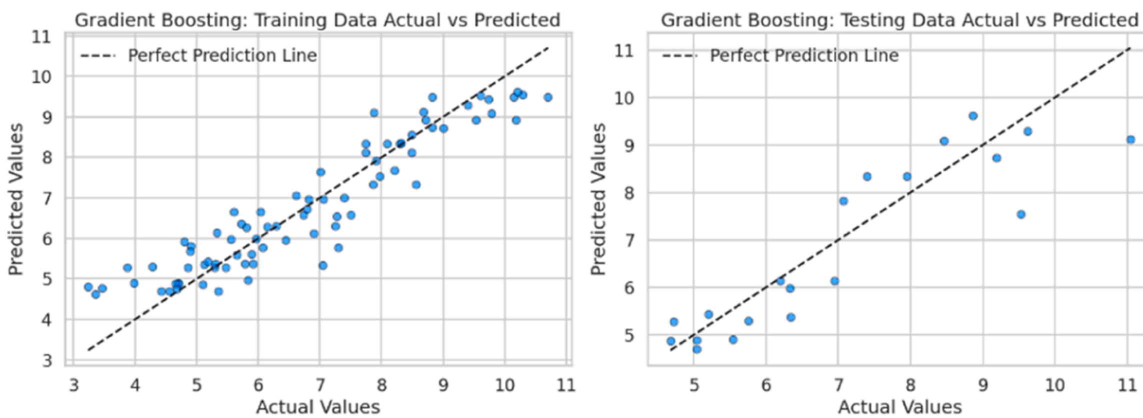

Fig. 8. Gradient boosting model performance on training and testing data (actual vs predicted values).

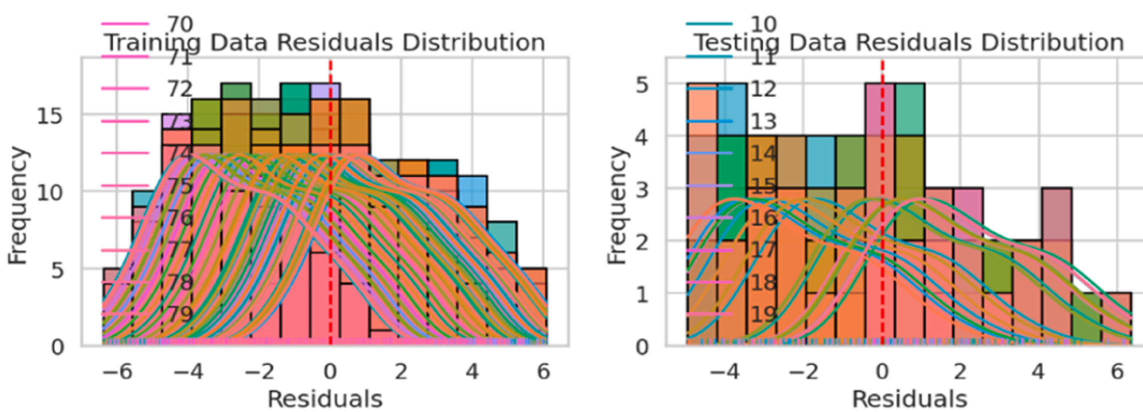

Fig. 9. Residuals distribution for training and testing data using gradient boosting.

managing energy intakes in smart homes for increased efficiency and lower costs.

Fig. 12 presents residual distribution in the context of smart home energy management between training (left) and testing (right) datasets. The residuals which are outcomes from the difference between the actual and predicted energy utilization are slightly shifted from 0's or centered at 0, particularly on the training datasets suggesting the energy usage is well estimated by the model. The values of the testing data residuals are slightly more dispersed, yet they are closer to zero, which means that the model performs well on unseen data. This analysis is very important for better control and decisions related to energy usage in smart homes as the model must provide a correct estimation of energy consumption to minimize costs associated with energy usage.

In Fig. 13, the regression line (blue) in XGBoost for home energy consumption prediction with smart home energy management is depicted, and this is about the training data (left) and testing data (right), and actual values correlated with the orange dots. The shaded area shown above the plotted curve stands for 1 standard deviation,

