A Performance Study of Cutting-Edge Technologies for Energy Consumption Prediction in Smart Buildings

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***Abstract*—Energy efficiency is crucial in modern smart building management. Effective energy management not only reduces operational costs but also promotes environmental sustainability by reducing carbon emissions. Additionally, optimizing energy usage improves occupant comfort and productivity, contributing to a healthier and more sustainable built environment. Recently researchers have focused on cutting-edge technologies to develop efficient models that predict energy consumption and ensure a trade-off between occupant, provider and environment needs. Among such technologies, Internet of Things (IoT), edge/fog computing, and federated Learning (FL) have significantly have proven their efficiency in this domains. In this paper, we provide a performance analysis of such technologies for energy consumption prediction in smart buildings. According to a set of defined criteria, we select some recent proposed techniques and we study their performance through various assessment metrics. Our idea behind such comparison is to identify promising techniques while using Friedman test and furthermore highlight further open research problems in the domain. Real-world data has been used to measure and evaluate each approach providing valuable insights for practical implementation and deployment in smart building environments.**

***Index Terms*—Smart Buildings, Energy Management, Predictive Models, Cutting-Edge Technologies, Friedman Test.**

I. Introduction

RECENTLY, energy efficiency has gained a significant attention from research and market communities, and it represents a key concern for companies, institutions, and governments. With the increasing number of population, the economic viability and the concerns mounted over environmental sustainability, the need to optimize energy usage has become essential nowadays [1]. One of the big contributors of energy consumption is buildings with their various purposes, e.g. residential, commercial, industrial, governmental, etc. Energy consumption in such buildings can be significantly influenced by external conditions, such as weather changes and meteorological factors, and internal conditions, such as the number of occupants and their behaviors. Such conditions can highly impact the use of heating and cooling systems, appliances and machines, and overall energy demand in buildings. Thus, understanding and analyzing these conditions influences are critical for developing effective energy management strategies and optimizing energy consumption in such buildings.

Cutting-edge technologies have emerged as an efficient solution for managing energy consumption in buildings. On one hand, the Internet of Things (IoT) is used as a pivotal technology that offers unprecedented opportunities to revolutionize energy management practices. By enabling seamless connectivity and data exchange among devices, IoT facilitates real-time monitoring and control, leading to more efficient energy consumption. On the other hand, the integration of Edge/Fog Computing (EFC) and Federated Learning (FL) will further improve the efficiency of energy optimization solutions. Hence, EFC decentralizes computing resources, enabling quicker decision-making and response to data generated by IoT devices, while FL allows collaborative and privacy-preserving across decentralized devices, leading to personalized and optimized strategies. The combination of such technologies in a one system allow the optimization of energy consumption in smart buildings.

Aiming to highlight the importance of cutting-edge technologies, particularly IoT, FEC and FL, in managing and predicting energy consumption, this paper presents a performance analysis study of the recent advances of such technologies in smart buildings. Our objective is two-fold: first, we perform an analysis and experimental comparative study of some selected research works according to a defined set of assessment metrics. The selection of existing techniques was based on their novelty, contributions, and publication in reputable journals. Considering that no technique is performing well for all the metrics, we then employ a statistical test, i.e. Friedman test, to determine promising techniques that stand out as the most efficient solution for addressing the multifaceted challenges in energy management systems. The simulation and experimental study was done using real-world data to measure and evaluate each technique while providing valuable insights for practical implementation and deployment in a smart building.

The remaining sections of the paper are structured as follows. Section II presents the comparative study of literature review techniques. Section III describes the performance metrics used in the comparative study. In section IV, we describe the simulations performed in this study along with the used dataset and the discussion of the results. In section V, we provide opportunities and future directions for ongoing researches. The paper is concluded in section VI.

II. Energy Consumption Prediction in Smart Buildings: A Comparative Study

Researchers have largely integrated cutting-edge technologies in designing energy consumption models dedicated to smart buildings [2–9]. In this section, we particularly focus on some promising techniques proposed recently in the literature and demonstrated efficient performance compared to other existing ones.

A. Energy Management in Smart Homes

The authors in [10] introduced an efficient approach to predict the energy consumption in smart home environments based on resident activities and behaviors. The proposed technique is a Markov-chain-based probabilistic model where the generated predictions are utilized by a developed comfort-aware energy-saving mechanism named as prediction- and feedback-based proactive energy conservation (PF-PEC). The aim of PF-PEC is to reduce the total energy consumption while maintaining standard human comfort levels. In addition, the authors implemented a fog-based Internet of Things (IoT) architecture to seamlessly integrate PF-PEC into real-world scenarios.