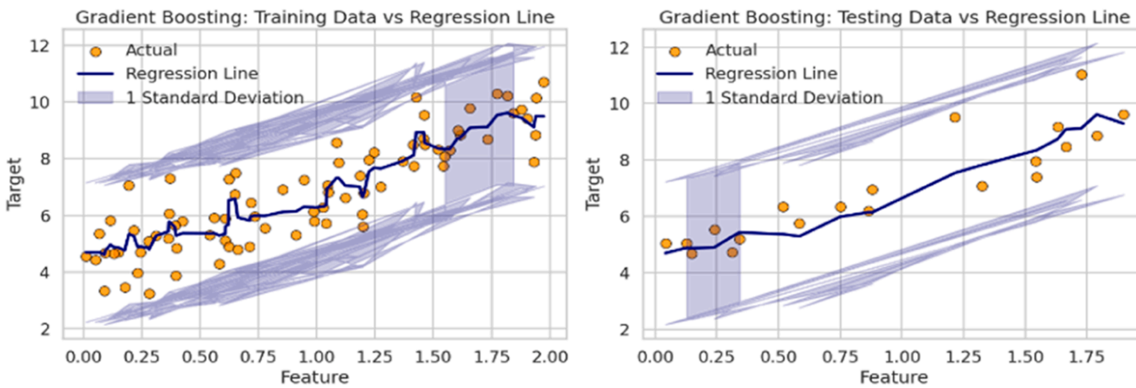

Fig. 10. Gradient boosting model performance on training and testing data with regression line and standard deviation.

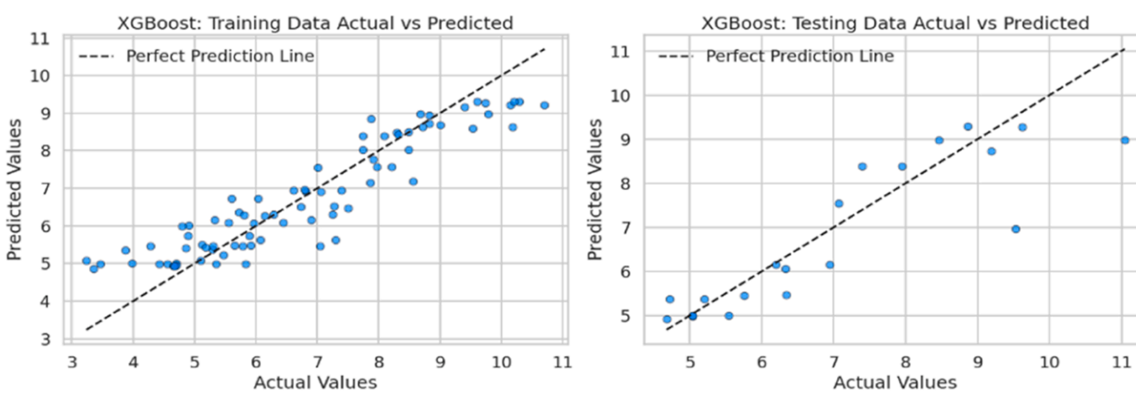

Fig. 11. XGBoost model performance on training and testing data (actual vs predicted values).

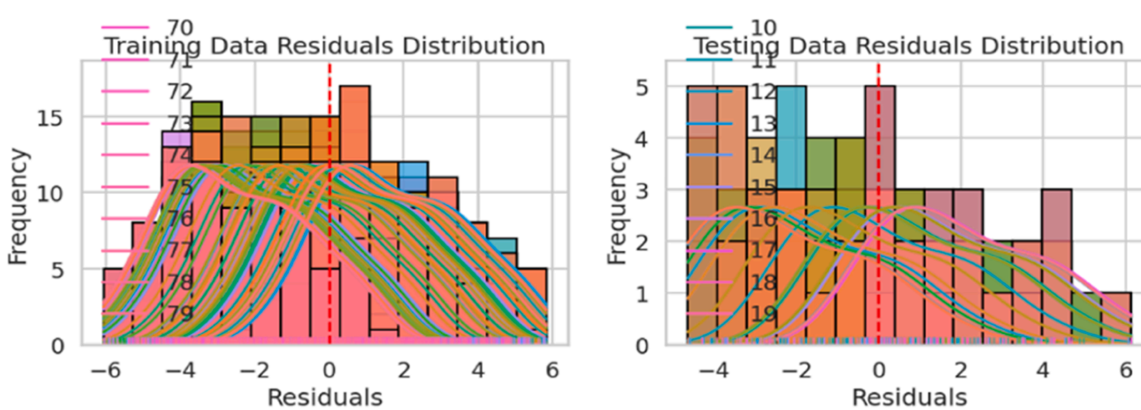

Fig. 12. Residuals distribution for training and testing data using XGBoost.

which shows how confident the model is in its predictions. The experimental results show that the regression line in the training set is very close to the actual value, which means the system accuracy is very high in the training state. Similar to the training data, the testing data also exhibits a good fit, but slightly larger standard errors, implying the model's ability to make reliable forecasts for new data. The model is effective in forecasting energy consumption, which is essential for optimizing energy management in smart homes.

Fig. 14 shows the comparison between the actual and predicted energy consumption values on data used for training and testing for the LightGBM Regression model for smart home Energy Management. In the training data, the predicted values are almost equivalent to the actual values, which depicts high accuracy in learning energy consumption patterns. The testing data exhibits the same trend though with more fluctuation, particularly at high values and this again can be attributed to the slight loss in accurate prediction of the unseen data. This signifies that the applied model is effective in predictive energy consumption efficiency which is useful in smart homes for efficient energy use.

Fig. 15 shows the residual plot for the training data set (left side) and the testing data set (right side) to evaluate how accurate the model is in the context of smart home energy management. The residuals where the difference between the actual energy consumption and the predicted values are significantly distributed around 0 in the training set means the model performs well on the training set. The residuals in the testing data are also revealing slightly more scatter but with fairly small mean values so the model seems to generalize well to new, unseen data points with only a moderate amount of error. This analysis is important to assess the ability of the proposed model to predict energy consumption,

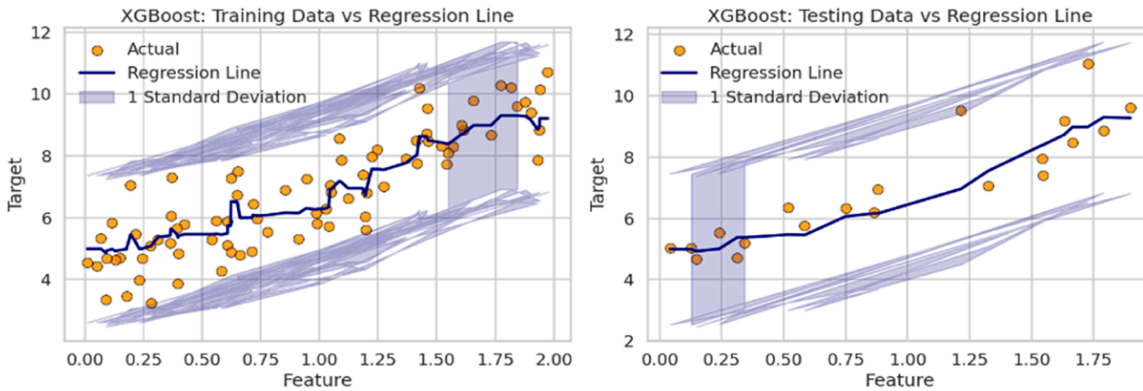

Fig. 13. XGBoost model performance on training and testing data with regression line and standard deviation.

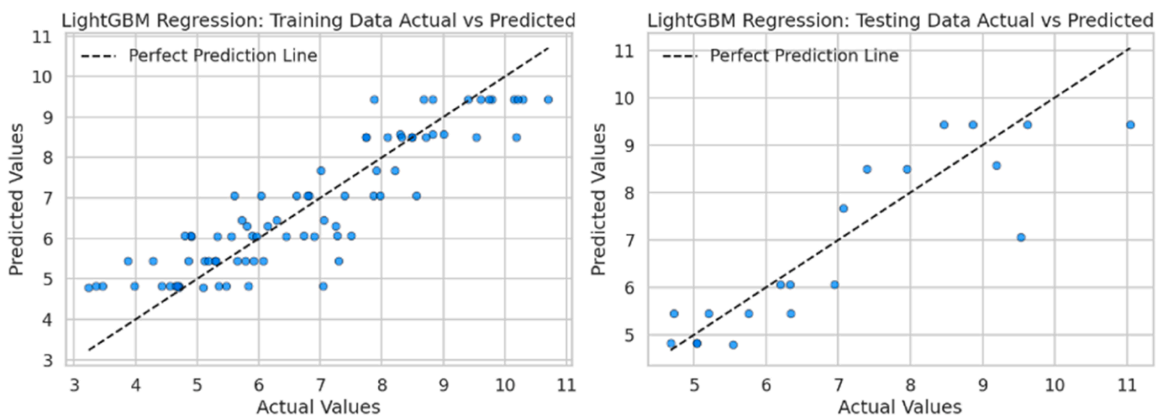

Fig. 14. Light GBM model performance on training and testing data (actual vs predicted values).