B. SHEMS for Residential Demand-Side Management

The authors in [11] presented a Smart Home Energy Management System (SHEMS) based on Tridium's Niagara Framework tailored for residential demand-side management. Basically, SHEMS focuses on optimizing energy usage and improving management practices within smart homes. It involves a two-stage Non-Intrusive Appliance Load Monitoring (NIALM) system: the first stage uses fog-cloud computing to analyze aggregated current and voltage measurements from a minimal set of plug-panel sensors for efficient load management of relevant electrical appliances. The second stage integrates Artificial Neural Networks (ANN) for more comprehensive data analysis. Indeed, such fog-cloud analytics play a crucial role in processing and analyzing data, ensuring the system scalability and responsiveness. Data are collected from electrical appliances that were targeted, learned, and recognized through AI including a laptop, hair dryer, steamer, electric fan, and vacuum cleaner.

C. Distributed FL-based Load Forecasting Mechanism

In [12] the authors study a federated learning based mechanism for load forecasting using smart meter data. This mechanism allows the training of a Long Short-Term Memory (LSTM) model using data from all participating smart meters, without necessitating the sharing of local data. Furthermore, the authors examine two alternative federated learning strategies: the first one is FedSGD, which conducts a single step of gradient descent on the client before consolidating updates on the server. The second one is FedAVG, which executes multiple steps before consolidation. Given the diverse nature of residential consumers, training a single model poses challenges due to variations in load profiles among consumers. The performance of both FedAVG and FedSGD models is tested on real-world data provided by London Hydro through Green Button Connect My Data (CDM).

D. Integrating FL and Clustering for Electrical Load Forecasting

The work presented in [13] introduced a hybrid approach for predicting individual household and aggregate electrical demands, with a focus on preserving data privacy through federated learning and edge computing. The proposed approach is based on: 1) FedAvg for data aggregation, 2) LSTM for time-series analysis and forecasting, and 3) a clustering method with hyperparameter tuning where clients are grouped based on their data similarities. Then, and algorithm is integrated into the federated learning stage in order to detect and remove consumers deterring the global model. Consequently, the training loss of clients in each round is assessed and compared to previous rounds to check whether it is getting smaller or not; the clients whose loss is 60% worse compared to 20 rounds ago are removed from the federated learning process. Such operation not only guarantees precise predictions but also tackles the crucial issue of data privacy in the realm of electrical load forecasting.

E. Residential Load Forecasting Using Modified FL

The authors in [14] aimed to achieve day-ahead forecasting for residential load by employing a customized federated learning algorithm, with a particular emphasis on customer demand management. The proposed approach entails training local models for clients within the federated learning framework using LSTM architecture. In addition, the approach allows the determination of each client local model performance for acceptance in the global model and the utilization of the Adam optimizer. Data collected from $3,226$ households of 40 buildings in Seoul, South Korea have been used in the training and validation of LSTM model.

F. Data Silos Problem using FL

An efficient approach for tackling data silos in building energy consumption prediction is presented in [15]. By harnessing federated learning and employing an Artificial Neural Network (ANN) model, the proposed approach enables collaborative model training across decentralized datasets. The incorporation of an ANN model highlights its capability to capture intricate patterns, enhancing the accuracy of short-term energy consumption predictions. In the training stage, operational data from 13 similar office buildings are used and are located in the cold climate zone with similar gross floor areas.

G. Comparative Study: A Summary

Table I summarizes the compared techniques according to some factors including the publication year, the approaches of cutting-edge technologies used in the architecture, and the used models and methods.

Table I
COMPARATIVE STUDY: A SUMMARY.

Ref.	Year	Cutting-Edge Technologies			Models
		IoT	FEC	FL	
[10]	2023	X	X		Markov-chain, PF-PEC
[11]	2021	X	X		SHEMS, NIALM, ANN
[12]	2022	X		X	LSTM, FedSGD, FedAVG
[13]	2022	X		X	FedAvg, LSTM, Clustering
[14]	2023	X		X	FedAAVG, LSTM
[15]	2022	X		X	ANN, Aggregation

III. PERFORMANCE METRICS DESCRIPTION

In order to evaluate the efficiency of the cutting-edge based techniques described in the previous section, we employ 7 performance metrics that are widely used in the literature to assess the energy consumption in smart buildings.