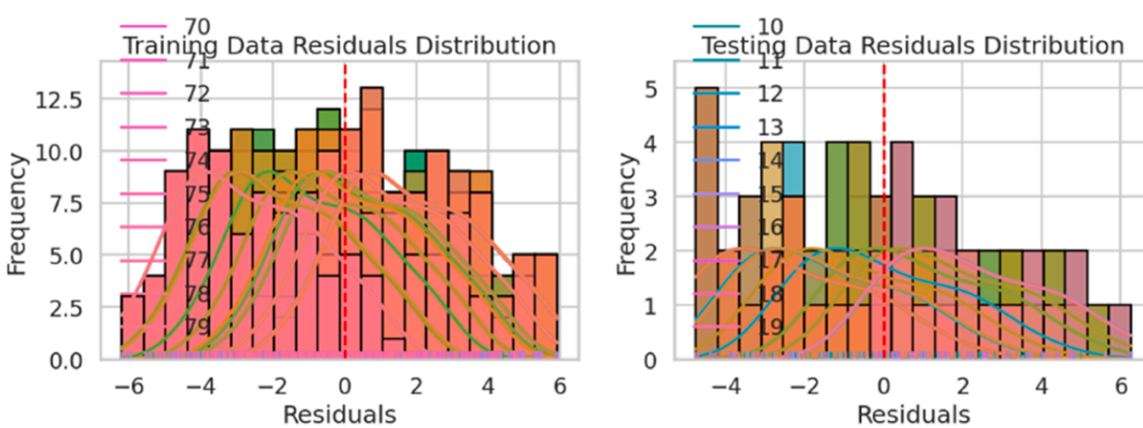

Fig. 15. Residuals distribution for training and testing data using light GBM.

which is important in managing energy consumption in smart homes.

Fig. 16 shows the actual energy consumption of a LightGBM Regression model to predict energy consumption for smart home energy management using both training and testing datasets with orange dots representing real energy consumption and a blue line representing the regression line. The area within the line equals one standard deviation, which indicates that the model has high confidence in its predictions. The training data set also shows a proper regression line where deviation bands are narrower around the actual values. In the testing data, however, the alignment is still good but the range of deviations is larger suggesting more variability in the unseen data.

Table 5 and Fig. 17 provide a detailed comparison of four local client models—Random Forest, Gradient Boosting Regressor, XGBoost, and LightGBM—across key performance metrics for both training and testing datasets. The performance is evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 score, which help assess the models' accuracy and generalization.

For the training data in the context of smart home energy management, the Random Forest model shows an MAE of 0.6097, MSE of 0.6234, and RMSE of 0.7896, with an R^2 score of 0.8221, indicating how well it explains the variance in the data. The Gradient Boosting Regressor reports an MAE of 0.5351, MSE of 0.4696, and RMSE of 0.6853, with an R^2 of 0.8660. For the XGBoost model, the MAE is 0.5947, MSE is

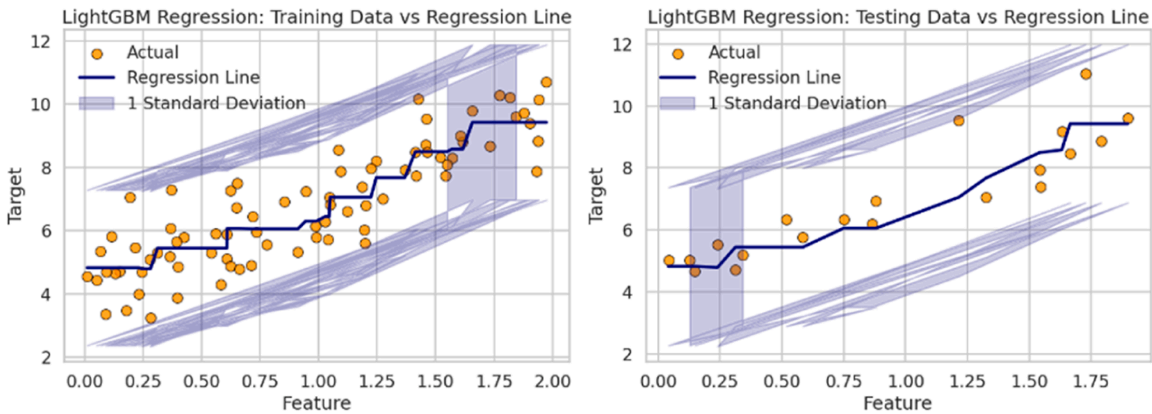

Fig. 16. Light GBM model performance on training and testing data with regression line and standard deviation.

Table 5
Comprehensive performance analysis of the local client models on training and testing.