1) Mean Squared Error (MSE): It is a statistical measure used to quantify the average squared difference between the predicted and actual energy consumption values, measured in kilowatt-hours (kWh). It serves as a measure of the accuracy of prediction models, while lower MSE values indicating better performance in estimating energy consumption. MSE is calculated as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{1}$$

Where:

- n indicates the number of observations.
- Y_i indicates the actual value for observation i
- $\hat{Y}_i$ indicates the predicted value for observation i

2) Root Mean Squared Error (RMSE): It is a metric used to quantify the typical magnitude of errors between predicted and actual energy consumption values. RMSE is calculated similarly to MSE, but it takes the square root of the average squared differences between the predicted and actual values. Lower RMSE values indicate better performance in estimating energy consumption. RMSE is often expressed in units of kWh, similar to MSE. RMSE can be calculated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \tag{2}$$

Where n, Y_i, and $\hat{Y}_i$ are similarly defined to those in Eq. (1).

3) Mean Absolute Error (MAE): It is a metric used to measure the average absolute difference between the predicted and actual energy consumption values with units typically expressed in kWh. MAE provides a straightforward measure of prediction accuracy, calculated by averaging the absolute differences between predicted and actual values. Like MSE and RMSE, lower MAE values indicate better performance in estimating energy consumption. MAE calculation is shown as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i| \tag{3}$$

4) R-squared (R^2): It is a statistical metric used to evaluate the goodness-of-fit of a predictive model. It indicates the proportion of the variance in the energy consumption data that is explained by the independent variables included in the model. R^2 values range from 0 to 1, with higher values indicating a better fit of the model to the data. R^2 is calculated according to the following equation:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \tag{4}$$

Where $\bar{Y}$ is the mean of the actual values Y_i.

5) Accuracy: It refers to the closeness of predicted energy consumption values to the actual energy consumption values, typically measured as a percentage (%). Accuracy is a measure of how well a predictive model performs in estimating energy usage patterns. Higher accuracy indicates that the model predictions closely align with the actual energy consumption data, while lower accuracy suggests discrepancies between predicted and observed values. The following equation show the calculation of accuracy metric:

$$Accuracy = \frac{NumberofCorrectPredictions}{TotalNumberofPredictions} \tag{5}$$

6) Average Latency: It refers to the average amount of time taken for a predictive model to generate predictions of energy consumption data, typically measured in seconds (s). Average latency measures the delay between the input of data to the model and the output of predictions. Lower latency values indicate quicker prediction times, allowing for faster responses to changes in energy consumption patterns.

7) Execution Time: It refers to the duration for a program to complete data processing, cleaning, model training, and prediction generation, typically measured in seconds (s). It covers loading, preprocessing, cleaning, model training, and prediction for energy consumption. Lower times mean faster processing, enabling quicker insights and responses to energy usage changes, vital for efficient energy management systems.

IV. PERFORMANCE EVALUATION

In our simulation, we used a HPE ProLiant ML150 Gen9 Server with a processor of 64-bit 6-core Intel Xeon CPU running at 1.7 GHz. In addition, the used RAM is 64 GB and the storage capacity is 240 GB SSD with 8 TB HDD. The server runs Windows Server 2012 R2. We implemented all techniques using Python.

A. Dataset Description

The Pecan Street dataset was used for simulations. It is a well-known benchmark dataset in the field of energy consumption prediction in smart buildings. This dataset is widely used for evaluating and benchmarking total energy consumption. It includes minute-interval appliance-level customer electricity use from nearly $1,000$ houses and apartments in Pecan Street's multi-state residential electricity use research, as well as

ERCOT market operations. For prediction purposes, we took 2 years worth of continuous electricity usage data of 12 houses comprising $17,428$ raw data from the Pecan Street dataset. Using one house of electrical usage was very low to predict so we chose a bunch of houses usage and used a summation of it as the electricity usage. The dataset contains 10 features for each record, which provide information about weather data from weather underground and energy usage data. Table II shows the feature description along with their measurement units.

Table II
DATASET DESCRIPTION.

Feature	Unit
DateTime	timestamp
TotalUsage	Kwh
Month	1-12
Temperature	Fahrenheit
Humidity	%
Hour of the day	0-23
Minute of the day	0-3599
Day of week	0-6
Weekend/Weekday	0/1
Holiday	0/1

B. Result Discussion

Table III shows the performance of each technique in terms of various tested metrics. The table reveals that all techniques show promising results for real-time monitoring of energy consumption in smart buildings and accurately predicting the occupant behavior and need. This demonstrates the powerful of cutting-edge technologies integrated in efficiently managing the energy in smart buildings. Furthermore, the following observations are eminent:

- There is no dominating technique that performs optimally according to all performance metrics.
- Edge and fog based techniques perform better in terms of computation compared to those based on federated learning (see results of average latency and execution time metrics).
- Techniques use neural network models, particularly LSTM and ANN, in their architecture give better prediction accuracy compared to those without neural networks.

Table III
RESULTS COMPARISON.

Approaches/ Metrics	[10]	[11]	[12]	[13]	[14]	[15]
MSE	92.8	23.27	**16.72**	19.99	42.53	16.77
RMSE	9.63	4.82	**4.08**	4.47	6.52	4.09
MAE	7.66	3.67	**3.03**	3.27	4.84	3.06
R^2	0.57	0.89	0.91	0.91	0.8	**0.92**
Accuracy	57.12	89.28	92.3	**94.82**	80.35	92.25
Average latency	**0.11**	0.54	0.99	0.92	0.88	0.68
Execution time	**0.26**	41.9	224.2	856.03	117.12	145.72

C. Best Approach Selection

The results of Table III demonstrated that the selection of the best approach should be highly dependent on the performance metrics. For instance, the technique proposed in [13] is considered as the best powerful one in terms of accuracy, but not for other metrics. To determine the best performant technique according to all metrics, a statistical test should be used. We focused on the Friedman test that is a non-parametric statistical method designed for comparing multiple related groups. Friedman test is an extension of the Wilcoxon signed-rank test and suitable for scenarios in which data may not adhere to a normal distribution. Additionally, such test is valuable in scenarios where the dependent variable is measured on an ordinal scale, and observations are paired or matched across all conditions or levels of the independent variable.

Typically, the procedure of applying the Friedman test involves ranking the data for each group independently based on the squared differences between the ranks of corresponding observations across different groups. The null hypothesis assumes no difference among the groups, while the alternative hypothesis posits a significant difference. If the p-value associated with the Friedman statistic is below the chosen significance level, the null hypothesis is rejected, indicating a significant difference among the groups. Then, post-hoc tests, such as bilateral test, can be employed to pinpoint specific group differences when the overall test yields a significant result. In our case, e.g. energy consumption in smart buildings, Friedman test is applied according to the following steps:

- We consider Table III as a matrix $\mathcal{M}[7][6]$, where 7 indicates the number of performance metrics and 6 represents the number of compared techniques. Thus, each column depicts the performance of one technique according to all metrics and each row depicts the performance of all techniques given one metric.
- For each metric m, we rank each technique t from 1 to 6 based on its performance.
- We calculate the sum of ranks R_t for each technique according to all the metrics: $R_t = \sum_{m=1}^{7} t_m$.
- We calculate the Friedman distribution:
$$\mathcal{F} = \frac{12}{M \times T(T+1)} \sum_{t=1}^{T} R_t^2 - 3 \times M(T+1) \qquad (6)$$
where M indicates the total number of metrics and T is the total number of techniques.
- We compared the computed Friedman result to the chi-squared distribution with $T-1$ degrees of freedom to obtain the p-value. In this study, we fixed p-value to 0.005 to minimize the risk level of rejecting the hypothesis.
- We finally apply Nemenyi test to perform pairwise comparison between the techniques. To do so, we calculated the average rank for each technique which serves as an aggregate measure of performance across all evaluated metrics. After determining the highest average rank, we identify the technique that, on average, performed the best across all metrics considered. In our analysis, the results show that he technique proposed in [12] acts as the best one existing in this domain.

V. Opportunities and Future Directions

Indeed, the literature review demonstrated huge researcher efforts to integrate cutting-edge technologies into energy management in smart buildings. However, the effectiveness of such integration is significantly impacted by internal and external building factors such as the number of residents, the weather conditions, etc. Such dynamic factors pose crucial challenges for the traditional energy management systems whether in the infrastructure or data analysis levels. Hence, there is a growing emphasis on improving the proposed solutions or developing new efficient ones that are adaptable to such factors. In light of this study, we provide opportunities and directions for ongoing researches to address some key considerations in the design and implementation of energy management in smart buildings. We also highlight strategies and technologies to enhance performance and resilience of the existing solutions.

A. Scalability

- *Description*: it refers to the ability of the smart building system to accommodate a growing number of edge devices, fog nodes, and data sources while maintaining performance and efficiency.
- *Challenges*: as the number of devices and data sources increases in smart building environments, scalability becomes a significant concern. Scaling machine/deep learning algorithms to handle a large volume of data distributed across edge devices and fog nodes without compromising performance and efficiency poses challenges.
- *Considerations*: designing scalable architectures and algorithms that can efficiently distribute computational tasks, manage communication overhead, and ensure synchronization among distributed components is crucial for energy management in smart buildings. Additionally, implementing mechanisms for dynamic resource allocation and load balancing can help address scalability challenges.