Performance Matrices for the Local Models	Random Forest		Gradient Boosting Regressor		XGB		Light GBM	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
MAE	0.6097	0.6396	0.5351	0.6468	0.5947	0.6149	0.6677	0.6746
MSE	0.6234	0.6655	0.4696	0.6730	0.5702	0.7711	0.6961	0.7665
RMSE	0.7896	0.8158	0.6853	0.8204	0.7551	0.8781	0.8343	0.8755
R^2	0.8221	0.8036	0.8660	0.8014	0.8373	0.7725	0.8014	0.7739

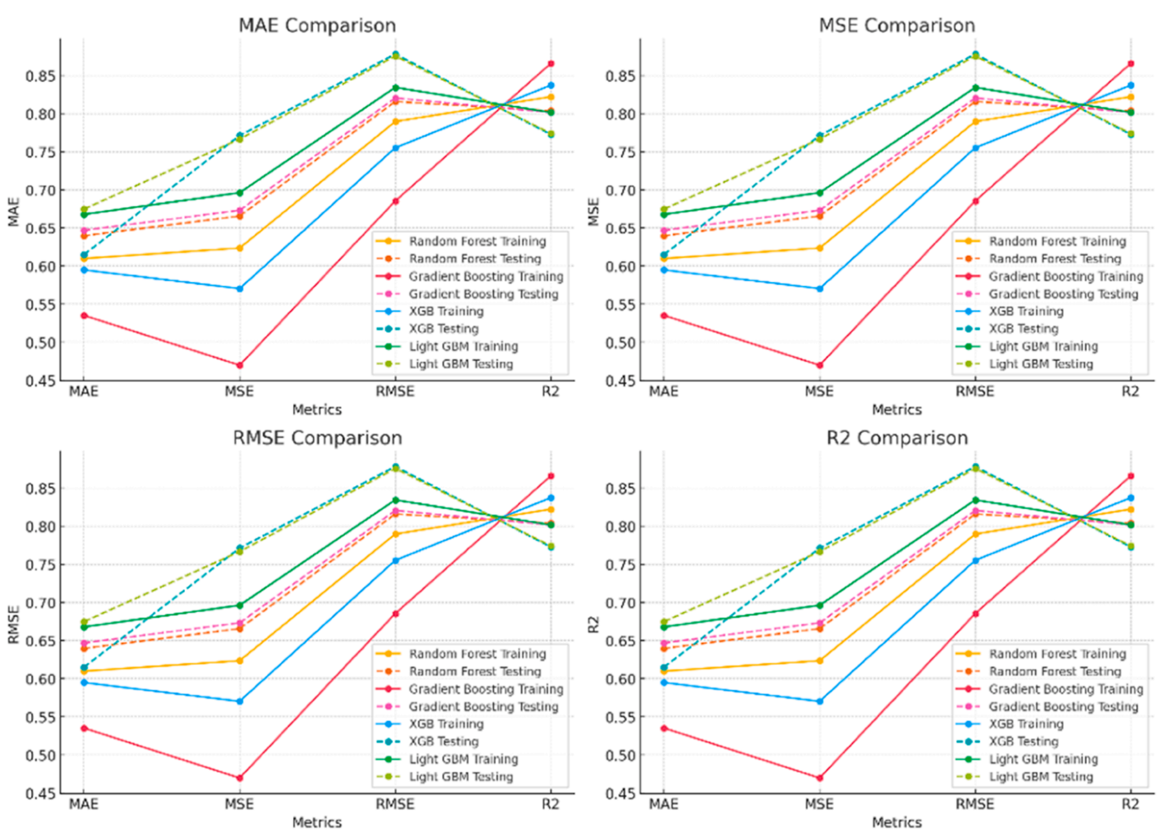

Fig. 17. Comprehensive performance analysis of the local client models on training and testing.

0.5702, and RMSE is 0.7551, with an R^2 of 0.8373. Lastly, LightGBM has an MAE of 0.6677, MSE of 0.6961, and RMSE of 0.8343, with an R^2 score of 0.8014.

In the testing data in the context of smart home energy management, the Random Forest model records an MAE of 0.6396, MSE of 0.6655, and RMSE of 0.8158, with an R^2 of 0.8036. The Gradient Boosting Regressor shows an MAE of 0.6468, MSE of 0.6730, and RMSE of 0.8204, with an R^2 of 0.8014. For XGBoost, the MAE is 0.6149, MSE is 0.7711, and RMSE is 0.8781, with an R^2 of 0.7725. LightGBM reports an MAE of 0.6746, MSE of 0.7665, and RMSE of 0.8755, with an R^2 score of 0.7739.

After the implementation of local client models, the performance results are fed into the global cloud server, where the FL concept is applied. This allows the aggregation of multiple local models without sharing raw data, preserving privacy. Through this process, the Random Forest model is selected as the best-performing global model for energy consumption prediction. The model demonstrated strong results with a Training MSE of 0.6235, indicating good accuracy on the local training data. In terms of testing performance, the model achieved a Testing MSE of 0.6656 and a Testing MAE of 0.6397, reflecting its ability to accurately predict energy consumption across different local clients and providing its effectiveness in smart home energy management on a global scale through federated aggregation.

Fig. 18 illustrates the performance of the Global Random Forest model for predicting energy consumption in smart home energy management. On the training data (left), the model's predicted values align closely with the actual values, as seen by the points clustering near the perfect prediction line, showing that the model has effectively captured energy consumption patterns. For the testing data (right), while the predictions still generally follow the actual values, there is more scatter, reflecting slightly lower accuracy on unseen data, which is expected in practical applications. The model performs well, making it useful for optimizing energy usage in smart homes.

Fig. 19 illustrates the residuals distribution for the Global Random Forest model applied to smart home energy management, comparing both training data (left) and testing data (right). Residuals represent the difference between actual and predicted values, and a distribution centered around 0 indicates accurate predictions. In the training data, the residuals are mostly centered near zero, showing a balanced and accurate prediction model. The testing data, though showing a slightly wider spread, still centers around zero, indicating reasonable predictive accuracy even on unseen data. This analysis helps evaluate the model's reliability for accurately forecasting energy consumption in smart homes, which is crucial for improving energy efficiency and management.

Fig. 20 compares the actual values (orange dots) with the predicted regression line (blue line) for the Global Random Forest model in the context of smart home energy management, shown for both training data (left) and testing data (right). The shaded area represents the 1 standard deviation, indicating the model's confidence in its predictions. In the training data, the regression line closely follows the actual values, with narrow standard deviation bands, suggesting the model has learned the energy consumption patterns well. In the testing data, the regression line still aligns with actual values, though with slightly wider deviation bands, reflecting more uncertainty in predictions for unseen data. This shows that the model performs effectively in forecasting energy usage, crucial for optimizing energy management in smart homes.

Fig. 21 shows SHAP dependence plot that explains the impact of a specific feature on the Global Random Forest model for smart home energy management. The x-axis shows the feature values, while the y-axis represents the SHAP values, indicating the feature's contribution to the model's prediction. Positive SHAP values mean the feature increases predicted energy consumption, while negative values reduce it. The colour gradient highlights the range of feature values, offering insight into how this feature influences the model's decisions, improving the transparency of AI-driven EMS in smart homes.

Fig. 22, the SHAP decision plot reveals a certain feature's influence on the Global model in relation to smart home energy control. The x-axis corresponds to the model output (predictive energy usage) and features are represented by the continuous colour range from blue to pink. Lower feature values put forward smaller usage of energy as per the predictions and higher feature values projected the opposite. This visualization aids in understanding the feature's impact on the model's decision-making making thus enhancing the understanding of energy consumption predictions in smart homes.

As illustrated in Fig. 23, the Local Interpretable Model-agnostic Explanations (LIME) plot provides insights into the contribution of each feature towards the predicted energy consumption in result of Smart Home energy management. The orange and blue bars reflect the positively (increasing) or negatively (decreasing) affecting feature on the predicted value. For instance, features such as col_0 and col_20 highly contribute to the push of this prediction up; on the other hand, features like col_7 and col_5 slightly pull the predicted energy usage down. The actual values of these features are provided on the right table, which enables a clearer understanding of what particular indices contribute to the energy usage predictions. This makes it easier for the users to gain knowledge and be in a position to control the energy consumption in smart homes.

Table 6 compares multiple ML models in terms of MSE for energy consumption predictions (Kim and Cho, 2019; Khan et al., 2021; Fan et al., 2019; Bouktif et al., 2018; Kim and Cho, 2019; Ullah et al., 2021; R. Singh et al., 2024; Tan et al., 2019). It is clearly shown that the proposed Global Model performs well with the lowest MSE of 0.6655, making it the most accurate model for energy consumption prediction.