B. Security and Privacy

- *Description*: both keys arise due to the decentralized nature of edge/fog computing and the sensitive nature of data collected from smart building environments.
- *Challenges*: protecting the privacy of data and ensuring secure communication between edge devices, fog nodes, and central servers is paramount. Edge devices may have limited security capabilities, making them vulnerable to cyber threats and attacks. Furthermore, federated learning involves sharing model updates and aggregated information across distributed nodes, raising concerns about data leakage and unauthorized access.
- *Considerations*: implementing robust encryption techniques, authentication mechanisms, and access control policies to safeguard data privacy and ensure secure communication is essential. Additionally, incorporating privacy-preserving techniques such as differential privacy and secure multi-party computation can mitigate privacy risks associated with federated learning.

C. Performance Management

- *Description*: it involves the optimization of system performance in terms of computational efficiency, latency, and throughput while minimizing energy consumption and resource utilization.
- *Challenges*: ensuring optimal performance of machine learning algorithms on resource-constrained edge devices and fog nodes is challenging. Factors such as limited processing power, memory, and bandwidth can impact the performance of distributed learning tasks. Moreover, coordinating model training and aggregation processes across heterogeneous devices introduces latency and communication overhead.
- *Considerations*: employing lightweight machine learning models, efficient communication protocols, and task scheduling algorithms can improve performance management in integrated edge/fog computing and federated learning systems. Additionally, leveraging edge caching and pre-processing techniques to reduce data transmission and processing overhead can enhance overall system performance.

D. Network Management

- *Description*: it involves overseeing the communication infrastructure connecting various devices within the smart building ecosystem, including edge devices, fog nodes, and central servers.
- *Challenges*: managing the network architecture in smart buildings presents challenges such as ensuring low latency, high reliability, and seamless connectivity across heterogeneous devices and communication protocols. Additionally, accommodating the dynamic nature of smart building environments, where devices may join or leave the network frequently, adds complexity to network management tasks.
- *Considerations*: implementing robust network protocols and architectures, such as 5G, Wi-Fi v6, and LoRaWAN, can provide high-speed, reliable connectivity tailored to the diverse requirements of smart building applications. Furthermore, integrating network management solutions with edge computing platforms can facilitate real-time monitoring, analysis, and optimization of network traffic, enhancing overall system reliability and responsiveness.

E. Cost Effectiveness

- *Description*: it involves optimizing the deployment and operation costs associated with integrated edge/fog computing and federated learning systems. This encompasses expenses related to hardware procurement, infrastructure setup, and ongoing operational expenditures.
- *Challenges*: deploying and managing edge devices, fog nodes, and central servers incur various costs, including hardware acquisition, infrastructure setup, and ongoing operational expenses. Additionally, federated learning necessitates substantial computational resources and communication bandwidth for model training and aggregation, leading to increased energy consumption and resource utilization.
- *Considerations*: adopting cost-effective hardware platforms, energy-efficient algorithms, and resource provi-

sioning strategies can help mitigate the financial implications of deploying and operating integrated systems. Furthermore, exploring cloud-based solutions for offloading computational tasks and leveraging serverless computing models can reduce infrastructure costs and improve cost-effectiveness.

F. Big Data Processing

- *Description*: it involves handling and analyzing large volumes of data generated by edge devices and sensors in smart building environments.
- *Challenges*: processing and analyzing big data in real-time presents challenges due to the distributed nature of edge/fog computing and the heterogeneity of data sources. Moreover, traditional centralized data processing approaches may not be suitable for handling the velocity, variety, and volume of data generated in smart building environments.
- *Considerations*: leveraging distributed data processing frameworks, stream processing techniques, and edge analytics algorithms can enable efficient handling and analysis of big data in integrated edge/fog computing environments. Additionally, employing data compression, filtering, and aggregation methods at the edge can reduce data transmission and storage overhead, facilitating real-time analytics and decision-making.

VI. Conclusions

Predicting the energy consumption in smart buildings will continue to emerge as a hot topic for research and market communities. This is due to the crucial need of reducing the operational costs and converging toward sustainable environment. Consequently, the integration of cutting-edge technologies, mainly IoT, edge/fog computing and federated learning, into smart buildings is demonstrating as a promising solution to overcome the challenges related to energy management in such systems. In this paper, we studied the performance of such technologies according to a set of defined metrics. By identifying potential techniques from the literature review, we implemented, tested, and identified promising techniques using Friedman test. In our evaluation, real-world data is used while providing valuable insights for practical implementation and deployment in smart building environments.

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