7. Conclusion

Several practical issues that arise in the context of smart buildings' energy management are data privacy issues, the requirement for fast decision-making, and the integration of distributed energy resources. In centralized systems, security difficulties arise as well as the lack of decision explainability when the model is an AI-based one, which often functions as a non-transparent 'black box'. These systems also do not fare well in scalability and flexibility as energy grids change over time. The proposed solution, FL and XAI, perfectly suits these challenges, as it will be further discussed. FL decentralizes model training; data are stored locally in nodes; and privacy is preserved while not requiring data

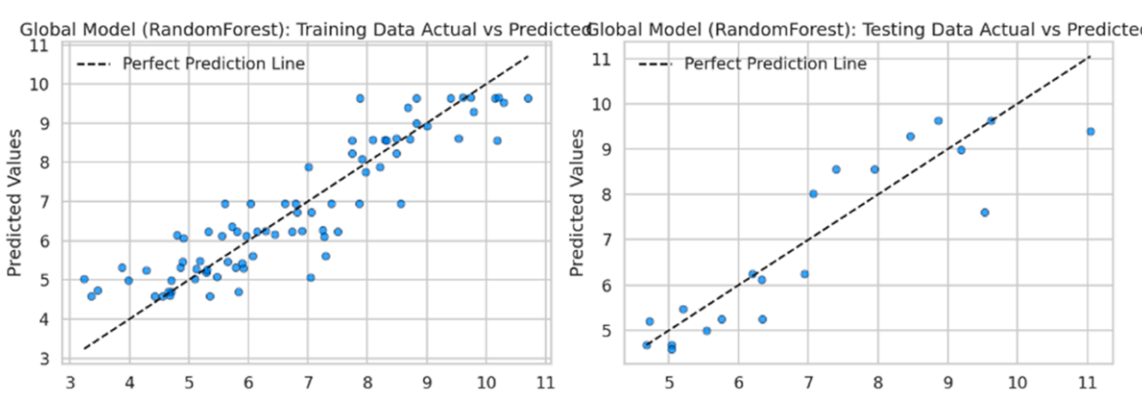

Fig. 18. Global model performance on training and testing data (actual vs predicted values).

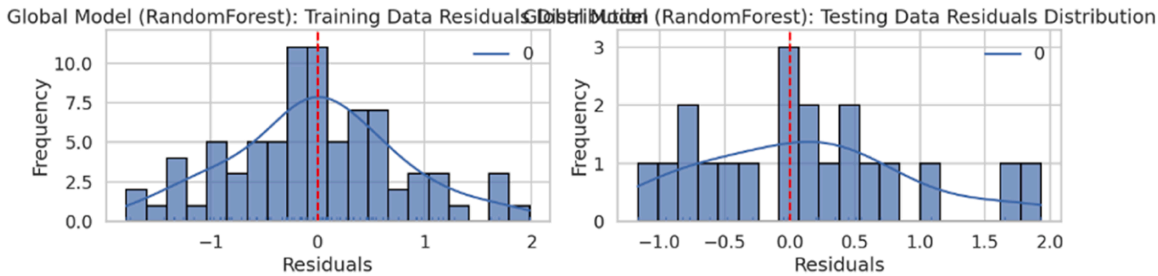

Fig. 19. Residuals distribution for training and testing data using light GBM.

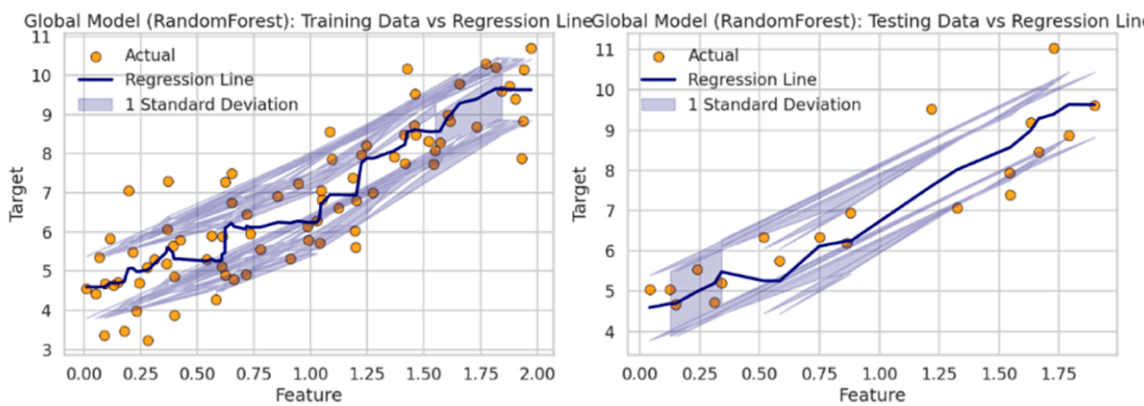

Fig. 20. Global model performance on training and testing data with regression line and standard deviation.

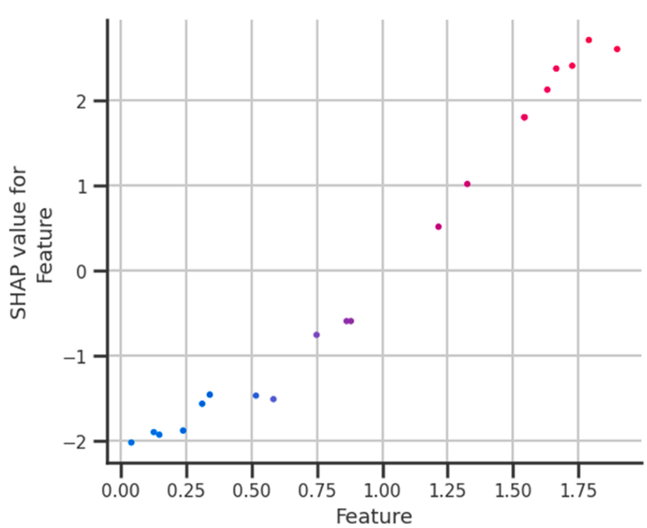

Fig. 21. SHAP dependence plot for feature impact on global model in smart home energy management.

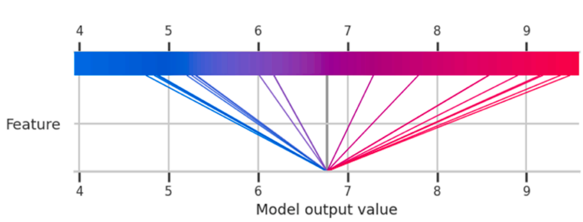

Fig. 22. SHAP decision plot showing feature impact on global model in smart home energy management.

aggregation for accurate decision-making. At the same time, XAI enhances the interpretability and comprehensibility of the AI's decisions, thereby reducing user uncertainty. This combination enhances system efficiency, scalability, and security, offering a flexible, transparent, and resilient framework for smart energy management in modern decentralized energy systems.

8. Limitations and future work

The proposed global model addresses key challenges like privacy and transparency but may face limitations, such as increased communication overhead in FL and challenges in fully explaining complex AI decisions with XAI, particularly for non-expert users.

In future, the paper will focus on reducing FL's communication overhead and enhancing XAI's interpretability. Expanding the model's adaptability to diverse energy datasets and smart city environments will also be explored.

CRediT authorship contribution statement

Khan Muhammad Adnan: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Farooq Muhammad Sajid:** Methodology, Formal analysis, Conceptualization. **Saleem Muhammad:** Writing – original draft, Software. **Shahzad Tariq:** Writing – original draft, Visualization, Methodology. **Ahmad Munir:** Writing – original draft, Visualization, Formal analysis. **Abbas Sagheer:** Writing – review & editing, Validation, Software, Methodology. **Abu-Mahfouz Adnan M.:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition.

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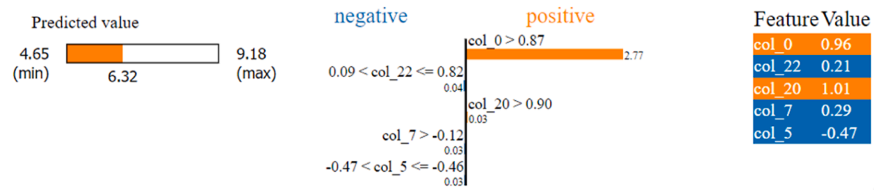

Fig. 23. LIME plot explaining feature contributions to predict energy consumption in smart home.

Table 6
Comparative analysis of the proposed global model with previous works.

References	Models	MSE
(Kim and Cho, 2019)	LSTM	0.7480
(Kim and Cho, 2019)	GRU	0.7432
(Kim and Cho, 2019)	Bi-LSTM	0.7235
(Khan et al., 2021)	CNN-LSTM	28.57
(Fan et al., 2019)	NN, RNN, LSTM	118.2
(Bouktif et al., 2018)	LSTM with Genetic Algorithm-based Time Lag Optimization	270.4
(Kim and Cho, 2019)	MLP	0.7621
(Ullah et al., 2021)	SVR based Ensemble learning algorithm using 10 fold	6.0581
(R. Singh et al., 2024)	Linear Regression	3.561
(R. Singh et al., 2024)	Support vector regression	3.059
(Tan et al., 2019)	LSTM	0.792
Proposed Global Model	Random Forest	0.6655

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The original contributions presented in the study are included in the article; further inquiries can be directed to the corresponding author.

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